# Pedagogical Companions to Support Teachers' Interpretation of Students' Engagement from Multimodal Learning Analytics Dashboards

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**Abstract:** Teaching demands educators adapt and improvise their instruction for each student's unique needs and capabilities across contexts. This requires teachers to observe their students, evaluate their ongoing learning, and offer individualized scaffolding and feedback and foster sustained growth and development. This challenging practice has been made even more difficult by the recent emphasis on data-driven instructional decision making from dashboards, further requiring teachers to become both pedagogical and data experts. Despite the development of dashboards to alleviate some of the load of collecting and aggregating complex multimodal student data, there is a need to provide support for teachers in analyzing, interpreting, and applying their students' real-time multimodal learning analytical data (e.g., metacognitive accuracy, negative emotions) in the form of pedagogical companions. Before we can begin the design and development of these agents, we must first understand how educators are currently approaching multimodal learning analytics (MMLA) that report on more than just performance-based outcomes. In this on-going work, we begin by briefly reviewing MMLA in teacher dashboards, teacher data literacy, and the role of pedagogical companions in teacher augmentation technologies. We then describe the development of an in-progress study exploring how three teachers currently use fictious MMLA on self-regulated learning (SRL) processes and the emerging trends we see from their data. Finally, we postulate what these results suggest about the needs that embedded intelligent pedagogical companions may fill in future dashboard and agent design.

**Keywords:** Multimodal learning analytics, teacher dashboards, agent design, pedagogical companion

## 1. Introduction

Teaching demands that educators continuously adapt to students' unique individual needs and capabilities, observe their students, evaluate the quality of learning, and offer support they believe would benefit each student while simultaneously improvising within the contextual constraints (e.g., time left in class) and affordances (e.g., instructional resources) of the dynamic classroom environment (An et al., 2020). This tremendous challenge has become more difficult by the recent emphasis for teachers to make data-driven instructional choices based on student achievement and learning progress data (Cowie & Cooper, 2016). However, pre-service teachers have repeatedly reported a lack of efficacy and foundational knowledge associated with data-driven decision-making (Dunlap & Piro, 2016).

In response to the need to augment and complement teaching and data-driven decision-making in the classroom, we have seen the development of many diverse technologies, including learning analytic dashboards (An et al., 2020). However, many of these technologies provide educators with data that are (1) focused on performance versus process; (2) unimodal versus multimodal; and (3) rely on teachers' data literacy skills. This provides a unique opportunity to embed pedagogical companions within dashboards to help teachers understand data and answer questions about evidence-based practices. However, before we can begin the design and development of these pedagogical companions, we must first understand how educators currently approach multimodal learning analytics (MMLA) that report on data beyond performance-based outcomes.

In our on-going work, we begin by briefly reviewing multimodal learning analytics (MMLA) and their role in teacher dashboards, the impact of teacher data literacy, and the role of pedagogical agents in teacher augmentation technologies. We then describe an in-progress study exploring how teachers currently use fictious MMLA on self-regulated learning processes and the emerging trends we see from the small data set collected from three teachers. Finally, we postulate what our preliminary findings suggest about the roles of embedded pedagogical companions in future dashboard design.

## 2. Related Works

Multimodal learning analytics (MMLA) is an approach for processing multimodal data (MMD) in educational settings to afford a holistic view of students' learning processes (Chango et al., 2022; Sharma & Giannakos, 2020). MMLA was developed out of the need to address limitations in existing approaches' (e.g., educational data mining) overreliance on single-channel data (Chango et al., 2022; Noroozi et al., 2020), and to address calls for increased efforts to triangulate constructs of interest using multiple channels of data. These data can include log files, eye-tracking data, audio recordings, physiological data (e.g., skin conductance), etc. (Liu et al., 2019; Noroozi et al., 2020). MMLA applications must incorporate a diverse range of data channels representative of multiple aspects of learning (cognitive, behavioral, and affective; including emotional and motivational dimensions), and focus on the interpretation of MMLA by teachers to provide meaningful information for teachers.

Teacher MMLA dashboards are defined as user interfaces which aggregate visual information and visualizations about students, learning processes, and/or learning contexts through the organization and visualization of data while including descriptive or predictive analyses to inform pedagogical decisions (Schwendimann et al., 2017). Dashboards can provide insight into students' engagement, behaviors, choices, patterns, and interests—individually or collectively—for use by the teacher to reflect on their instructional decisions (Caspari-Sadeghi, 2022; Verbert, et. al, 2014). Dashboards typically consist of three layers: (1) raw data, (2) artifacts of analysis (e.g., data tables), and (3) presentation (e.g., visualizations; Olshannikova et al., 2015). Gaps in educational literature exist with respect to which types of data and visualizations are most suitable for teachers, particularly in context of data literacy (An et al., 2020; Schwendimann et al., 2017). As discussed by An et al. (2020), dashboards differ in their main focus, from designing data to be quickly interpretable to displaying information publicly within the classroom, to presenting information privately to the teacher. There remains a dearth of design guidance for MMLA dashboards as a result of this incohesive research examining teachers' use of these different visualization strategies. We argue that the gap in literature and lack of success in incorporating MMLA into teacher dashboards stems from the educational fields' lack of understanding of how to properly support teachers' data literacy for the use of MMLA for instructional decision-making.

Data literacy refers to the understanding of presented data for decision-making (Mandinach et al., 2013). Teachers are limited in their understanding of modern data gathering methods and data visualizations which negatively impacts how MMLA can be used to support teacher instruction and subsequently learners' education (Holstein et al., 2019). To address this limitation, further development of standardized objective measures of data literacy is needed where teachers' data literacy competencies need to be more thoroughly understood to support MMLA use (Bonikowska et al., 2019). While teachers and students should be included in the collaborative design of learning tools, these populations' understanding of modern data collection and visualization methods may be limited (Holstein et al., 2019). Designers should consider including pedagogical companions within MMLA dashboards to support teachers' data literacy and data-driven decision-making.

Previous work has explored the role of pedagogical agents in intelligent tutoring systems as teaching assistants (Yacef, 2002), human-agent teaming (Bruni et al., 2019), function allocation (Feigh & Pritchett, 2014), and human-AI complementarity (Holstein et al., 2019). However, a very limited scope of literature has addressed the intersection of these developments to *investigate the design and use of pedagogical agents to support teachers' interpretation of data visualizations of student's engagement data shown using dashboards*. When agents have been combined with dashboards, they have tended to be implemented as background intelligence within decision-support systems or chatbots (e.g., Mekni, 2021). Thus, our current work seeks to extend this prior research on pedagogical agents through an analysis of their use within MMLA dashboards to support teachers' interpretation of and decision-making based on MMLA (i.e., as a pedagogical *companion*).

## 3. Current Study

The aim of this study is to understand how teachers use MMLA dashboards that display performance and self-regulated learning data about their classrooms without any prior training to assess data literacy and the type of scaffolding that pedagogical companions should provide. Previous research suggests that despite the emphasis of using data to make instructional decisions, current dashboards focus on unimodal performance data. While newer dashboards have incorporated process data, there is still much to be understood in how teachers interact and use such data. In order to address the current gaps, we propose the following research questions:

1. *What type of data and how long do teachers consult in the dashboard prototype environment to assess student engagement? Is this different between types of instruction and engagement?*
2. *What are some of the concerns or questions teachers raise about the data, visualizations, or dashboard?*

Given the research briefly reviewed above, we hypothesize that we will see many trials having the longest total page time duration performance data. Additionally, we hypothesize that teachers will have questions about data and visualizations that contradict one another, how to interpret physiological data, and how to interpret data visualizations that are unfamiliar to them.

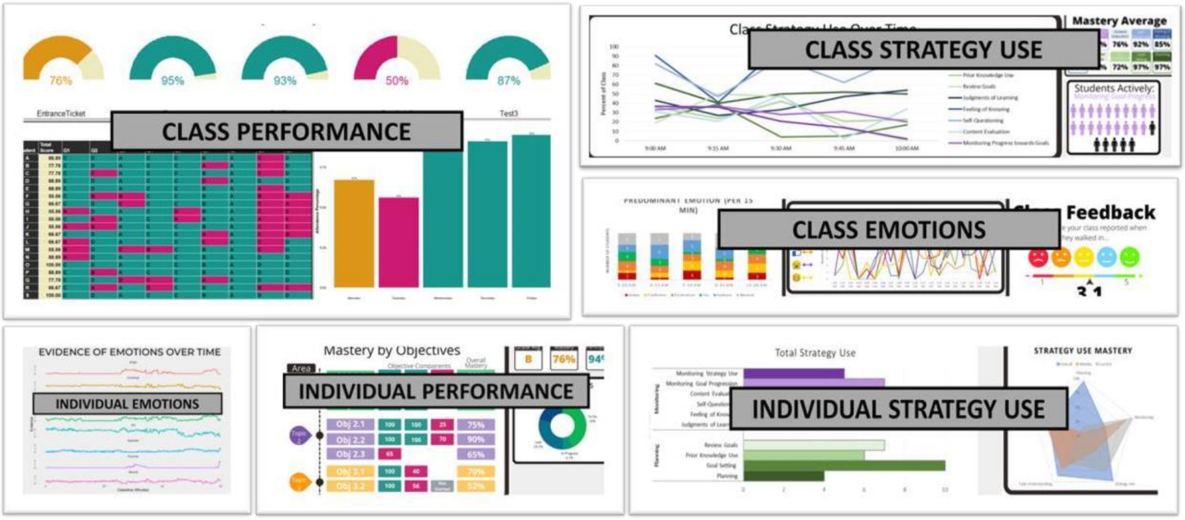
## 4. Methodology

We are conducting a 2 x 5 within-subjects study (instructional format x engagement type) to examine the relationship between Instructional Format (Online or Classroom) and Engagement Type (Cognitive, Behavioral, Emotional, Agentic, or All) on in-service and pre-service teachers' interpretation of student engagement. Participants (N = 3; 1 in-service, 2 pre-service) follow a think-aloud protocol while examining fictitious students' level of engagement and expressing their own instructional decision making across 10 trials within the MetaDash prototype environment (Wiedbusch et al., 2021). Participants complete a demographic, teaching experience, and data use pretest, think-aloud training, and environment training before beginning the experiment.

During each trial of the experiment, participants are shown a scenario page, containing a scenario description, contextual image, navigation grid for data pages, and button for proceeding to the next scenario. The scenario description provided at the top of the screen included one of 10 single-sentence textual vignettes of a teacher's observations of two students ("Student A", "Student B"), followed by the question *"How would you interpret each student's level of engagement and learning? Please explain. If you were to make any instructional changes at this moment, what would they be and why?"*. The contextual image provided at the left-side of the screen provided a small image contextualizing the scenario but not displaying any relevant information. The navigation grid provided on the right-side of the screen displayed graphic buttons navigating the participant to new pages within the environment each displaying different data visualizations, organized as a 3 (source of data; performance, strategy use, and emotions) x 3 (data subject; Student 1, Student 2, and Class) grid. The types of data and visualizations that were displayed are detailed in Figure 1. All data were randomly generated but consistent across participants, with no intentional diegetic relevance or other visual pattern corresponding to the scenario. From the main scenario page, participants were directed to click the buttons of the navigation grid and to navigate to any of the subordinate pages in any order and as frequently as they would like. Participants were asked to think-aloud while viewing the information on the main scenario page and subordinate pages of fictitious students' data and to answer the target question provided in the scenario description, before proceeding to the next scenario. Once participants completed all 10 trials, they were asked to complete a posttest on their opinions on data use. The experiment took about 1.5 hours to complete. At the end of the experiment, all participants were debriefed, thanked for their participation, and compensated.

**Figure 1:**

*Data visualization examples of student engagement and performance data*




## 5. Initial Findings

Given our limited data size, we are unable to report any statistical testing but instead report descriptive statistics (frequency and average time in mm:ss each participant spent looking at data pages for classroom scenarios) and can examine trends that begin to emerge. for all classroom trials in Table 1. Due to brevity, we do not examine the student types (high/low engagement and class) levels, nor context (online versus classroom), but will extend our analysis to these factors in future analysis.

Table 1. *Frequency and Average Time for Trials Based on Engagement type and Data type*

| Engagement Type | Data Type | Participant 001 | | Participant 002 | | Participant 003 | |
|---|---|---|---|---|---|---|---|
| | | Count | Time (mm:ss) | Count | Time (mm:ss) | Count | Time (mm:ss) |
| Agentic | Cognitive | 1 | 2:46 | 3 | 2:53 | 4 | 6:52 |
| | Emotion | 1 | 1:34 | 3 | 3:35 | 3 | 7:30 |
| | Performance | 3 | 3:46 | 3 | 3:00 | 4 | 7:49 |
| Behavioral | Cognitive | 0 | - | 2 | 4:00 | 3 | 2:50 |
| | Emotion | 1 | 1:57 | 3 | 1:36 | 1 | 3:11 |
| | Performance | 2 | 5:41 | 5 | 2:53 | 3 | 3:14 |
| Cognitive | Cognitive | 1 | 3:07 | 4 | 2:01 | 4 | 2:54 |
| | Emotion | 2 | 3:17 | 3 | 7:40 | 3 | 5:16 |
| | Performance | 2 | 4:35 | 3 | 5:44 | 2 | 4:13 |
| Emotional | Cognitive | 0 | - | 4 | 2:47 | 4 | 6:14 |
| | Emotion | 4 | 2:43 | 3 | 2:19 | 3 | 2:08 |
| | Performance | 3 | 3:33 | 5 | 6:23 | 5 | 2:16 |
| All | Cognitive | 0 | - | 2 | 2:15 | 2 | 5:14 |
| | Emotion | 2 | 2:54 | 3 | 2:24 | 3 | 2:39 |
| | Performance | 2 | 1:25 | 3 | 2:20 | 3 | 4:13 |

There are some patterns that have already emerged from this data. First, most participants spend an average of 3:53 minutes on each data page across trials, but we see individual differences. Additionally, we see similar individual differences in how often participants visited each data page. This suggests just as there is not a one-size-fits-all approach to teaching students, teachers have unique approaches to data use and the type of data literacy support needed should be adaptive and individualized. Table 1 also shows the length and frequency of the type of data that teachers visit does not seem to be affected by the engagement type of the scenario provided. This is surprising as one would expect when faced with a scenario describing cognitive engagement, teachers might spend more time focused on the cognitive data. We do note that there is one potential exception for emotion-engagement scenarios, but more data is needed. Our preliminary findings indicate teachers are either unaware of the type of data they should be consulting based on the limited scenario descriptions, or that they are consciously choosing to approach the data in similar ways across all scenario types. Finally, teachers appear to be visiting and spending more time examining the performance data pages compared to cognitive and emotion data pages. This is unsurprising as the data that they are most familiar with or expected to currently use in their instruction is performance and grade based MMLA.

To address our last research question, we examined participants' think-aloud transcripts. While we have not finished development of a coding scheme, some interesting themes are beginning to emerge that may help future analysis. For example, we expected teachers to raise more questions about data that seemed to contradict one another within a trial. While some participants did recognize they did not make sense, *"That's odd… I don't know how a student with a 97% grade average … 96%... a high A or whatever is feeling confused so much,"* (quote from Participant 2), they did not question the quality of the data. That is, teachers treated the data as objective infallible truth, a fact that MMLA researchers know is a dangerous assumption. Additionally, the think-aloud transcripts reveal that our participants seem to be primarily using top-down approaches to data use. That is, they are interpreting the scenarios prior to examining any data and then looking for data to support their findings. Participant 3 highlights this when she spent over 5 minutes explaining how one particular trial was *"definitely a behavioral issue. I see this all the time, and a lot really recently. This is 100% behavioral… something going on at home. Or another class. This is a behavior issue. [sigh] I mean some kids just have an attitude and you have to roll with it."* This conclusion was drawn before any data was examined, suggesting that educators may be using MMLA dashboards to provide administrators or other stakeholders with evidence of their conclusions, but not drawing conclusions from the data at all.

## 6. Preliminary Implications for Artificial Companions and Teacher Dashboards

Our ongoing data collection will continue to provide a very rich data set for which we can continue to explore some of the analyses in this paper as well as expand to future analysis. These analyses will help us in the future design and development of pedagogical companions to support teachers in their data-driven instructional decision making. Preliminary results suggest that teachers do not consider the context before determining what data to consult. We envision a pedagogical companion that makes suggestions about the most appropriate data for use. Alternatively, this companion may also metacognitively prompt a teacher to reflect on what type of data they would ideally like to consult and why before analytics are available. The teacher may have to justify why certain data is appropriate for making an instructional decision. By introducing conversational natural language processing into this system, even if an educator does not have strong data literacy, they could describe what it is they think they are observing and ask the companion to provide data about their subjective views. For example, if a teacher believes a student is getting frustrated and that is why they are disengaging with the lesson, they could tell the companion and ask for emotional state data about that student. We can imagine the companion then providing historical data about how the student typically feels during a lesson, how they feel when they struggle, and how they are currently feeling. This does not require that a teacher necessarily understand what type of data they need, but rather they are provided with relevant information from the pedagogical companion as they describe what they are observing. However, we must be careful to mitigate data cherry picking. Our preliminary results suggest that teachers rely on top-down approaches to using MMLA. As such, future pedagogical companions should be able to scaffold bottom-up, or data-driven, approaches to interpreting student engagement by focusing educators' attention to critical data as it occurs. For example, we can imagine the companion alerting the teacher to high frequencies of negative feelings-of-knowing metacognitive judgements. Even if the teacher was not originally aware that the class was not confident in their understanding of the topic, the companion could provide visualizations of judgement frequency distributions, problem attempts, and facial expressions of confusion. This helps address the detection of engagement, but we must also consider how to support teachers' application of this data for instructional decision making. Ideally, the teacher could ask their pedagogical companion if they apply a certain instructional strategy, what the data would then look like. In response, the companion would then provide a predictive simulation of future data, or even a comparison of multiple strategy outcomes for the teacher to then choose from.

Through our future work, we will address the challenge of providing teachers support as they use MMLA with a greater diversity of channel combinations to better represent complex learning phenomenon in their dynamical interpretation of student engagement and learning. As this work continues, we will make actionable and clear suggestions of what best practices and considerations should be made based on how teachers are currently using MMLA data without any support.

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