Math Teachers' In-class Information Needs and Usage for Effective Design of Classroom Orchestration Tools

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Abstract. Effective design of classroom orchestration tools depends on purposeful collection, analysis, and presentation of learning analytics (LA) to teachers. However, researchers have raised concerns regarding their acceptance and adoption in real classrooms, emphasizing the critical role that teachers can play in their design. To engage teachers in identifying their analytics needs during class time, we conducted classroom observations, interviews, and a focus group with ten grades 3 to 8 math teachers. Our thematic analysis of the data led to findings about teachers' in-class information needs and usage, which we integrated with existing models of teachers' sensemaking and decision-making in LA systems to generate a conceptual model of math teachers' in-class information needs and usage. Our model captures interconnections across categories of (a) information needs for in-class sensemaking (events, event causes, student profiles) and (b) information usage for in-class decision-making (interventions). We illustrate the connections between different instances of these categories through five case scenarios. Based on our model, we propose strategies for supporting the design of orchestration tools aiming to integrate cross-domain analytics for overall student growth, balance automated assistance and teacher control, and manage information overload for teachers. Our findings offer valuable insights for LA communities in grounding the design of classroom orchestration tools on teachers' actual needs.

Keywords: Teacher Models · Teacher-facing Analytics · Human-AI Co-orchestration · Classroom Orchestration · Human-centered Learning Analytics · Contextual Inquiry · Focus Group.

1 Introduction

Prior work has strongly advocated for involving stakeholders such as teachers, students, and parents in the design of learning analytics (LA)-based classroom orchestration tools [21, 17, 19], such as through co-design or participatory design [19]. This involvement enhances designers' understanding of end-users' needs and incorporates expert feedback into designs [27]. Involving stakeholders only in the latter stages of design, such as for prototype evaluation may restrict their feedback to existing prototypes [7, 27]. Accordingly, researchers emphasize the importance of understanding how instructors manage various in-class activities without specific technologies in use [14]. This understanding could inform the effective design of orchestration tools that align with teachers' real-world daily tasks.

To this end, our work explores the information needs and usage of grades 3 to 8 math teachers within real classroom settings. We conducted observations, interviews, and focus groups with teachers within classrooms that do not currently implement classroom orchestration tools. In our analysis of these data, we aimed to identify the kinds of information that teachers need and use in real-time. The research questions that guide our inquiry are as follows:

- RQ1. What data do grade 3-8 math teachers want to collect about their students during class time?
- RQ2. How do grade 3-8 math teachers intend to use student data?
- RQ3. How can understanding these data needs and usage support the design of orchestration tools?

We synthesized the themes we found from our data analysis with prior models of teachers' sensemaking and decision-making in LA systems to develop a conceptual model of math teachers' in-class information needs and usage (Section 4.1). In particular, our model distills our findings into two central categories: (1) *Information Needs for In-class Sensemaking* and (2) *Information Usage for In-class Decision-making*. It is important to acknowledge that while prior studies have identified similar categories of information needs and usage, our study focuses on the interconnections among a range of information needs and usage in various domains. Drawing on our conceptual model, we provide a theoretical basis to support orchestration tools in (1) providing cross-domain analytics for overall student growth, (2) balancing automated assistance and teacher control through enhancing tools' transparency, and (3) managing information overload for teachers through timely and on-demand delivery of analytics.

2 Related Work

2.1 Classroom Orchestration and Human-AI Co-orchestration

Classroom orchestration is a multifaceted task involving real-time management of various activities against multiple constraints such as time, curriculum, and alignment to educational standards [8]. This becomes even more critical in early education, where teachers follow more diverse educational objectives including enhancing students' social-emotional and cognitive development [28]. In these environments, teachers play a dual role as both student mentors and nurturers, highlighting the complexity and significance of their responsibilities.

Over time, orchestration has evolved to include AI agents assisting teachers in orchestration tasks (i.e., *Human-AI Co-orchestration*). This integration facilitates the assignment of certain pedagogical tasks to teachers, students, and AI agent [14]. For instance, Pair-up, a teacher-facing co-orchestration tool, can automate the task of pairing students for peer learning [33]. It also assigns the roles of tutor and solver within each pair, thereby alleviating some of the orchestration tasks from teachers. Moreover, AI agents are increasingly capable of automating the interpretation of student data and offering higher-level analytics to teachers, enabling the provision of timely intervention suggestions and even automating certain interventions (e.g., providing students hints while problem-solving) [4, 33].

Prior work has found various challenges with the shift towards Human-AI Co-orchestration, such as finding the right balance between automated assistance and teacher control [4, 14]. While over-automation risks diminishing teachers' ability to tailor instructions based on their specific educational context, under-automation might leave teachers burdened by tasks they would rather leave for the system and save some time for other high-priority responsibilities. In this study, we developed a model of teachers' in-class information needs and usage, designed to support orchestration tool designers to assess the tools' analytical capabilities when considering task automation. Also, our model offers a theoretical basis for enhancing the transparency of orchestration tools, a key strategy for granting teachers meaningful control over these tools.

The adoption of orchestration tools also poses the risk of cognitive overload for teachers, especially when tools present a significant volume of analytics that teachers have to process [4, 9]. Teachers often have very limited time to decipher analytics, which impacts the actionability of information provided by orchestration tools [16, 15]. To address this, prior work has proposed delivering analytics tailored to ongoing classroom activity, presenting analytics based on priority and providing details on demand [4]. Within this work, our model suggests a possible approach for delivering analytics to teachers in orchestration tools, focusing on providing analytics at proper times and upon teacher requests.

2.2 Enhancing Classroom Orchestration with Learning Analytics

Classroom orchestration tools can provide teachers with a range of real-time analytics, such as insights into students' current actions and processes, step-by-step views of students' solutions [3], thought processes (e.g., students' chains of reasoning for their work) [17], performance and common errors [12], sequences of states (e.g., idle, misusing the software) [15], misconceptions [16], emotional states [10], and the effects of previous teacher interventions [21, 15]. These insights could encourage interventions such as teacher-student communication, aids to help learners re-focus (e.g., when idling or distracted), providing timely praise [3], suggesting assignments [33], and strategic student grouping for class activities [29]. Despite these capabilities, prior studies indicate that analytics choices are often influenced by the availability of data without an in-depth analysis of teachers' needs [16]. Our conceptualization of early education teachers' in-class information needs and usage points to the need for orchestration tools to prioritize collecting, analyzing, and presenting a variety of interconnected analytics vital for students' growth across multiple domains (e.g., fundamental skills, social-emotional learning).

Teachers' interactions with LA systems are often framed within models of sensemaking and decision-making [31, 26]. These models suggest that teachers begin using LA with specific educational questions in mind (e.g., emerging out of teachers' curiosity, pedagogical intentions, or prompted by the system) and then interpret and analyze data related to students' learning activities to address initial questions. The next step involves decision-making, where teachers consider alternative courses of action and select among them. In our study, we delineate both the analytics requirements for sensemaking and the usage of analytics in decision-making, highlighting the interconnections between these two processes.

3 Methodology

As suggested by prior studies, we conducted methodologies grounded in Human-computer Interaction (HCI) literature to capture the authentic needs and values of math teachers [23, 18, 19]. Our exploratory work is divided into two phases: we first conducted contextual inquiry through direct observations of math classes followed by semi-structured interviews with the teachers. Second, we conducted a focus group session with another set of math teachers. Research methods across participant recruitment, screening, research consent, study protocol, and analysis methods were approved by our institutional IRB.

3.1 Participants

We recruited teachers across public elementary and middle schools in a state in the northeast United States by distributing recruitment posters to school officials and teachers. The recruitment poster directed interested teachers to a screening survey that collected information on their contact details (for follow-up) and their teaching experience (school affiliation, current and previous grades taught, total years of teaching experience, and their current role as either the primary instructor or a teaching assistant). We recruited a total of five math teachers who taught at the grade 3-8 levels across four different public schools to participate in class observations and interviews.

Due to teachers' unavailability for class observation, we decided to augment our data with focus group interviews with another set of teachers. Using the same recruitment strategy, we were able to recruit five other math teachers at the grade 3-8 levels across a different set of four schools. We summarize participant profiles in Table 1. Each participant was compensated with a $100 USD gift card for their participation, distributed according to school district regulations.

3.2 Field Observations and Interviews

In preparation for the field observations, we briefed the teachers on our study procedures, obtained their consent, and had them select a class they believed to be representative of their typical teaching activities. We also obtained the

Table 1. Participant Details: Columns indicate (left to right) participant's assigned ID (*T*-lead teacher, *TA*-teaching assistant), type of participation (*O*-Observation, *I*-Interview, *F*-Focus group), school, grade level of observed class, grade levels previously taught, and total years of teaching experience (self-reported).

ID	Partici-pation	School	Grade Observed	Grades Taught	Teaching Exp. (Years)
T1	O, I	S1	G6	G6, 7	10
T2	O, I	S2	G6	Kindergarten, Preschool, G1-3, 6	35
T3	O, I	S3	G3	G1, 3	6
T4	O, I	S3	G3	Preschool, G1, 3	30
T5	O, I	S4	G3	G2, 3, 4	11
T6	F	S5	-	G3-6	2
TA7	F	S5	-	G5	3
T8	F	S6	-	G8	5
T9	F	S7	-	G4, 5	1
TA10	F	S8	-	G3	1

required permissions from school district officers (superintendents, principals) for our on-site class observations. We conducted the observations and interviews between March and May of 2023. The first author conducted all overt non-participatory observations in person and took observation notes. Classroom observations were video and audio recorded using a digital camera on a tripod at the back of the classroom to minimize distractions. The observations also provided us with context for refining our interview questions around our observations of what the teachers were doing during their classes. We interviewed each participant remotely via Zoom a few days after each observation.

The semi-structured interviews ran between 35 minutes to an hour and were audio and video recorded and transcribed. We asked teachers about their general experiences as educators to gain some context around their teaching, their affective perception of their teaching experiences (e.g., enjoyable, frustrating), and teaching strategies. We also asked specific questions regarding the in-class activities we observed (e.g., group work, student presentations). We also proposed hypothetical scenarios to encourage teachers to talk freely about their information needs regardless of their current constraints and our observations from their classes.

3.3 Focus Group

We conducted a two-hour remote focus group discussion via Zoom with five math teachers. The meeting was video and audio recorded and transcribed. The session began with an introduction to the study and meeting attendees, followed by a structured discussion around in-class activities identified from our observation phase (Section 3.2). The teachers discussed their thoughts and experiences on the types of information that teachers seek during each activity and their potential use for in-class decision-making. We asked questions about information that teachers cannot currently obtain during class, encouraging them to discuss their desires for accessing information beyond existing limitations. The focus group study expanded on findings from the field observation, brought in early-career teachers to broaden our sample, and enriched our data with varied experiences from different schools.

3.4 Analysis Approach

We first analyzed the video recordings, transcripts, and observation notes from the field observations and the interviews through collaborative Thematic Analysis [5] and Interpretation Sessions. We began by inductively generating initial codes from each teacher's class observation and interview data and associating the teachers' utterances with codes to ensure that codes are driven and primarily supported by the data. Our bottom-up approach focused on extracting comprehensive codes without premature exclusion of any of them. We triangulated across interview and observation data to accurately capture the context of the codes we were generating. We also maintained records of relationships between codes. For example, we recorded cause and effect dynamics or how specific codes (e.g., teachers' information needs) informed other ones (e.g., teachers' pedagogical interventions). In a subsequent round of coding our data, we collaboratively reviewed and refined the codes and their relationships.

We then categorized codes into two primary groups: (1) teachers' in-class information needs, and (2) how teachers intend to use such information. Reviewing the existing models of teachers' interactions with LA systems [31, 26], our analysis situated the first group within the sensemaking process and the second within the decision-making process. Thus, we are presenting our results within these two processes (Section 4.1).

We conducted another round of inductive coding using our focus group data. This enabled us to cross-reference new insights from the focus group with our initial findings from the field observations and interviews. From this process, we generated additional codes and found similar codes and themes that helped reinforce our prior analyses. The final conceptual model derived from our analysis is shown in Figure 1 and its components are described in the following section.

4 Results

We developed a conceptual model of math teachers' information needs and usage and provided case scenarios from our data that illustrate teachers' needs and uses around the components of this model (Section 4.1). We also describe our model's potential impacts on the design of classroom orchestration tools (Section 4.2).

4.1 RQ1 and RQ2: A Conceptual Model of Math Teachers' In-class Information Needs and Usage

One of the results of our work is the development of a conceptual model (Figure 1) categorizing teachers' information needs for in-class sensemaking and their

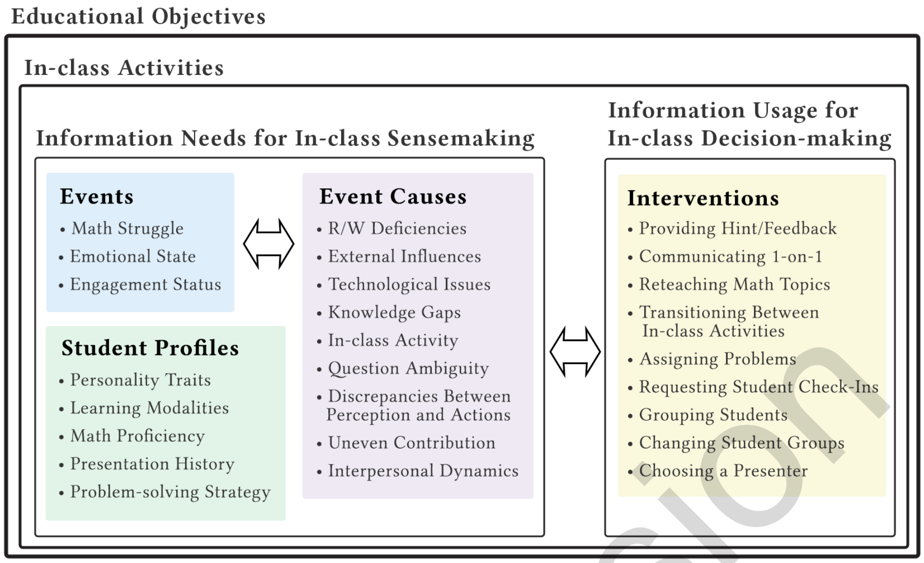

Fig. 1. A Conceptual Model of Math Teachers' In-class Information Needs and Usage

application in decision-making. Below, we describe each component of the model and present five case scenarios from our data that exemplify how teachers utilize various information categories in their decision-making.

Educational Objectives and In-class Activities. Alongside math learning, social-emotional learning is a common objective articulated by our teachers across all their in-class activities. Research indicates that children who better comprehend emotions and social behavior often achieve higher math scores, suggesting a link between emotional comprehension and academic performance [6]. Emotional states can not only enhance attention and motivation but also support learning engagement [30]. In line with this, our participants highlighted the importance of identifying students' emotions across in-class activities, as T4 noted: *"[...] if they're emotionally really not there [...] if they're really being set up by something else in the classroom, until I can get that in control, no matter what I teach them, they're not going to be ready to learn"*.

Learning design defines educational objectives and the pedagogical plans, including in-class activities, for educators to achieve these objectives [20]. We identified common in-class activities from our data such as individual problem-solving, group activities, and student presentations and we found that certain educational objectives are linked to specific activities. For example, T4 noted that student presentations improve oral skills: *"I feel like that [presentation] helps them with their explanation skills, helps them with oral skills [...]"* and T1 highlighted their role in improving peer evaluation skills: *"[...] if I see a mistake on the board, I'll say, one of these has a mistake. What is the mistake? So then* *that's [...] ability to analyze someone else's work."*. Similarly, group activities are noted to enhance teamwork skills. Understanding the various in-class activities and their respective educational objectives is key in determining the appropriate data types for collection, analysis purposes, and effective presentation to teachers. We illustrate in the case scenarios (towards the end of this section) how teachers' information needs can differ based on the in-class activity. Thus, in our model, the outermost layers, *Educational Objectives* and *In-class Activities*, directly influence teachers' in-class information needs and usage.

Information Needs for In-class Sensemaking. Our analysis identified three main categories of real-time information needed for in-class sensemaking by math teachers: *Events*, *Event Causes*, and *Student Profiles*. *Events* are classroom occurrences that can stem from various causes and are essential for teachers' awareness. Events and their causes can emerge in two ways: teachers might first observe an event and trace its causes, or they might notice a cause and look for their potential effects (i.e., events). For example, a teacher may notice a student's *emotional state* (e.g., a student is bored) and realize that an *in-class activity* is a potential cause, or they may first recognize an *external influence* affecting a student (a cause) such as a reported conflict with parents, and then discern its potential effects on the student's *emotional state*.

Teachers utilize information under the *Student Profiles* category to personalize interventions, matching students' unique needs and preferences. For instance, they might examine students' preferred *learning modalities* and adjust their interactions with students accordingly—e.g., T4: *"[...] some of my students definitely are just hands-on. Others want to draw it out. Others want to manipulate things. And I think if I could see exactly like their way of learning [...]"*

Information Usage for In-class Decision-making. We identified a range of common *Interventions* utilized by teachers in their classrooms (Figure 1, right). We also found an interplay between information needs for in-class sensemaking and information usage for in-class decision-making. This interplay shows that teachers' interventions are either responses to immediate classroom events or planned interventions requiring in-the-moment information for execution. For example, a teacher might notice the event of *math struggle* for a student group and *provide hint/feedback* to address it. The other way could be a plan to *group students* for an in-class activity and looking for specific real-time information, such as students' *math proficiency*, for strategic grouping. We will elaborate on group activities in Scenario 4.

Below are five case scenarios illustrating practical examples of teachers' information needs and usage: The first three detail classroom events, their potential causes, and teacher interventions across all in-class activities, while the last two focus on the specific information needs tied to two specific classroom activities.

Scenario 1: Math Struggles, Causes, and Potential Interventions. During all in-class activities, teachers often monitor students' math struggles either at an individual level or a broader class level—T1: *"[...] if there's a [math] problem that [students] are, many groups are struggling with [...]"*. Students' areas of struggle may take various forms including misconceptions, common errors, and multiple failed attempts [16, 15], however, awareness of the causes of these struggles is also key to taking effective interventions. Our participants highlighted various causes; for example, T3 talked about their district-level assessment and that *knowledge gaps*, *technological issues*, and *question ambiguity* can be potential causes of math struggles: *"We're able to look at okay, which standard? Were they just not getting overall? [...] Which questions? What was the questioning? [...] What were they missing? [...] Was it the technology part of it? Was it just them missing having too many gaps?"*

Teachers consistently seek insights into students' thought processes in solving math problems, including their reasoning about their overall approach and specific steps. This insight often reveals *discrepancies between perceptions and actions*, a frequent cause of math struggle. T4 cites an example of interacting with a struggling student: *"[...] show me what you're doing. Explain to me what you think you're doing, or what you think [the problem] wants you to do"*

Additionally, we found that math learning is often intertwined with reading/writing (R/W) skills, with teachers reporting that students' math struggles are not solely mathematical but may stem from *R/W deficiencies*, as T1 explains: *"So, sometimes I'm also gauging whether, If they don't understand [...] the problem, or they do not know how to do it mathematically [...] because some of them I don't know if they can read so well."*

After understanding the root causes of math struggles, teachers choose among a variety of interventions including *assigning problems* to students, *communicating 1-on-1*, or *reteaching math topics*. T1 discussed reteaching math topics when several groups face struggles: *"If there's a problem that they are, many groups are struggling with, then I'll kind of use that problem on like, we'll go over it"*. T4 mentions assigning targeted math problems based on identified student struggles: *"[...] depending on where they're struggling, have them work on that [standards]"*

Scenario 2: Emotional States, Causes, and Potential Interventions. While positive emotions play a critical role in successful learning, negative ones (e.g., anxiety, stress) can hinder learning performance significantly [30]. Our teachers explained various triggers of emotional states, which are essential for deciding effective interventions. For instance, *external influences*, such as hunger or family conflicts, can impact a student's focus and emotions. A teacher's response to such emotionally driven states might include *communicating 1-on-1* with the student, as T1 explains: *"Maybe talk to them like 1-on-1 and just say like, I know that you're going through a lot [...]"*. Another common trigger is *in-class activities*. T3's interaction with students exemplifies this: *"So, did [the activity] kind of made you [...] a little anxious because it was so fast? Raise your hand if it made you a little anxious."*. In these situations, a teacher might decide *transitioning between in-class activities* to evoke positive emotions. T1 explains that group activities can evoke positive emotions: *"It makes doing the work a little bit more fun when [students] are with their peers"*.

Scenario 3: Engagement Status, Causes, and Potential Interventions. Student engagement is closely linked to positive outcomes including academic success, school completion, and psychological well-being [32]. Our participants shared insights on information aiding in engagement monitoring during different in-class activities. For example, in group activities, teachers want to know if students are on-task or off-task: *"When they're in groups, they tend to get a little bit more chatty [...] So that's why I just walk around and make sure the groups are on-task"* (T1). Being off-task might relate to the group's *interpersonal dynamics*: *"I know that this person and this person, they can't be in the same group, they're not going to work well together [...] They're going to get into an argument, or they're going to fool around"* (T3). During student presentations, teachers find it helpful to know if students are actively listening: *"[...] see the [students] that are not presenting if they're paying attention because usually that [presentation] leads to distraction"* (T9). A common strategy to boost engagement is *requesting student check-ins*, where teachers ask students to indicate their engagement, for example, through specific hand signals.

Scenario 4: Managing Group Activities. The efficacy of group activities depends on grouping students strategically, monitoring groups actively, and providing personalized support [17, 22, 13]. Our participants emphasized the significance of *grouping students* based on *personality traits* that can lead to harmonious and effective collaboration. For instance, T1 focuses on creating groups that encourage shy students to participate more: *"I'm also figuring out what groups are working well, because It's helpful to know [...] who works well with each other, especially with shy people. [... Are] there specific people that they can work with that [get] them [...] to talk a little bit more?"* Moreover, grouping students with varied *math proficiency* can facilitate mutual learning: *"It's also good if you have a student who's struggling, and one who's stronger, they can [...] maybe help the other"* (T4).

As for group monitoring, prior studies highlight the need to flag groups that are in most need of help [22, 17], or insights into how much support each group has received and the duration they have waited for support [2, 1]. We found that, in addition to events and their causes (Scenarios 1-3), group activities can have unique causes for specific events. For example, T3 talked about *uneven contribution* of team members during group activities that could cause *math struggle* for the groups: *"Because [...] there are some students that could sit back and [think that others are] gonna do it for [them]"*.

Depending on the events and their causes, teachers choose among varied interventions such as *providing hint/feedback*, *communicating 1-on-1*, or *changing student groups* in response to more significant issues. For example, in cases of bullying within groups, T8 changes group compositions: *"if it comes to a point of bullying, I will [...] remove a person from the group [...]"*.

Scenario 5: Managing Student Presentations. Teachers consider various information when *choosing a presenter*. For instance, they look for students' *problem-solving strategy* to select presenters who can expose diverse approaches to the class, with each potentially resonating differently with individual students: *"[...] they might use a little bit different language [...] that can reach different students, especially different math brains work differently"* (T5). Information on students' *presentation history* also assists teachers in giving students presentation opportunities to improve their skills.

During presentations, teachers search for potential events and their causes. For example, T9 looks for potential math struggle in a student's presentation and whether the thought processes is a potential cause: *"Kind of look through how [presenters] think, and seeking out various ways that students are thinking about each problem set"*. Teachers also monitor the *engagement status* of students who are not presenting.

4.2 RQ3: Using the Conceptual Model to Support the Design of Orchestration Tools

Cross-domain Analytics for Overall Student Growth. The limited acceptance and adoption of orchestration tools, including real-time learning dashboards, have been linked to their failure to provide context-specific and actionable information [21, 15, 24]. Research indicates that analytics offered by these tools are often chosen based on analytics availability without carefully considering end-users' actual needs [16]. To bridge this gap, we used methodologies grounded in HCI to identify teachers' information needs and usage, avoiding biases toward any specific technological solutions.

Our findings highlight the need for orchestration tools to offer a wider range of analytics, moving beyond subject-specific analytics to include factors influencing student growth in various domains. In math classrooms, for instance, while many orchestration tools focus on math-related analytics [17, 33, 23], our findings indicate that early education teachers also place significant value on students' social-emotional learning. For example, teachers often look for insights into students' emotional states due to its supporting role in math learning [30]. Teachers look for students' personality traits to foster stronger bonds with them and personalize interventions. Furthermore, in elementary and middle school, students simultaneously develop skills across various core subjects. Thus, challenges in one area (e.g., reading/writing) can impact their performance in another (e.g., math). This interconnectivity demands orchestration tools that accommodate analytics across disciplines.

Another notable finding relates to the importance of supporting a range of in-class activities. For example, both our observations and interviews showed that students' in-class presentation is a key activity in math classrooms that is aimed at enhancing competencies in public speaking and peer communication. Orchestration tools can be designed to help teachers decide who gets to present their work and offer features for monitoring students' status during presentations (e.g., engagement status). However, many current orchestration tools lack features and analytics to support classroom presentations. This oversight could inadvertently diminish the significance of these activities in students' multi-dimensional growth.

Balancing Automated Assistance and Teacher Control. AI-based orchestration tools can automate various tasks for teachers such as automating data interpretation to show higher-level data, recommending interventions provided by decision-making algorithms, and even taking pedagogical actions instead of teachers, such as giving specific hints and reminders [4, 33]. However, in educational environments, requirements and constraints can evolve constantly [8]. For instance, educational standards and curricula may undergo significant changes from one semester to the next. Likewise, classroom dynamics, including peer interactions and teacher-student interactions, are subject to variation. These fluctuations can significantly impact the efficacy of automated assistance, requiring the ongoing involvement of teachers in the design and development of orchestration tools. This collaborative approach ensures that these tools are routinely refined and aligned within the contexts, needs, and constraints of the educational landscape.

One approach to facilitating teachers' effective use of orchestration tools and their meaningful participation in offering constructive feedback is through enhancing the tools' transparency. Such transparency should include explanations of the capabilities and limitations of the tool [34, 11]. For example, it can detail the specific criteria the tool utilizes to generate recommendations and the criteria it cannot consider. Maintaining transparency allows teachers to evaluate the alignment of the tool's features with their educational values, make necessary adjustments, and maintain meaningful control over the use of these tools [11].

Our model contributes to the process of enhancing transparency. For example, consider an orchestration tool that identifies a math struggle and recommends an intervention. Our model emphasizes the comprehensive analysis of possible causes, including a math knowledge gap, technological issues, discrepancy between perception and action, reading/writing deficiencies, and emotional states. Using this understanding, the tool can provide explanations on the rationales behind its recommendations, detailing both the factors it considered and those it did not. This approach allows teachers to have effective control over deciding about technology's recommendations. For instance, if the tool identifies a gap in math knowledge as the root cause of a student's math struggle and proposes reteaching a math topic, it is crucial for teachers to know that the analysis may not cover all bases, such as reading/writing skills—another potential factor contributing to the math struggle. Openly communicating the tool's limitations empowers teachers to refine the recommendations based on their own preferences, knowledge about students, and other unique needs of their classrooms.

Managing Information Overload for Teachers Prior studies have emphasized the limited availability of a teacher's attention during an ongoing class session [16, 15]. Researchers have proposed strategies to manage information overload for teachers in Human-AI Co-orchestration, with task automation being a key approach [4]. Yet, as discussed earlier, granting teachers meaningful control over such automation requires the enhancement of the tool's transparency, particularly through explanations of how the tool works. These explanations could increase the cognitive load on teachers. Thus, utilizing additional strategies to manage information overload becomes essential. One approach is filtering analytics based on ongoing classroom activity [4]. In this study, we detailed typical in-class activities and teachers' information needs to manage each of them.

Another strategy involves prioritizing the communication of critical information that requires teachers' prompt attention, with the option to provide details upon request [4]. Our model suggests initially notifying teachers about critical events such as math struggles, emotional states, and engagement status. Should teachers seek further explanations, the tool can present the potential causes behind each event. Based on the teacher's decision to address an event, the system can recommend interventions. It may also offer insights into student profiles (e.g., personality traits, learning modalities) enabling teachers to tailor and execute decisions more effectively.

5 Conclusion and Future Work

We developed a conceptual model that identifies the in-class information needs and usage of grade 3 to 8 math teachers, describing their interconnections and providing a theoretical basis for the development of classroom orchestration tools. We suggest the integration of cross-domain analytics, balancing automated assistance and teacher control by enhancing the tool's transparency, and managing information overload by effectively filtering and prioritizing the analytics. We used methods grounded in HCI, including contextual inquiry and focus groups aiming to support learning analytics communities in designing orchestration tools that have a meaningful impact on teachers' classroom practices.

Limitations of our work include observing one classroom per teacher. While we expanded our insights through interviews and a focus group, future research should consider longitudinal studies (e.g., an academic semester or year) to gain a more thorough understanding of in-class practices. A vital element in teachers' sensemaking and decision-making processes is evaluating the impact of teachers' interventions on students' learning [26]. This can inform teachers' future decision-making. Future research can investigate the analytics that aid teachers in evaluating the outcome of their interventions.

Our findings illuminate the diversity of teachers' information needs and usage. Future work should additionally explore privacy concerns in the extensive collection and analysis of student data [4], striving for a balance between data comprehensiveness and privacy. Another research direction can be on optimally presenting this information in LA system interfaces, such as LA dashboards, maintaining simplicity and glanceability [25].

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