Using Teacher Dashboards to Customize Lesson Plans for a Problem-Based, Middle School STEM Curriculum

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ABSTRACT

Keeping K-12 teachers engaged during students' learning and problem solving in technology-enhanced, integrated problem-based learning (PBL) has been shown to support deeper student involvement, and, therefore, better success learning difficult science, computing, and engineering concepts and practices. However, students' learning processes and corresponding difficulties are not easily noticed by teachers as students learn from these environments as processes are captured through mouse clicks, drag and drop actions, and other low-level activities. As such, teachers find it difficult to set up meaningful interactions with students while also maintaining the focus on student-centered learning. Little research has examined dashboard-supported responsive teaching practices for K-12 PBL. This study examined 8 teachers as they used a co-designed teacher dashboard to assess and respond to students' learning and strategies during an integrated, PBL STEM curriculum. Teachers completed a series of 5 "planning period simulations" leveraging the dashboard and think-aloud protocols were implemented, supported by semi-structured interview questions, to enable the teachers to verbalize their thought and evaluation processes. Content analysis and epistemic network analysis were conducted to analyze the simulations. Understanding how teachers use dashboards to support evidence-based teaching practices during technology-enhanced curricula is critical for improving teacher support and preparation.

CCS CONCEPTS

• **Applied computing → Education**.

KEYWORDS

responsive teaching, teacher dashboards, co-design, computational modeling

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1 INTRODUCTION

Prior research has demonstrated the importance of teacher engagement in students' developing ideas and strategies to support their STEM learning. In applications of student-centered learning approaches, such as problem-based learning (PBL), this engagement poses challenges as teachers must interpret and respond to student progress in ways that target learning and problem-solving needs while also maintaining the intent of the learning design (e.g., not always address a specific knowledge gap through direct instruction) [10]. Technology-enhanced approaches can mitigate these challenges by visualizing student learning and problem-solving behaviors to support teachers using orchestration technologies such as teacher dashboards [34]. However, little research has targeted (1) dashboard-supported responsive teaching for K-12 PBL [43] and (2) processes that middle school science teachers use to bridge the noticing and understanding of AI-based instructional support with the determination of an evidence-based pedagogical response [8].

Understanding how teachers use dashboards to support evidence-based teaching practices during technology-enhanced curricula is critical for improving teacher support and preparation and serves as the context for this research. Through a systematic co-design process with expert (prior experience with the learning environment) and novice (no prior experience with the learning environment) teachers, we have created the Responsive Instruction for STEM Education (RISE) dashboard [22] to support the implementation of a technology-enhanced, PBL curriculum known as Science Projects Integrating Computing and Engineering (SPICE) [24]. The goals of the RISE dashboard are to support teachers in: (1) noticing and responding to students' learning successes and opportunities (e.g., misunderstandings), (2) facilitating student integrated learning of science, computational thinking (CT), and engineering across multiple, linked representations, (3) aiding student-centered development of productive problem-solving strategies, and (4) promoting student communication and application of their developing integrated knowledge through class and group discourse and problem solving.

In addition, prior research has emphasized the impact learning through multiple, linked representations [2, 24], productive problem-solving strategies [48], and collaborative, open-ended problem solving [19, 23] have onlearning in our technology-enhanced, PBL approach. However, more research must target the complex task of translating what we know as scientists and researchers into a language that classroom teachers can interpret and convert to actionable information [46]. In this first step, we aim to evaluate the strength of RISE in supporting teachers' application of those PBL pedagogical processes.

This study examined eight teachers' use of a RISE to assess and respond to students' learning and strategies during SPICE. Teachers completed a series of 5 “Planning Period Simulations" leveraging the dashboard. Think-aloud protocols were implemented, supported by semi-structured interview questions, to enable the teachers to verbalize their thought and evaluation processes. Our analyses focus on the research question: **How do expert and novice teachers implement responsive teaching to customize lesson plans using RISE?**. To answer this question, we first conduct statistical analysis on the coding of expert and novice teachers' simulation discourse to identify the types of student work (e.g., performance scores, strategies applied) teachers notice and how they respond (e.g., teacher lectures, class discussions, group activities). Codes were developed based on prior work in responsive teaching (c.f., [10, 30]). We then conduct epistemic network analysis (ENA; 12) evaluating the temporal discourse patterns expert and novice teacher implement as they complete each planning period simulation. We compare the networks and provide initial findings based on the results. Finally, we provide researcher identified vignettes that examine teacher differences based on the ENA findings.

In this paper, we first provide background on technology-supported responsive teaching as well as an overview of research targeting teachers usage of dashboards to support their practice. We then describe our instructor-support technology known as the RISE dashboard and outline the co-design procedures taken to systematically design and develop this tool. Next, we provide our methods, including the instructional context, our procedures for implementing the planning period simulations, our participants, and the data collection and analyses processes. Next, we present our results and we conclude with a discussion of the results, limitations of our work, and future directions.

2 BACKGROUND AND RELATED WORK

This work targets the novel exploration of teachers' responsive teaching practices as they leverage a co-designed dashboard to evaluate student learning and problem solving, and develop evidence-based lesson plan customizations as needed.

2.1 Responsive Teaching for PBL in Science

Science and math education reform has led to the promotion of fluid classroom environments that allow for pedagogical adjustments during instruction [40]. This pedagogical decision-making paradigm leverages responsive teaching in which the teacher makes in-the-moment pedagogical decisions based on what and how students are thinking, assessed through what students are saying or doing [6, 18].

This responsive approach is in contrast to traditional methods, in which lesson plans are predetermined and direct students' “flow of thought” [18]. This predetermined, traditional approach limits student opportunities to develop and assess their own ideas, which is needed for inquiry learning [28] and open-ended learning approaches that include learning-by-modeling [47] and learning-by-design [7, 45], such as that targeted in this proposed research.

Attending and responding to the disciplinary substance of student ideas is considered a core teaching practice in science, math, and engineering [11, 29, 32, 36]. Responding to student ideas as they unfold in class has proven to help students engage in science practices [11, 18], focus student attention on the disciplinary substance of their thought [44], and improve students' conceptual understandings (e.g., 16, 37). This process is akin to formative feedback, providing students information to support adjustments in their thinking, guide them towards the desired learning goals, and improve knowledge development [39].

However, Van Es and Sherin note that successful applications of responsive teaching requires teachers to develop new ways to engage in and interpret classroom interactions [40]. The complex, challenging practice of responding to student ideas requires that teachers consider and evaluate copious amounts of classroom information (e.g., student discourse, performance) as well as the intrinsic and extrinsic constraints of the classroom environment (e.g., learning standards and objectives, time, assessment needs), and make in-the-moment decisions on what and how to engage in their students' ideas [6, 40].

The complexity of this practice can be exacerbated during problem-based learning due to:

(1) teachers' limited background in computing and teaching using technology [4],
(2) the decreased visibility of student thinking, as it is now applied through mouse clicks and other user-interface interactions and, therefore, not easily or readily apparent to the teacher (an important feature of lesson design to support teacher noticing; e.g., National Council of Teachers of Mathematics, 2014),
(3) problem-based learning is akin to open-ended learning, in which students may implement a variety of problem-solving approaches during solution construction [43, 48] that teachers must grapple with and engage in, and
(4) software constraints or user-interface difficulties that may impact teachers' abilities to adequately respond to student thinking or issues [43].

For instance, if applying an established framework such as the Technological Pedagogical Content Knowledge (TPACK) framework [31] to the teaching of computational modeling in science, a teacher may need to have knowledge in the science domain and in computing or computational thinking (CT), in methods for supporting each student as they learn and integrate each domain as well as in managing and evaluating classroom progress, and they must have sufficient comfort with and knowledge of the technology to implement and engage in the curriculum with their class. Moreover, teachers must understand how each component interrelates (e.g., in order to support a student as they debug a computational model, the teacher must be able to use both their science and computing knowledge as well as features of the technology to productively support). Finally, while these environments support key processes highlighted in state and national standards, these strategies are often not engaged in by teachers during instruction [43]. This is particularly challenging for teaching through student-centered learning approaches such as PBL, as teachers must interpret and respond to student progress, represented through data visualizations on a dashboard, in ways that target learning and problem-solving needs while also maintaining the intent of the learning design [10].

These experiences motivate a deeper understanding of what it means to notice student thinking during technology-enhanced, problem-based learning and the processes teachers take in the transition from their interpretation of student learning and problem solving to the creation of evidence-based pedagogical responses supportive of the problem-based, student-centered learning design.

Learning analytics research has progressed significantly and has led to the development of instructor support-technology proven effective for teaching with intelligent tutoring systems, collaborative learning scripts, and much more. However, research on teachers' usage of instructor-support technologies such as dashboards is still scarce, especially for the implementation of problem-based learning curricula [10] and for K-12 STEM classrooms [22].

A careful analysis of prior research representing dashboard-supported responsive teaching results in the identification of key research opportunities and directions involved in the understanding of how teachers use dashboards, and how to support them. These include (and illustrated in Figure 1):

(1) co-designing learning analytics and visualizations, including how to best integrate teacher insight [46], improving transparency in algorithm development [20], and supporting teacher agency in data vizualization selection [1],
(2) understanding teachers' noticing processes as they interpret what is presented via data visualizations such as dashboard, including Campos et al.'s recent work in which they developed a typology of responses to data visualizations [8], and
(3) understand how resulting teacher interpretations of dashboard visualization facilitate evidence-based pedagogical actions, of which there is a dearth of research [8].

To our knowledge, limited research exists that explores how teachers notice, interpret, and develop evidence-based responses to students learning and problem-solving strategies for a K-12 PBL curriculum in science [22]. Moreover, there is a need to understand how resulting teacher interpretations of dashboard visualization facilitate evidence-based pedagogical actions [8]. Unfortunately, not a lot of information can be found on the pedagogical actions teachers take as a result of using instructor-support technology, such as dashboards, especially for K-12 instruction. This research provides novel findings on example pedagogical responses resulting from the noticing, interpretation, and reasoning about student data during a problem-based, middle school science curriculum.

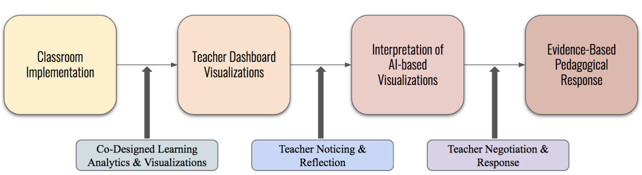

Figure 1: A dashboard-supported responsive teaching process, adapted from [8].

3 CO-DESIGN OF RISE DASHBOARD

This research focuses on teachers' responsive teaching practices supported by a teacher dashboard for a problem-based learning curriculum known as SPICE.

3.1 Instructional Context: SPICE

SPICE supports teachers in the implementation of the SPICE Challenge [24]. The SPICE is a three-week, NGSS-aligned unit that challenges students to redesign their schoolyard using different surface materials to minimize the amount of water runoff after a storm, while adhering to a series of design constraints. These include the overall cost and accessibility, while providing for different functionalities for the schoolyard [24]. The problem-based learning curriculum consists of five core units, illustrated in Figure 2. These units include: physical experiments, conceptual modeling, paper-based computational thinking tasks, computational modeling of the water runoff phenomenon, and engineering design, in which students use their computational models to redesign their schoolyard. This learning context is authentic and relevant to students facing similar problems (limited usability and pollution) in their own schools, therefore, the SPICE is potentially engaging and personally meaningful to the learners [24]. The SPICE targets NGSS performance expectations for upper elementary and middle school Earth science and engineering design curricula, emphasizing the movement of surface water in a system after heavy rainfall and the human impact of this runoff on the environment, and leverages evidence-centered design [35] for the systematic creation of summative and formative assessments to evaluate student learning in science, computing, and engineering.

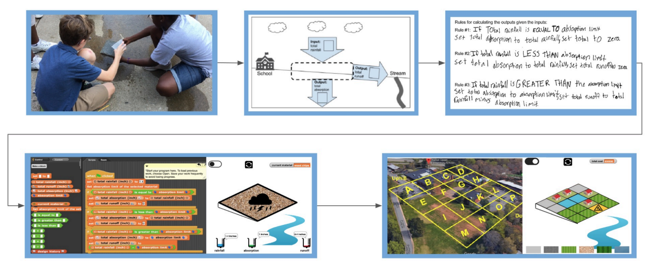

Figure 2: The SPICE curriculum sequence.

We focus this paper on Planning Period Simulations that target students' efforts to construct a model of a scientific process, i.e., water runoff after a heavy rainfall. These curriculum lessons offer unique perspectives on how teachers evaluate student data as pedagogical planning requires the evaluation of items such as how well students are translating their developing science knowledge into computational form, understanding the multiple paths students can take to successfully construct a computational model in science, and identifying successes and opportunities students are having in using difficult computational constructs such as conditional logic. Moreover, in the Background we identified teachers' limited background in computing as an issue for implementing such problem-based learning approaches and this allows us to examine ways in which the dashboard can help novice teachers.

3.2 Creating the RISE Dashboard

The dashboard leveraged in this work was created through a series of co-design design sessions with expert and novice SPICE teachers. In addition, the dashboard components were grounded in past work on supporting teachers in the integration of scientific inquiry and

PBL (e.g., [10, 34] and visualizing feedback at individual, group, and class levels (e.g., [15], as well as providing teachers' agency in dashboard visualization selection [1] and supporting teachers' sensemaking about classroom performance [8]. For a more detailed presentation of our design process, please see [22].

As a first step, researchers used student data from prior implementations to increase our knowledge about how students learn and problem solving during SPICE. This involved the systematic analysis of student science, computing, and engineering learning as demonstrated through summative and formative assessments, evaluating the impact of student learning over a sequence of multiple, linked representations, and identifying key learning and problem-solving strategies students use to construct computational models and engineering design prototypes, based on their user actions in the learning environment, that support their learning in each domain [24].

Then researchers initiated the co-design sessions by first using low-fidelity prototypes (e.g., linked data visualizations) and contrasting student artifacts as boundary objects to discuss, negotiate, and come to an understanding about what information teachers need about their students so they may better help their student during this student-centered, problem-based curriculum. Feedback from these sessions were used to inform the creation of the first high-fidelity prototype. In the second design sessions, we integrated the use of the high-fidelity prototype into a professional development workshop with SPICE teachers. As we reviewed the curriculum and discussed instructional strategies with participating teachers, we used the dashboard as a tool to discuss prior student performance on each lesson and assessment. Teachers thought aloud, describing what they noticed, how they interpreted the results, and possible actions they might take knowing this information. Researchers intervened and responded to questions as necessary. Teachers also provided us with more specific recommendations for user-interface adjustments (as opposed to abstract ideas from the first session). The research team used results and feedback from this session to create the RISE (Figure 3) dashboard, used for the Planning Period Simulations.

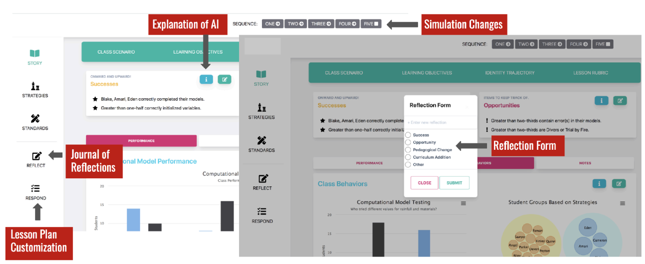

Figure 3: RISE Dashboard

The RISE dashboard consists of three core student result pages: the Story, the Strategies, and the Standards. The Story provides an overview of the class performance based on key immediate, or landing page, feedback recommended by teachers. This included text-based feedback highlighting class successes and opportunities using performance (items scored by pre-defined rubrics) and strategies (productive and unproductive strategies pre-defined based on the impact on student learning results). Interactive data visualizations, such as the grouping of students based on strategies, with additional performance-based results, could be accessed using information in the bottom right visualization shown in Figure 3. The Strategies page provided a progression of student performance over the course of the curriculum (e.g., up to the "day" simulated in each planning period simulation) and the strategy group they currently are identified with. Finally, the Standards provided a data table of all students with their scores on each completed curriculum task and identified strategy groups. All data visualizations in which artificial intelligence was used to calculate or provide feedback included an explanation of analysis done (for example, a modal pops-up with the information when the blue button with an "i" is clicked).

The RISE dashboard is equipped with a Reflection Tool in which teachers can add reflections as they reviewed the results (identified as "Reflection Form" in Figure 3) and select categories for the type of reflection. Submitted forms were populated on the Reflection page based on the category selected (the page link is identified on the left-side menu bar in Figure 3). In the Reflection page, teachers can reorder and reorganize reflections as they see fit. Finally, teachers are also provided a Response page. This page includes the current class plan for the next class and tools to plan for any adjustments they deem necessary based on student performance. Finally, teachers are provided a number of curriculum resources, including learning objectives and lesson plans relevant for the "day" to aid in their evaluation process.

4 METHODS

4.1 Participants

Eight middle school STEM teachers (5 female, 3 male) participated in the planning period simulations. The teachers were from varying urban and rural locations, including Tennessee, Illinois, Virginia, New York, Wyoming, and the US Virgin Islands. All teachers consented to participate in the Vanderbilt University IRB-approved study.

For this analysis, we divided the group based on their prior experience with computational modeling in science. Expert teachers are defined as teachers (n=4) that had prior experience and training integrating computational modeling into their science classrooms. In this case, three of the teachers had previous training and classroom experience with SPICE and one had prior classroom experience with our core computational modeling environment [23] integrating similar curricula in physics and marine biology. Novice teachers are defined as middle school teachers with no prior experience integrating computational modeling in science. Therefore, the core difference between the teachers, for instance, related to the TPACK framework, discussed above, is that expert teachers had: (1) increased prior content knowledge in computational thinking (training and implementation of computational modeling and block-based programming), (2) increased pedagogical content knowledge specific to supporting and orchestrating computational modeling in science (e.g., prior experience supporting student difficulties and successes, linking multiple domains or representations), and (3) increased technology knowledge in terms of understanding of the learning environment and its tools. However, all teachers had prior experience in the science domain and all had least 5 years of middle school teaching experience.

4.2 Planning Period Simulation

We focus this paper on five Planning Period Simulations in which teachers would enact five 15 minute "planning periods" by utilizing the RISE dashboard to review and reflect on student, group, and class performance and then develop evidence-based lesson plan customizations for the "next" class day. These simulations were inspired by the Teacher Moments research at MIT [3]. Student data used for each simulation was pulled from prior SPICE implementations in an approach similar to the Replay Enactment protocol [20] . Student data from the prior implementations were de-identified and students were given gender-neutral names. The five simulations were selected based on the average summative assessment performances in science and CT (e.g., one simulation included a class that had an above average pre-test performance in science, but a below average pre-test performance in CT).

Each teacher first completed a 90-minute professional development session led by the research team in which they learned about the SPICE curriculum. For each simulation, a research team member first described the class scenario, including the class performance on the pretest and other class results prior to the simulation "day" (e.g., on the science conceptual models). Teachers then had 15 minutes to complete the simulation exercise. Fifteen minutes was selected based on an estimated class period time length of 60 minutes and an average estimated class roster of 4 classes per teacher, therefore 15 minutes per planning period for each class.

Using a think-aloud protocol, teachers reviewed student results and feedback provided on the RISE dashboard, interpreted what they saw, and customized class lesson plans for the next day (as they saw fit). Prior research has noted the benefits of think-aloud protocols on tasks involving building interpretations [9], including providing a low-entry barrier [8] and tracing users' thinking [33]. In order to obtain verbalizations that accurately reflected the cognitive processes teachers implemented during responsive teaching, we refrained from providing detailed instructions or interpretation of results. Instead, we utilized prompts such as "what possible actions would you take with this group?" and answered questions about technology that did not impact class evaluations (e.g., describing how to use the reflection form). This approach is modeled after Campos et al.'s approach for evaluating teacher sensemaking [8]. This helped minimize issues concerning bias in data if researcher support or feedback impact teachers' responses [38].

Finally, researchers completed an observation sheet during the simulations. The observation sheet consisted of a table for researchers to identify (1) discussed idea (e.g., computational model scores), (2) visualization targeted, when applicable (e.g., bar graph of class performance), and (3) keywords used or links made (e.g., poor initialization of science variables score during computational modeling relating to prior science performance). These observations were used to support our analysis approach, discussed below.

4.3 Data Collection and Analysis

All Planning Period Simulations were conducted virtually and recorded using a video conferencing platform. In total, we had approximately 12 hours of video data, which we transcribed using an online transcription service. For the purpose of this paper, we segmented the transcripts into episodes of pedagogical reasoning [21]. In this case an episode of pedagogical reasoning was initiated when the researcher completed the opening statement about the class scenario and ended when the teacher submitted their customized lesson plan. These segments formed the base unit of analysis to answer both research questions.

To conduct this analysis, we first divided the episodes of pedagogical reasoning into smaller excerpts related to idea units, in which a single topic was discussed [27], in order to balance our units of analysis. This resulted in 735 idea units. A coding scheme (described in Table 1) targeting noticing and interpretations was developed by leveraging past work the analysis of responsive teaching during video clubs [30] and teacher dashboard usage [10] and incorporating additional categories pertinent to our work, including teachers' discussion of problem-solving strategies.

We also developed a coding scheme to evaluate teacher discussions on evidence-based response creation. To do so, we targeted discourse that discussed the social level [14] of the activity (e.g., teacher lecture, class activity, group activity, or individual activity) and the context of the response (e.g., is the response focused on conceptual knowledge, problem-solving behaviors, linking multiple representations, or technology issues). The codes for evidence-based responses can be found in Table 2.

Researchers met to code idea units using these schemas together. Differences were discussed and refinements were made to the coding scheme. The researchers then coded 20 percent of the idea units and achieved good IRR agreement ($k > 0.80$). The researchers discussed differences and once they were resolved, the main author coded the remaining idea units.

To answer our research question one, we utilized epistemic network analysis (ENA) [12] to interpret how expert and novice teachers interpret and respond to students science and CT knowledge and problem-solving strategies as they construct their computational models. Recent code-and-count analytic approaches have been criticized for ignoring temporal contexts of discourse, which is particularly relevant to the understanding of the processes teachers implement from using and understanding data visualizations of student learning to enacting evidence-based pedagogical responses. ENA has been shown to overcome this limitation and find temporal relationships in data [12]. In education, ENA has been used to analyze collaborative problem-solving [25], how collaboration support science knowledge construction [5], and understanding students' assessment responses [26]. More recently, ENA has been used to evaluate the impact of alerting dashboards for teachers on student learning through science inquiry [13], and serves as the motivation for our analytical approach.

These coded units were used to build the epistemic networks. The epistemic networks (see Figure 5) were created using the ENA online graphical interface (epistemicnetwork.org). Nodes represented the codes from Tables 1 and 2. The lines (and strength of the lines) represent the connections between nodes and the frequency of co-occurrence. This allows us to evaluate temporal patterns in discourse and we evaluate differences in epistemic networks of expert and novice teachers during the episodes of pedagogical reasoning to answer the research question.

Table 1: Coding Scheme for Teacher Dashboard Evaluations

Code	Definition *(Teaching Knowledge)*	Example
Curricular (CURR)	Questions or comments focused on the teachers own understanding of the ideas in the lesson *(SPICE-specific Pedagogical)*	“How much instruction do students get to complete the first rule?”
Descriptive (DESC)	Discussed content-based information they obtained from the dashboard *(Pedagogical)*	“OK so 12 students completed their model correctly.”
Interpreting Performance (N-PERF)	Questions or comments focused on the simulation students’ understanding of the science, CT, engineering concepts *(Domain-Specific Content; Pedagogical)*	“Ok, it looks like they really do not understand how to calculate total runoff when rainfall is greater than”
Interpreting Strategies (N-STRAT)	Questions or comments focused on the classroom students’ application of strategies *(PBL Content; Pedagogical; Technology)*	“It looks like this class is really struggling with testing materials” “There are a lot of divers!”
Integrating Multiple, Linked Domains (N-MLR)	Questions or comments focused on the sequencing of content and trajectories of student learning *(Domain-Specific Content; SPICE-specific Pedagogical)*	“Another benefit of testing materials is that I can help them relate it to the science experiments we did."
Regulative (REG)	Reflections on the teacher’s pathways of exploring the dashboard or strategies they used to interpret the visualizations *(Pedagogical)*	“I love looking at bar graphs so I will go there first”
Instructional (INST)	Questions or comments focused on the resources and pedagogical moves used to convey science, CT, or engineering ideas *(SPICE-specific Pedagogical)*	“I’m not sure if the debugging task is in the right place.”
Technology (TECH)	Thoughts on how to explore the dashboard and to look at different visualizations, including recommendations for dashboard adjustments *(Technology)*	“I’m looking for students that moved to more productive strategies. It would be nice to highlight or color those changes.”

Table 2: Coding Scheme for Teacher Responses

Code	Definition *(Teaching Knowledge)*	Example
Teacher Lecture (LECT)	Teacher plans to add class lecture on a topic based on data *(Domain-Specific Content; Pedagogical)*	“Students are struggling with initializing variables and so do I so I will add 5 minutes at the beginning of class to connect their struggles to mine.”
Class Activity (CLASS)	Teacher plans to add activity involving the class as a whole *(Domain-Specific Content; Pedagogical)*	“I will have Taylor present how they completed the first rule and I will be sure to ask questions or discuss how students can check if the rule is correct”
Group Activity (GROUP)	Teacher plans to add activity in which students work in groups *(Domain-Specific Content; Pedagogical)*	“I will group Divers and Strategist so that Divers can see the importance of testing materials”
Individual Feedback (IND)	Teacher schedules individual student feedback based on data *(Domain-Specific Content; Pedagogical; Technology)*	“This student continues to struggle in science, so I will set aside time as the class works to help them with their science knowledge”
Conceptual (CONC)	Teacher response targets domain-specific knowledge *(Domain-Specific Content)*	“We will discuss the difference between total absorption and absorption limit”
Strategy (STRAT)	Teacher plans activity demonstrating productive testing strategies *(Domain-Specific Content; PBL Content; Technology)*	“We will do the debugging tasks together and I will demonstrate the benefits of testing different values of rainfall or materials”
Linking Multiple Domains (LMD)	Teacher plans activity that links multiple domains (Domain-Specific Content; SPICE-specific Pedagogical)	“This class is going back outside to continue testing different rainfall values, and then implementing similar tests on the computer!”
Technology (TECH)	Teacher response targets the use of a technology tool (e.g., clicking on the design history table) *(SPICE-specific Technology)*	“This student has not changed any materials. I will demonstrate how to tomorrow”

5 RESULTS AND DISCUSSION

5.1 Teachers’ responsive teaching practices using RISE

Following the data processing of the 8 teachers there were 453 idea units generated by the expert teachers and 278 idea units generated by the novice teachers. We argue it was partly due to the nature of the idea units. For example, novice teachers had a greater amount of Curricular codes, a median of 12 per simulation by the novice teachers and 3 by the expert teachers, which include questions or comments focused on teachers understanding of the curriculum. These idea units typically involved researcher response, and, therefore, a higher number of researcher input during the allotted 15 minute time.

Figure 4 illustrates the breakdown of noticing codes (labels identified in Table 1). As seen in the novice teacher pie chart on the right, novice teachers spent almost half of their time discussing the curriculum and the dashboard technology. Interestingly, both expert and novice teachers had about the same number of idea units targeting performance and student strategy interpretations (in yellow and green in Figure 4). novice teachers had a median of 9.5 and expert teachers 9 segments targeting the interpretation of student performance. In addition, novice teachers demonstrated a median of 8 interpretations of student strategy usage while expert teachers had a median of 12 (we argue the higher amount by the expert teachers is reflective of teachers' experience with testing strategies from prior classroom implementations). The key difference between the groups in terms of noticing and interpreting involved interpretations of the results from the perspective of multiple-linked representations, with novice teachers not demonstrating any such segments, while it was the focus of 7% of expert teacher noticing. This is important as it connects to our dashboard goal of supporting teachers in facilitating the integrated learning of science, CT, and engineering through multiple, linked representations. While it did support expert teachers, more work needs to be done to support novice teachers. In addition, these results impacted teachers evidence-based response codes, as illustrated by the ENA graphs in Figure 5.

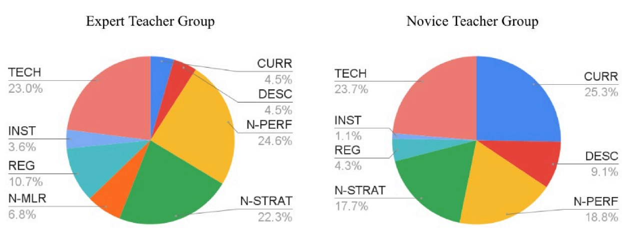

Figure 4: Expert and novice teacher noticing results.

Following the coding of the pedagogical episodes, we ran epistemic network analysis to evaluate the links between idea units. The highest three link probabilities for the novice group of teachers were (1) class-level activity response and strategy response (0.36), (2) class-level activity response and concept-targeting response (0.28), and (3) individual student response and concept-targeting response (0.26). The expert group's highest link probabilities were (1) class-level activity response and concept-targeting response (0.38), (2) class-level activity response and multiple-linked representations-targeting response (0.37), and (3) collaboration-level activity response and strategy-targeting response. These results seem to indicate a link between the role of interpreting student results on the dashboard from the perspective of multiple-linked representations and developing responses that support students in making those links. In addition, it is interesting to note that expert SPICE teachers were more likely to customize lesson plans to target strategy improvements using a collaboration approach (e.g., pairing students to compare debugging processes) and novice teachers were more likely to rely on individual student responses when faced with conceptual issues (e.g., speaking one-on-one to a student struggling to initialize needed variables).

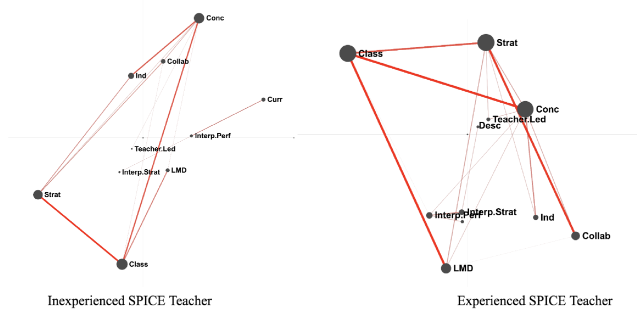

Figure 5: ENA Graphs

Overall, these results demonstrate that teachers reflected on the data and developed evidence-based responses at multiple social levels. In addition, both groups were able to develop pedagogical customizations that targeted both conceptual knowledge improvements, and the development of problem-solving skills or strategies using the dashboard. The results also demonstrate that novice teachers tended to focus on their more general prior pedagogical and domain-specific knowledge to create evidence-based responses, while expert teachers focused on their SPICE-specific knowledge to support their response development. We hypothesize that data visualizations or tools to aid in data visualizations, such as those developed by van Leeuwen to support teachers interpretation of collaborative learning results [42], may better support novice teachers in their noticing and interpretation processes centered on SPICE-specific needs, while expert teachers may benefit from the presentation of more general, or higher-level, response options to support deeper reflection and response negotiation.

5.2 Teacher Vignettes

One major limitation of this analysis approach, is we are not able to see the processes that transition teachers from noticing and interpreting to the development of those evidence-based responses identified in these figures. To do so, two researchers identified example teacher vignettes covering a key ENA result and practice discussed previously: supporting students' understanding across multiple linked representations.

For example, a novice SPICE teacher was weighing different options for lesson customizations, including running another physical science experiment, and said *"I'm still thinking about the materials. How to get them to transfer that original [engineering design] grid you'd set up to, you know, to that they have to have the different values for the materials. Because it's still more than half [that aren't testing].And that's why I told you, I love to see the Data Summary. I think those avert connections between the lab experiment [in science] and the [computational] model. We make those implicitly as adults, but I think it needs to be you know, it it needs to be more obvious for a younger brain. Yeah. To connect the model to the real thing."* In this example the teacher recognized that as adults, we may automatically connect the SPICE computational modeling practices (e.g., testing the computational model with different materials) to the material experiments conducting in the previous SPICE unit; however, more effort needs to be made to support students in deriving those links because understanding these connections can be very useful during the playground design task.

Similarly, an expert SPICE teacher was reasoning about why they wanted to return to the multiple conceptual models students make during the science unit in order to help them identify patterns in the computational model representation. The teacher said, *"That's that was my point about the multiple representations, because they're figuring out the patterning. But do they really know what that's doing? Realistic. What the actual [model is doing]. That it's raining this much, and this much runoff is this and as much as absorbed and all that. So that's where you're doing something like where we're having to literally explain. So here's what you coded. And here's what it did. Why did it do that? What actually dos that mean?"* In this example, the teacher reflects back on it being necessary to specifically ask students about what a model represented or meant and that students struggled with it. The use of multiple, linked representations here is to help students make the connection between patterns identified in the conceptual model to the computational model and, hopefully, support their understanding of what the computational model represents. Moreover, although not explicitly discussed, these multiple representations are also helping the transition from the conceptual model (e.g., understanding the conservation principle in science) to the construction of a computational model (which requires additional thinking and application about specific CT concepts and practices).

6 CONCLUSIONS AND FUTURE IMPLICATIONS

This research presents a novel exploration into the processes teachers take to notice and interpret learning analytics from a co-designed dashboard and then reason and enact evidence-based pedagogical adjustments through lesson plan customizations. In particular, this research illuminates differences between expert and novice teachers' dashboard-supported responsive teaching practices as they prepare to teach a problem-based learning curriculum.

Despite efforts to promote data-informed decision making in the classroom, there is scarce research examining how teachers utilize instructor-support technology such as teacher dashboards [17]. This is exacerbated in the context of problem-based learning designs, as teachers must not only understand complex data analyses of students' problem-solving behaviors, they must leverage that information to design evidence-based pedagogical adjustments that enact a student-centered approach to learning. Evaluating teachers evaluation processes not only contributes to our understanding of how data promotes changes in instruction [17], but it can:

- support the development of tools to aid in teachers' noticing by interpreting the complex learning analytics [41] that target their background and experience (such as supporting novice teachers understanding and confidence in the curriculum and the impact of student results on students' learning trajectories, as seen in our work),
- improve resources to support evidence-based responses (e.g., teachers anecdotally recommended a list of expert teachers customizations based on similar class results as those in the simulations to support response decision making in the future),
- improve teacher training on responsive teaching for PBL (e.g., in the future after novice teachers have completed their simulations, they could be presented with examples of what expert teachers did in the same situation and reflect on the options), and
- improve visualization of feedback based on teachers' pedagogical needs (e.g., supporting teacher and coach sensemaking using data visualizations [8]).

In our work, although novice teachers utilized greater time on better understanding the curriculum (as expected due to lack of classroom implementation), all teachers (1) implemented responses that targeted student-centered learning design, (2) interpreted and evaluated student problem-solving strategies and integrated that interpretation into classroom responses, and (3) created group activities to support students communication about their developing problem-solving skills and knowledge. We believe this demonstrates the effectiveness of our dashboard in supporting both expert and novice teachers plan for the integration of a problem-based learning curriculum. We believe future work should explore the use of simulations such as these to increase teacher experience and comfort in dashboards that target not only performance, but students behaviors and problem-solving strategies as they complete such a complex curriculum.

We recognize limitations in our work. On the one hand, the low participation number for this study resulted in analyses focused on depth instead of breadth. Future work should increase the participant cohort to validate if these results hold and to better ensure that teacher preparation is inclusive and supports equity in future problem-based learning applications. In addition, in terms of the selection of classes for each simulation, we recognize a limitation in the use of a high- vs low-performing dichotomy in the selection of classes as that approach may not fully represent the nuances learning and problem solving behaviors from a classroom context. Future work in selecting data for simulations (and co-design) can look into more nuanced approaches to evaluating classes, groups within classes, and individual students. Finally, we aim to complete a full, iterative dashboard cycle in which the participating teachers will implement SPICE (supported by the accompanying RISE dashboard) in their classrooms, and then researcher-teacher partners will reflect on their simulation and classroom experiences.

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