# Leveraging Multimodal Classroom Data for Teacher Reflection: Teachers' Preferences, Practices, and Privacy Considerations

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Technology Enhanced Learning for Inclusive and Equitable Quality Education

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## Abstract

Teacher reflection is essential for K-12 classrooms, including effective and personalized instruction. Multimodal Learning Analytics (MMLA), integrating data from digital and physical learning environments, could support teacher reflection. Classroom data collected from sensors and TEL environments are needed to produce such analytics. These novel data collection methods pose an open challenge of how MMLA research practices can ensure alignment with teachers' needs and concerns. This study explores K-12 teachers' perceptions and preferences regarding MMLA analytics and data sharing. Through a mixed-method survey, we explore teachers' (N = 100) preferences for analytics that help them reflect on their teaching practices, their favored data collection modalities, and data-sharing preferences. Results indicate that teachers were most interested in *student learning analytics* and their *interactions* and *ways of motivating students*. However, they were also significantly less accepting of *collecting* students' audio and position data compared to such data about themselves. Finally, teachers were less willing to *share* data about themselves than their students. Our findings contribute ethical, practical, and pedagogical considerations of MMLA analytics for teacher reflection, informing the research practices and development of MMLA within TEL.

K. B. Yang and C. Borchers contributed equally to this research.



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## Keywords

Multimodal Learning Analytics | Teacher Tools | Privacy | Teacher Reflection


## 1 Introduction and Background

Technology-enhanced Learning (TEL) accelerates the integration of learning analytics tools in authentic classroom practices (e.g., [6, 12, 24]). Analytics produced through TEL have been recognized for their potential to enhance teaching and learning by enhancing teachers' perception and decision-making processes [20]. Specifically, recent frameworks in the field of artificial intelligence in education have highlighted the opportunity of analytics to augment human strengths while compensating for weaknesses and related needs [11]. The present study asks what preferences, needs, and considerations of teachers can inform analytics that support a critical component of teacher professional development: teacher reflection [20]. Related to the teachers' learning to notice framework [9], teacher reflection may involve behaviors, teachers' identifying noteworthy features of classroom interactions (attending); and using teachers' knowledge and experiences to make sense of what is observed (interpreting). Prior research found that teacher reflection scaffolds critical thinking, provides a source of knowledge construction in teaching, and promotes self-regulation in teachers [18]. Prior work also studied teachers' preferred adoption and suggestions technology to support teacher reflection [23]. However, more work is needed to understand how reflection tools can be designed to fit teachers' routines and consider teachers' practical need to balance workload and to customize analytics [20].

Multimodal Learning Analytics (MMLA) is defined as "a set of techniques that can be used to collect multiple sources of data in high frequency (video, logs, audio, gestures, biosensors), synchronize and code the data, and examine learning in realistic, ecologically valid, social, mixed-media learning environments" [10]. The advent of MMLA promises to enrich the understanding of educational contexts by integrating and analyzing data from teachers and students across digital and physical learning environments, including physiological, behavioral, and environmental cues [6]. For example, Lee et al. studied the theoretical and instructional design aspects of how multimodal learning technologies settings by outlining the conceptual landscape and potential gaps [16]. Olsen et al. used temporal analysis of multimodal data to predict the outcome of collaborative learning [13]. The cardiopulmonary resuscitation (CPR) tutor uses multimodal data streams (i.e., kinematic and electromyographic data) to predict mistakes and automatically provide audio feedback and support learners in improving their CPR performance [8].

Thus, MMLA promises to improve educational technology design that supports teacher reflection. MMLA seeks to provide a more holistic view of the classroom, as it may capture traces of teacher and student behaviors (such as student engagement, performance, cognition, and emotional states), thereby enabling a more informed approach to teachers' reflection on instruction and learning. While analytics can offer valuable insights into teaching and learning processes, there is a significant gap in understanding which data elements and analytics are most beneficial for teachers [2, 25]. Recent literature reviews reported that MMLA solutions often focus on developing computational models, capabilities, and analytics for research purposes rather than researching stakeholder preferences, privacy concerns, and reluctance to share sensitive data [1, 25]. Cukurova et al. highlight that MMLA, venturing into complex territories with scarce guidelines and regulations, needs special consideration for vulnerable populations, such as children, so as not to contribute to a surveillance culture or invade privacy [6, 19]. Given the potentially invasive nature of using multimodal data and AI in classrooms, there is a lack of in-depth discussions of ethical and practical considerations when designing and using MMLA [21]. Involving teachers in the design of intelligent tools can facilitate MMLA technology adoption in classrooms. Studying teachers' considerations of MMLA analytics and data collection practices in classrooms allows us to compare the acceptance of data modalities needed to generate MMLA. The acceptance of data collection methods and modalities might not always overlap with what downstream analytics teachers are interested in.

Our research probes these challenges in the context of designing a teacher reflection tool. We address three research questions: RQ1: What analytics on *teaching* and *student learning* do teachers want to use in reflection practices, and why? RQ2: What data collection modalities on *teaching* and *student learning* would teachers allow in their classroom, and why? RQ3: With whom are teachers willing to share analytics about *themselves* and *their students*, and what privacy concerns might they have, and why?

Advancing teacher reflection tool design, we aim to identify teachers' preferences and effectively integrate analytics into educational practices in a manner that respects privacy and fosters an environment conducive to learning. This study seeks to pave the way for the development of analytics for teacher reflection, to enhance teaching and learning and to discuss the ethical considerations inherent in using MMLA data. These insights on such teachers' preferences and considerations could inform future TEL research and practice.

## 2 Methods

To answer our research questions, we conducted a survey with teachers to probe into their reflection practices and preferences, especially about their analytics preferences.

### 2.1 Participants

Participating teachers were recruited using Prolific. Teachers were asked to consent before participating in the study and received $20 USD as compensation. The sample included 100 teachers ages 20–62 ($M = 38.15$, $SD = 11.11$), including 64 female teachers, 35 male teachers, and one non-binary teacher. Teachers were located in the US, had English as their primary language, and had taught in primary, middle, or high school. Additional teacher demographic information is in Table 1.

**Table 1. Teacher professional and demographic data based on survey responses.**

## 2.2 Survey Questions Corresponding to Research Questions

The survey is based on literature at the intersection of teacher development, reflection practices, and multimodal data in classrooms [7, 18,19,20]. Before deployment, two PhD students conducted pilot sessions and refined the survey. The survey was hosted online using Qualtrics. The survey lasted approximately 40 min. Teachers were prompted to imagine that they have an intelligent augmenting tool capable of observing their classroom and then using that information about their class to support their reflection. In that way, the survey provided accessible language to explain MMLA to participants.[1]

The first research question (RQ1) related to teachers' preferences for specific analytics about themselves and their students in the context of reflection. Teachers were asked in the survey: "What kind of information about teachers (including yourself) would you like to have access to when reflecting? Imagine you have superpowers and can easily observe and pull out information about your classroom". Teachers selected their top three preferences out of nine options and then ranked them (Table 2). Similarly, teachers ranked their preferences for student learning constructs out of nine options concerning the usefulness of constructs for teacher reflection (Table 3).

The second research question (RQ2) related to teachers' acceptance of data collection modalities related to teaching and student learning. Teachers ranked four modalities on their level of acceptance: audio, video, location data, and log data from interactions with learning systems (Table 4). Teachers then separately rate both data collection modalities for teacher data and student data (there is an additional option of a smartwatch in gathering physiological data for teachers' data, which was excluded from the analysis to ensure comparability of rank distributions between teacher and student data).

The third research question (RQ3) related to teachers' willingness and concerns regarding data sharing about themselves and their students. Teachers responded to seven checkboxes for different stakeholders (Table 5), representing their willingness to share data and analytics of interest regarding their students' learning and teaching practices. It was possible to check all or none of the options. The data collection modalities related to data sharing were limited to what teachers had previously indicated they would be willing to collect, assuming that teachers would not be willing to share data they do not find acceptable to collect in the first place.

## 2.3 Analytical Methods

**Quantitative Survey Data.** For RQ1, we report how often teachers chose a given analytic item among their top three preferences, including 95% binomial confidence intervals, to estimate uncertainty regarding preferences in the sampled population. We chose this statistical measure over median rankings due to considerations of statistical power: while probabilities of being chosen by teachers in their top three are less fine-grained than estimations of specific ranks, they can be estimated with higher statistical certainty.

For RQ2, we compared the rank distributions of teacher preferences for student data and their own. We report teachers' median acceptance rank for each of the four data items to be ranked separately for data about students versus data pertaining to teachers. Medians are more appropriate for ranked data than means, as ranks cannot be assumed to be normally distributed. We also reported whether teacher preference rankings were significantly different for student data compared to teachers' data, based on two-sided nonparametric Wilcoxon signed-rank tests.

For RQ3, we calculated estimates of how likely teachers were to select each stakeholder for data sharing. For each comparison, we also conducted a nonparametric, two-sided binomial test (well-suited as it does not assume distributional properties). The goal was to ascertain whether teachers' willingness to share data for the same stakeholder significantly differed for students compared to teacher data.

**Qualitative Survey Data.** We collected open-ended text responses from teachers on questions where teachers explained why they selected their three most preferred analytics options and their rankings. Three coders employed the thematic analysis approach to analyze open-ended responses. Thematic analysis [7] involves identifying, examining, and interpreting patterns or themes within qualitative data. We reviewed the responses to distill and categorize key themes and insights. We coded and analyzed each response individually through affinity diagramming using an online board (i.e., Miro). Three coders cross-checked each others' coding to enhance the reliability and reduce individual bias.

## 3 Results

**Table 2. Teacher preferences for *teacher analytics* expressed in probabilities of being included in their top three preferred analytics, including 95% confidence intervals.**

**Preferences for Teacher Analytics.** Table 2 lists the frequency of teachers, including each teacher's analytic in their top three analytics for reflection. **Teachers were most commonly interested in data about ways of motivating their students (44%), and interacting with students (43%).** "*Teachers have to be able to keep their students engaged by keeping them motivated. Without motivation most of what the teacher explains' will be lost*" (T78). Some teachers believed student motivation is linked with teachers' emotions and classroom environment, and want to know how to effectively motivate their students: "A teacher's emotions are sensed by the students, even when you think they do not. The mood of the teacher will set the tone for the class, so it is important to be positive and supportive [...]" (T34). As to how to motivate students, some teachers found it important to understand students' emotions and socio-emotional learning: "To motivate and help students it's important to get down to their level and join their world by seeking to understand where they come from first [...] I like to prioritize social-emotional development and understand where a student is coming from (because as people we essentially make choices based upon our feelings)" (T36). Teachers were also interested in analytics about their responses to students asking for help or feedback (35%), and general instructions to students (33%). Teacher T4 pointed out that clear, well-structured instructions are crucial in preventing misunderstandings and maintaining a positive learning environment. **Teachers were particularly interested in seeing and reflecting on their responses to student requests for help or feedback.** Teachers expressed interest in being aware of noteworthy events in the classroom that might have escaped their notice, for example, incidents such as cheating or student mistreatment, which could occur unknowingly: "I would love to know if someone slyly pulled out a vape, used it and put it away without me noticing. I would love to know if someone got away with cheating, and I would also want to know if someone mistreated someone else without me knowing about it" (T58). **Teachers were least interested in their questions to students (18%) or their emotions during teaching, such as stress and frustration (15%).** Many teachers viewed collecting data about their emotions as unnecessary, privacy-invading, and limiting: "This data also feels like it could be used against me and might make me more self-conscious and attempting to limit the ways in which I express myself" (T38).

**Preferences for Student Analytics.** Teachers were most interested in *student learning and progress* (55%) (Table 3). One teacher explained how it connected to reflection, "*Knowing student learning and progress would help me know what the weakest and strongest areas of my teaching are. This could help me help students better, revise my teaching, and reach them better*" (T58). Teachers also favored students' feedback on their teaching and information about students' engagement (35%) over information regarding misconceptions, common errors, and emotions (ranging from 22% to 27%). One teacher mentioned, "*There is no way I can help a student if they are off task or not focused on the learning outcome*" (T31), indicating the necessity of understanding student disengagement for effective teaching. Teachers needed to comprehend students' challenges and their emotional well-being. For example, "*The number one data point that is not always known is any issues the student is having. If they are in a gang, doing drugs, suicidal, had a death in the family, or having friend issues all play into their engagement at school*" (T16). 18% of teachers picked student mastery of skills and knowledge.

**Table 3. Teacher preferences for *student analytics* expressed in probabilities of being included in their top three preferred analytics, including 95% confidence intervals.**

## 3.1 RQ2: What Data Collection Modalities on Teaching and Student Learning Would Teachers Allow in Their Classroom, and Why?

**Table 4. Teachers' acceptance of data collection modalities, as median ranks, separately for data about students and data about teachers, including two-sided pairwise Wilcox rank tests comparing acceptance between teacher and student data.**

Table 4 describes the median ranks of teachers' acceptance of different data collection modalities, of their own and students' data. **First, log data emerged as the most accepted modality for *student data*.** Teachers think students' log data help them reflect, as, *"behaviors while using the educational software would help me understand if I am monitoring students enough or in the right way"* (T46). Some teachers, though, had concerns about not knowing how to effectively leverage and use student log data. Student log data was followed by a tie of audio and video data of students. Student location data was the least accepted among all options. In contrast, teachers' general preferences for different data collection modalities for *teacher data* were more mixed, lacing a clear trend or consensus among teachers as to what type of data collection they would accept or feel comfortable with. Specifically, all four data collection modalities ranged from median ranks of acceptance between 2 and 3, which are around the middle of the 1–4 range.

We conducted two-sided pairwise Wilcox rank tests comparing if teachers were significantly more accepting of each data collection modality for their students' data than their own. Two significant differences emerged. **First, teachers were significantly less accepting of collecting student location data as compared to their own location data ($p < .001$).** From qualitative analysis, teachers had quite polarizing opinions regarding collecting location data. Some teachers thought it might **help teachers reflect on their teaching behaviors** or found it intriguing, e.g., *"Knowing how I moved around the classroom could be very helpful regarding classroom management, such as places I'm missing consistently or places that I visit too frequently. Do I move around too much or too little, etc."* (T28). On the other hand, many teachers had **privacy concerns over using teacher location** and strongly disagreed about collecting location data in school: *"I hate the idea of something similar to GPS because I feel like that is way too much monitoring with little control"* (T93). Other reasons for reluctance included teachers **not seeing its relevance with learning**: *"I think information related to position or software interaction is the most limited because they share the weakest correlation* *with teacher efficacy in my opinion"* (T44). Some teachers expressed that it may not be helpful for a small class size as teachers may already know their routes and visit frequency. The survey kept it open on how the location tracking happens, thus teachers may have different assumptions (e.g., many assume GPS collection).

Second, **teachers were significantly less accepting of collecting audio data of their students compared to audio recordings of themselves** ($p = .002$), whereas such difference for *video* was not found. The primary advantage teachers saw in video data was that it contained the most comprehensive information *"...including emotions, verbal instructions, and other features of teacher-student interactions"* (T44). Teachers also thought videos could remind them of things they may have missed during class. *"Things are easily missed when attention is split across an entire classroom, and this can point out some of those missed moments"* (T68). The disadvantages of video data teachers saw related to privacy concerns, and teachers may be uncomfortable with video recording in their class. As for audio, the advantage was that teachers thought it could remind them what happened in class: *"I think audio is going to be helpful because then you can listen back to the lesson and the questions asked and reflect on what went well and what they need more help on"* (T22). Teachers thought audio data may have fewer privacy concerns than videos, though it contains less information.

## 3.2 RQ3: With Whom Are Teachers Willing to Share Teacher and Student Data?

We asked what stakeholders teachers would be willing to share their own and their students' data with (where teachers could check all or no boxes) and computed the percentage of teachers willing to share data with each particular stakeholder called out in that question. The results are summarized in Table 5.

First, regarding teachers' general levels of data sharing acceptance, **principals emerged as the most accepted stakeholders with which data was shared, both for student (56%) and teacher data (41%).** Legal restrictions also play a role in data sharing: *"Sharing students' data with other people except the principal is not legally appropriate"* (T60) or *"We are only allowed to share student data with the administration"* (T43). **Regarding their own data, teachers were more comfortable sharing data with other teachers teaching the same subject (29%) than with any other colleague in their school (15%) or colleagues in the same teaching year**

**(18%).** A similar relative ranking emerged for the sharing of student data. Notably, teachers were more likely to share their data with coaching experts over subject coordinators (27% compared to 20%) while the opposite was true for student data (26% compared to 23%).

Comparing the relative acceptance of sharing teacher compared to student data with the same stakeholder, **teachers were generally less willing to share their data (26%) than their students' data (14%) based on the "(share with) no one" option.** This difference was statistically significant ($p = .002$). Many teachers believed sharing students' data needed consent (e.g., from students and parents). 38% of teachers were willing to share students' data with colleagues from the same subject, and significantly fewer teachers were willing to share data about themselves (28%, $p = .030$). Teachers thought data sharing with colleagues might benefit teaching, and especially preferred data to be de-identified: "*Sharing with colleagues, particularly if done without identifying information, could help me in receiving feedback for making improvements*" (T11). Similarly, **teachers were significantly more willing to share their students' data compared to their own data with their principal ($p = .002$)**. Teachers thought sharing students' data with the principal could help support teachers: "*I think the principal, as the head of the school, would find the information valuable for making informed decisions and supporting teachers effectively*" (T70).

**Table 5. Teachers' willingness to share data with stakeholders in percentages of marked "check all that apply" boxes across teachers, with *p*-values of two-sided binomial tests.**

## 4 Discussion

Multimodal Learning Analytics (MMLA) seeks to leverage multiple sources of data in high frequency (e.g., video, log data, audio, and position data) to provide a more holistic view of the classroom [10]. MMLA captures traces of teacher and student behaviors and holds promises to inform educational technology design that supports teacher reflection. Despite the MMLA's potential to generate rich analytics through classroom sensors and TEL learning environments, there is a lack of research that designs MMLA solutions around teacher preferences, needs, and concerns [1, 25]. To address this gap, the present study investigates teachers' perceptions and preferences regarding the potential use and data sharing of MMLA to support reflection on their teaching practices.

Our first research question (RQ1) asked what analytics teachers would prefer most. **For teacher analytics, teachers expressed the strongest interest in data about their ways of motivating students and interactions with students**. This teacher preference poses a methodological challenge to capture students' motivation accurately and attribute changes in student motivation to teacher-student interactions. Although challenging and requiring rich interaction data, prior work has proposed methods to analyze teacher discourse via TEL (e.g., [4]). Teacher-student conversations could be analyzed through similar methodologies to speak to how positive, inclusive, or conducive to students' motivation interactions are. However, a more fundamental research challenge may arise from an incompatibility between teachers' preference to *not* capture student audio and location data (needed for detailed descriptions of teacher-student interactions) and their desire to view analytics about teacher-student interactions. A middle ground could be to capture teacher position data only at the expense of richer descriptions of interactions, for example, by measuring how commonly teachers visit particular students [13]. **For student analytics, teachers expressed the strongest interest in knowing students' learning and progress,** but somewhat surprisingly expressed the least interest in seeing students' skill and mastery of the software. While students' skill mastery data has been used in intelligent support for learning, teachers may not relate this data to their teaching practices, potentially due to teachers having limited knowledge or training of interpreting software log data and correlating it with students' skill mastery. As an alternative interpretation, the discrepancy could also relate to teachers in our sample not trusting the accuracy with which the tutoring software estimates learning or could be a reflection of excluding the (presumably less accurate) estimation of learning if the construct of learning itself is already included in teachers top three choices (which would mean that this finding can be attributed to our survey methodology). More qualitative investigations (e.g., via follow-up interviews) could elucidate this issue further.

For RQ2 (related to what data modality teachers accept for data collection), we found **teachers generally were most open about log data collection and much more accepting of students' log data than teacher log data**. Teachers were least accepting of teacher and students' location data (a relatively new modality [1, 25]), primarily due to privacy concerns or a lack of knowledge on how location data can be relevant to learning. Prior work, however, has shown promises (e.g., [15]), for teachers to distill aspects relevant to student learning by viewing their location data analytics and reflecting on their teacher visits. This difference between recent research trends and teacher preferences is notable, pointing to a potential neglect of MMLA research trends to incorporate teacher preferences into research priorities: if teacher preferences are not considered at early stage analytics development, eventual adoption of TEL tools supported by MMLA could suffer.

For RQ3 (teachers' data sharing preferences), **teachers are most willing to share data with principals and colleagues teaching the same subject (e.g., math)**. Sharing with other colleagues, however, is decidedly less preferred. **Teachers are also less willing to share their data than their students' data**. Combining RQ2 and RQ3, teachers find it *both desirable and acceptable* to use students' log data, which can convey student learning and progress, which teachers were interested in. Notably, there was no clear modality that teachers accepted most or least regarding the collection of their own data. This could point to a potential lack of understanding of nascent MMLA research practices and what each teacher data modality would entail when collected in K-12 classrooms. We gathered some evidence for this interpretation based on teachers' open-ended responses related to teacher log data, for example, which some teachers were unclear about. If our interpretation is true, then more is to be done to convey to classroom stakeholders the potential value of these different teacher data modalities, and collect MMLA in a manner that respects classroom norms (e.g., as done in Pugh et al. [18]).

The present study revealed surprising insights that could inform TEL research practices. **First, for student analytics, teachers were most interested in seeing student learning situations but expressed little interest in accessing information from learning software about student mastery and progress**. As discussed, this finding could open research opportunities to study further if teachers are unable to relate learning analytics on mastery and progress to their teaching practices or lack trust in such analytics (irrespective of knowing how to interpret them). Second, we found **teachers favored seeing students' engagement and overseeing their misconceptions and common errors,** potentially due to teachers in our sample considering engagement to be more fundamental for learning or more relevant for reflection. Third, teachers were more protective of their students' data regarding some data ***collection*** modalities compared to data about themselves (audio and video). This finding supports the need for guidelines to preserve children's privacy [6]. This aligned with Prinsloo et al.'s review on MMLA and student privacy which suggest drafting ethical guidelines, and mentioned potential concerns of MMLA encroaching on students' 'personal spaces, bodily integrity and data privacy' [21]. Still, teachers are more willing to ***share*** data about their students than their data (specifically with colleagues from the same subject domain). From qualitative results, teachers think sharing student data can help school administrators improve education, but sharing their own data may raise concerns about self-consciousness, risking creating a surveillance culture or hurting teachers' teaching autonomy.

*Implications on Reflection Tool Design.* Our study found teachers found it both desirable and acceptable to collect students' **log data**, to support teachers' reflection. There is, however, usually an abundance of log data, and the design challenge for teacher reflection tools is to develop 1) intuitive representations that teachers can make sense of and find interpretable and 2) simple visualizations that teachers can quickly glance at. A human-centered perspective is needed, as argued in prior MMLA discussions [1, 9, 17, 18]. Additionally, with the rapid advancement in natural language processing, TEL research increasingly uses audio data to understand the learning process and create teacher-facing analytics [3, 4, 22]. From our study, teachers found **video and audio data** helpful and may support them to reflect on how they motivate students and whether they are getting the required attention. Processing video and audio data, however, can be time-consuming. One practical design challenge is understanding what teachers consider note-worthy events and how to capture these *key events* in video and audio, which AI models and generative AI agents could help detect. Finally, given teachers' privacy concerns, one idea could be using AI models that can mask faces in video to reduce privacy concerns (e.g., [17]). As for **location data,** given its nascent stage, researchers may need to convey to classroom stakeholders its potential values in capturing teacher-student interaction for TEL and its relevance to student learning (e.g., it may show whether struggling students have been adequately attended to and visited). Researchers also need to decrease privacy concerns by safeguarding data and collecting them less intrusively [2, 15].

One potential limitation of our study is that our sample represents US teachers. The USA might have different cultures and attitudes toward data sharing and collection compared to other countries [14] (c.f., FERPA). Furthermore, teachers might have interpreted the listed data collection modalities and analytics differently depending on their preconceptions about them. More work is needed to study teachers' preconceptions about different data collection modalities, which presents an opportunity to improve how TEL communicates and shares its nascent research with the broader public. Further, as our survey presents a first step toward capturing teacher needs and preferences for analytics-based reflection, future in-depth teacher interviews and related value-sensitive design methodologies are crucial to ensure adequate considerations of stakeholder concerns in future tool design and deployment [5]. Such methods could also uncover specific values of teachers relevant to reflection tool design.

## 5 Conclusion

The present study provides evidence of teachers' preferences for using Multimodal Learning Analytics (MMLA) tools in education, focusing on their ethical, practical, and teaching concerns. Practically, we inform tool designers and researchers of what *teacher and student analytics* should be considered when designing classroom reflection tools for teachers (e.g., in-class interaction and progress). Theoretically, we revealed new insights regarding analytics that teachers find desirable and acceptable and findings about, for example, teachers' differing attitudes towards *collecting* and *sharing* teachers' and students' data. These insights have important implications for emerging MMLA research in TEL, for example, tradeoffs between in-depth analysis of teacher-student interactions for MMLA (which teachers were interested in) and teachers' preference for not collecting student audio data (which are required for rich analytics of teacher-student interactions). The finding that teachers were overall less willing to share data about themselves than about their students poses another open research challenge for future work. Despite these challenges, we argue that by understanding what teachers need and value, we can develop MMLA tools that are effective and centered around educators' needs.

## Notes

1. A digital appendix including all survey questions featured in this study is available at https://tinyurl.com/ectel24-teachersurvey

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