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Teaching with Analytics: Towards a Situated Model of Instructional Decision-Making

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Abstract

The process of using analytic data to inform instructional decision-making is acknowledged to be complex; however, details of how it occurs in authentic teaching contexts have not been fully unpacked. This study investigated five university instructors' use of a learning analytics dashboard to inform their teaching. The existing literature was synthesized to create a template for inquiry that guided interviews, and inductive qualitative analysis was used to identify salient emergent themes in how instructors 1) asked questions, 2) interpreted data, 3) took action, and 4) checked impact. Findings showed that instructors did not always come to analytics use with specific questions, but rather with general areas of curiosity. Questions additionally emerged and were refined through interaction with the analytics. Data interpretation involved two distinct activities, often along with affective reactions to data: reading data to identify noteworthy patterns and explaining their importance in the course using contextual knowledge. Pedagogical responses to the analytics included whole-class scaffolding, targeted scaffolding, and revising course design, as well two new non-action responses: adopting a wait-and-see posture and engaging in deep reflection on pedagogy. Findings were synthesized into a model of instructor analytics use that offers useful categories of activities for future study and support.

Notes for Practice

- Integrating the use of learning analytics into teaching practices to inform instructional decisions takes time; the gap from "interesting" to "actionable" is the most important to bridge with pedagogical support.
- Instructors' use of analytics can be stimulated and supported through opportunities for collaborative interpretation and development of ongoing support networks with other instructors.
- Learning analytics tools can support processes of use through targeted features such as question generation, flagging patterns for later review/action, and prompts to check the impact.
- Learning analytics tools can support actionability by aligning information structures with common pedagogical concerns and offering relevant reference points for comparison.
- Involving instructors throughout analytic tool development and conducting early studies of analytics use in-situ can provide important insight into tool design for local actionability.

Keywords

Learning analytics, analytics use, data-informed decision-making, instructional improvement, instructional dashboards, pedagogical support, teaching analytics, learning analytics design, learning analytics implementation

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1. Introduction

Learning Analytics as a field is concerned with developing and applying analytics to educational data in order to better understand and support teaching and learning (Siemens et al., 2011). Importantly, the aim is not just to advance technical methods, but to make a difference in practice. As the field matures, attention has correspondingly expanded from an initial focus on developing increasingly sophisticated tools, techniques, and systems for working with educational data (Greller & Drachsler, 2012), towards attention to the ways in which such analytics can actually impact teaching and learning. The question of impact is inherently a human-centred one, as "analytics exist as part of a socio-technical system where human decision making and consequent actions are as much a part of any successful analytics solution as the technical components" (van Harmelen & Workman, 2012, p. 4).

Focusing on impact, instructors are a particularly important and impactful class of analytics users. On the front lines of education, instructors are already engaged in the ongoing activity of collecting and making sense of information about their students' learning to guide their teaching (Borko & Shavelson, 1990) whether informally as an aspect of their daily teaching practices or more formally through a process of teacher inquiry (Cochran-Smith & Lytle, 1999). However, it would be naïve to presume that simply providing them with new types and greater amounts of data via analytics would lead to straightforward benefits (Spillane, 2012). Rather, the process of using data to inform decisions in real-world educational settings is a decidedly non-trivial one in which instructors need to translate system-provided information into locally meaningful knowledge and subsequently use it to guide their pedagogical activity (Kitto, Buckingham Shum, & Gibson, 2018; Wise & Vytasek, 2017). It is thus necessary to study how instructors work with and act on learning analytics in authentic teaching contexts (Wise, Knight, & Ochoa, 2018) and develop robust conceptualizations of these processes.

Prior work has approached this issue through multiple lenses, including that of teacher inquiry, learning design, orchestration, and institutional support. The current study seeks to move the field forward by integrating these different perspectives and empirically interrogating the different activities involved in instructors' analytics use. First, existing work is synthesized to generate a template for inquiry. We then investigate the experiences of five university faculty members working with an analytics dashboard to unpack the nuanced practices of analytics use in a small number of authentic teaching settings. The findings are integrated to generate a model that offers a set of useful categories for conceptualizing instructors' analytics use and making recommendations for analytics design and implementation to support actionability and impact.

2. Literature Review

In recent years, instructor-facing learning analytics have transitioned from an area of research innovation to a technology that is used in practice. Initial work focused on designing tools for usability to support instructors in working with student learning data. For example, Ali, Hatala, Gašević, and Jovanović (2012) conducted an experimental study that documented the importance of effective visualization for instructors to grasp the value of a tool, relate information to real situations, and have constructive ideas for tool use. A second phase of work moved into examining usage in real teaching situations, focusing on how much tools were employed and when, as well as what features were accessed. For instance, Dazo, Stepanek, Chauhan, and Dorn (2017) found a low frequency and overall levels of usage of an analytics dashboard for an online video and annotation system by 14 instructors given access for the course of a year. Tarmazdi, Vivian, Szabo, Falkner, and Falkner (2015) investigated a single instructor's use of a teamwork dashboard during a single semester, finding that the instructor used the sentiment analysis graph and the team role analysis features most regularly. Across these studies, a common issue that arose was instructor difficulties in integrating the use of the analytic tools into their daily teaching activities. For example, to probe the low levels of usage found, Dazo et al. (2017) conducted a follow-up focus group with six instructors, which revealed that despite high levels of excitement and enthusiasm for the tools, they found it hard to relate the information provided by the tools to their teaching concerns. This led to a third phase of work focusing on understanding how instructors translate analytic data into actionable information in order to better support this process. These efforts have approached the issue through multiple lenses.

The first strand of work draws on the longstanding tradition of teacher inquiry, a process in which instructors identify pedagogical questions of interest, collect relevant evidence from their classroom, and analyze and reflect on this information to generate answers (Cochran-Smith & Lytle, 1999; Hansen, & Wasson, 2016). There is an emphasis on not only changing teaching practices as a result but also coming to a better understanding of oneself as an evolving practitioner and becoming a designer of one's own professional growth (Rust, 2009). Recently, several studies have suggested both that learning analytics can support the different steps of the teacher inquiry cycle, and that the teacher inquiry cycle can offer a framework for making analytic information actionable. For example, Avramides, Hunter, Oliver, and Luckin (2015) found that a process of teacher inquiry emerged in a secondary school in the use of student analytic data by 13 teachers working under the guidance of school leadership. They also suggested a modified teacher inquiry cycle (consisting of nine steps from trigger and question refinement to new inquiries and change enactment) to take into account analytics-specific issues related to identifying questions and collecting data. Sergis and Sampson (2017) examined how learning analytics were being used to support each step of the teacher inquiry cycle by conducting a systematic literature review. They found that analytic data was most helpful for inquiry questions related to analyzing the elements of course design, that the most common type of analytic data used was assessment scores and student engagement information, and that reflection on course design based on these data sources occurred regularly. This ties into a second strand of work focused on how learning analytics can play a role in the process of learning design.

The overarching concept of this second strand of work on learning analytics and learning design is to consider how the collection and analysis of student data can feed into an iterative process of creating learning activities, materials, and plans to achieve an educational aim (Mor, Ferguson, & Wasson, 2015). Lockyer, Heathcote, and Dawson (2013) theorized two different conceptual categories of analytic information that can be used by instructors as part of learning design: checkpoint analytics (whether students access the necessary resources) and process analytics (how students complete the learning tasks). More recently, Bakharia et al. (2016) conducted interviews with instructors to identify what types of analytics could inform their learning designs and found a desire for analytics that show student engagement with particular activities and changes in student engagement over time. Moving from conceptual frameworks to studies of analytics-in-use, Xhakaj, Aleven, and McLaren (2017) investigated how learning analytics dashboards were employed by teachers for class preparation. Based on interviews and observations, they suggested that the analytics representing student learning progress on particular materials informed the teachers to confirm or reject pre-existing ideas and then adapt their lesson design accordingly.

A third strand of work has focused on how analytics can be a powerful source of real-time information to help instructors monitor learning progress and flexibly adapt their teaching through orchestration (Dillenbourg, 2013). Studies have looked at the ways in which instructors make sense of data and use this information to dynamically adapt available pedagogical and technological resources to help the student make progress and achieve goals. For example, Molenaar and Knoop-van Campen (2018) examined analytics use by 38 primary school teachers and found that teachers reflected on and interpreted the analytics by activating their existing pedagogical knowledge about their students and course context. They further found that the teachers responded to their interpretations by giving progress- and task-feedback to both individuals and the class as a whole. Tan, Koh, and Jonathan (2018) similarly investigated how an analytics dashboard supported teachers' daily practices in a high school and reported that the teachers used the data to inform whole-class and targeted scaffolding actions, at times showing the analytics to students to facilitate engagement and metacognition.

Distinct from the above micro-level considerations of instructor analytics use in classrooms, a final strand of work has focused on macro-level implementation of institutional supports for translating analytics into action. For example, Rienties et al. (2016) brought together instructors, administrators, and learning analysts at their university to understand the information made available by a predictive analytics system and develop a menu of response actions. This informed the use of the system by five tutors. Findings showed that the analytics helped the tutors in two ways: engaging in a regular cycle of student monitoring and deciding when to contact at-risk students. Their study also emphasized the importance of sharing such lessons learned as part of larger efforts to build up institutional knowledge and community around analytics use. More recent work has expanded these efforts to develop guidelines in support of analytics adoption across their institution (Herodotou, Rienties, Verdin, & Boroowa, 2019).

3. Conceptualizing Instructors' Process of Analytics Use

The processes described above do not occur in isolation from each other (Mor et al., 2015), but are intertwined as instructors use analytics to help identify and answer classroom questions (teacher inquiry), consider the structure of course activities and resources (learning design), and adapt teaching methods responsively to real-time classroom needs (orchestration), often with the help of strategic scaffolding (institutional support). Understanding analytics use as a comprehensive process requires an integrated framework for thinking about the interpretation of data and its translation to action across these varied activities. This study makes progress on this need by working towards a model to specify the different "pieces of the puzzle" of instructors' analytics use and consider the associations among them. As a first step, the existing literature is synthesized to generate a template for inquiry into instructor analytics use.

3.1. Analytics Use as Sense-Making and Response

On a global level, the majority of studies describe instructor analytics use in two-parts involving some form of sense-making and a response to the information. While usually described in a linear sequence of understanding leading to potential action (Figure 1a), results of any actions taken could also influence the understanding (Figure 1b).

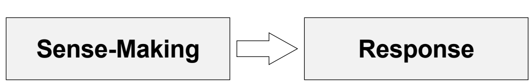

Figure 1a. Basic scheme of instructor analytics use.

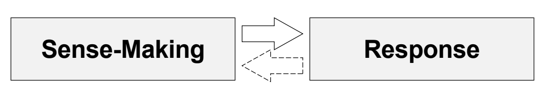

Figure 1b. Iterative scheme of instructor analytics use.

3.1.1. Sense-Making

Both within and outside of the tradition of teacher inquiry, importance has been placed on the practice of question identification to drive sense-making of analytics (Avramides et al., 2015; Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012). It is also possible that initial examination of data can help generate specific questions that can then be answered with more careful examination (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013). Data interpretation has been described as involving the activities getting oriented to the overall data and then applying focused attention to specific data (van Leeuwen, van Wermeskerken, Erkens, & Rummel, 2017); however, if instructors find the process of orienting to the data challenging, they may stop there and never engage in focused attention (Dazo et al., 2017). In addition, instructors may use information about student and course context to aid in the interpretation (Herodotou et al., 2017; Molenaar & Knoop-van Campen, 2018).

3.1.2. Response

Existing work on response to analytics has focused primarily on the different kinds of instructional actions that can be taken. In whole-class scaffolding (a form of orchestration), instructors make a decision about how they will do something for the entire class based on the analytic data. For example, an instructor may devote additional time to explaining a concept if the data suggests a substantial portion of their students do not yet understand it (Xhakaj et al., 2017). In targeted scaffolding (another form of orchestration), the instructor directs attention to specific students based on the analytic data. For example, if certain students seem to be less active or less successful than others, the instructor might provide tailored support through email or appointment (Herodotou et al., 2017; Tarmazdi et al., 2015). Apart from orchestration, instructors may use analytic information to revise their learning design (Lockyer et al., 2013). This is possible in small ways while a course is in progress (e.g., Herodotou et al., 2017) or, more commonly, by making changes to the composition and organization of class materials and activities for future offerings (Mor et al., 2015). A natural extension of taking an action is to examine if it has achieved the intended impact on student activity and learning (Verbert et al., 2013); however, this has not frequently been examined in the literature.

3.2. A Template for Inquiry into Instructor Analytics Use

Brought together, the synthesis above suggests a template for inquiry into an iterative process of analytics use flowing between questions, data interpretation, action, and evaluation of impact (see Figure 2).

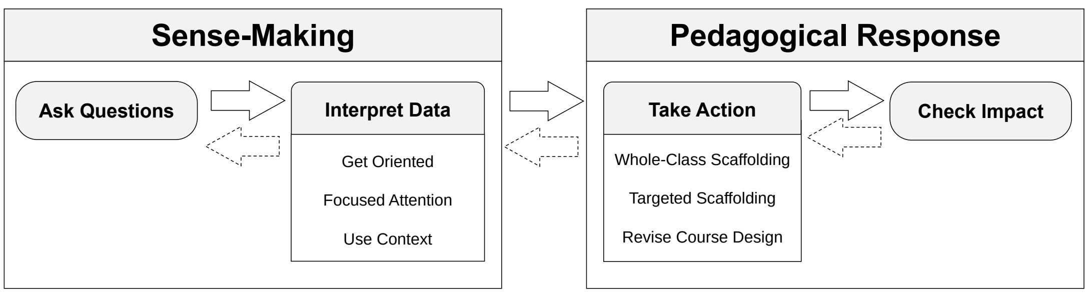

Figure 2. A template for inquiry into instructor analytics use.

This template for inquiry guides the current research into the experiences of five faculty members using an analytics dashboard over the course of a semester through the following research questions:

RQ1. How do instructors ask questions of the analytics?
RQ2. How do instructors interpret the analytics?
RQ3. How do instructors respond to the analytics?
RQ4. How do instructors check the impact of actions taken in response to the analytics?
RQ5. What are other important aspects of instructors' process of analytics use?

The goal of this study was to probe in depth how each of the four previously suggested activities involved in instructor analytics use occurred, validating or revising characterizations previously made in other teaching contexts and identifying additional aspects (and possibly additional activities) specific to the case of university instructors.

4. Methods

4.1. Research Partnership

This study examined five instructors' use of a learning analytics dashboard made available to them during the course semester. All instructors were faculty members at the same large U.S. private university. The dashboard roll-out was part of a pilot project led by the university's Instructional Technology Learning Analytics Team (ITLAT), part of a unit within IT that develops and supports the use of technologies for teaching and learning. In this pilot project, ITLAT worked to develop and roll out a learning analytics dashboard in consultation with five self-selected faculty members and one course administrator. The pilot project was carried out on a small scale to confirm the concept and practicability of the dashboards for further revision in advance of large-scale university-wide application.

The researchers belong to an independent centre at the university that focuses on the scholarly study and development of learning analytics. The initial dashboard development by ITLAT took place prior to the founding of the research centre; the researchers became aware of and involved in the project during the initial pilot of dashboard use by instructors (see Section 4.4). At this point the researchers partnered with ITLAT to facilitate a study of how instructors utilized the dashboard, with the intent of developing research-based guidance to inform the revision of the dashboard, provide input into the analytics implementation process, and contribute to the field's collective knowledge base about analytics use in practice.

4.2. Learning Analytics Dashboard

4.2.1. Dashboard Development and Implementation Process

In the design phase, initial meetings were held by ITLAT with each instructor to jointly build a use case that documented their course context and a set of pedagogical questions of interest to them (e.g., "which students are not engaging with the online content in my course?") and the specific kinds of student activity and performance information they would like to see (e.g., count of student-level clicks per week on distinct resources in the system). Based on the use cases, ITLAT developed a learning analytics dashboard that draws on data from multiple university systems, including the registrar, the LMS, and integrated tools (e.g., streaming video, quizzing system). As each course utilized a unique profile of online tools, the exact views and visualizations in their dashboards varied (examples are provided in Section 4.2.2). When the dashboard was released early in the term, ITLAT met one-on-one with each of the instructors to introduce them to the tool and walk them through the features. Instructors then had access to the dashboard for the rest of the term, were encouraged to use it to support their teaching, and were invited to reach out to ITLAT with any questions they encountered.

4.2.2. Learning Analytics Dashboard Features

The dashboard involved in this study was designed to provide instructors with various information about the activity and performance of their students in a specific course. When accessing the dashboard, instructors could choose from among three to five distinct views (depending on the tools the instructor used), each of which incorporated distinct analytic metrics of student learning activities and performance (e.g., student access of course site and resources, video viewership information, results of online quizzes, and student survey responses). For example, one view displayed the number of times and duration for which each course resource was accessed by each student. This view was intended to help instructors both identify students who were not engaging with the material (see sample question in Section 4.2.1) and recognize which course resources were heavily or infrequently accessed (see Figure 3). Another view displayed quiz results by item at the class level, which could answer instructor questions related to item difficulty and completion (see Figure 4). Due to the large amount of data in distinct systems, dashboard data was refreshed (updated) every night throughout the semester.

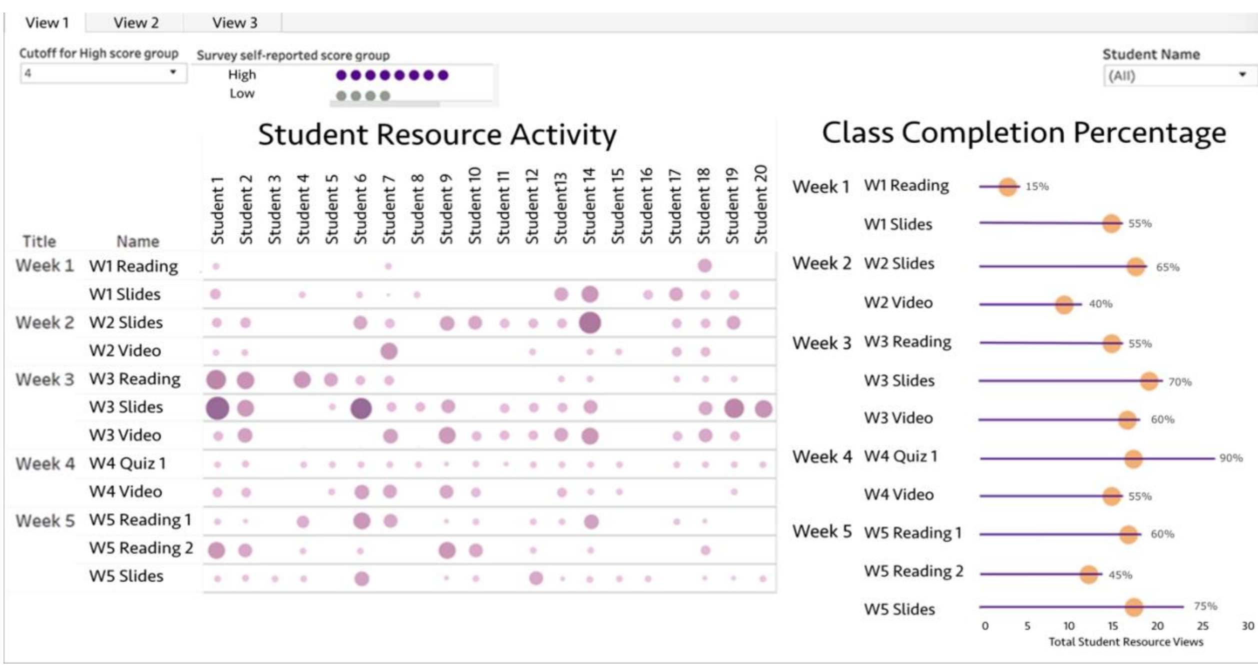

Figure 3. Example dashboard view of resource access.

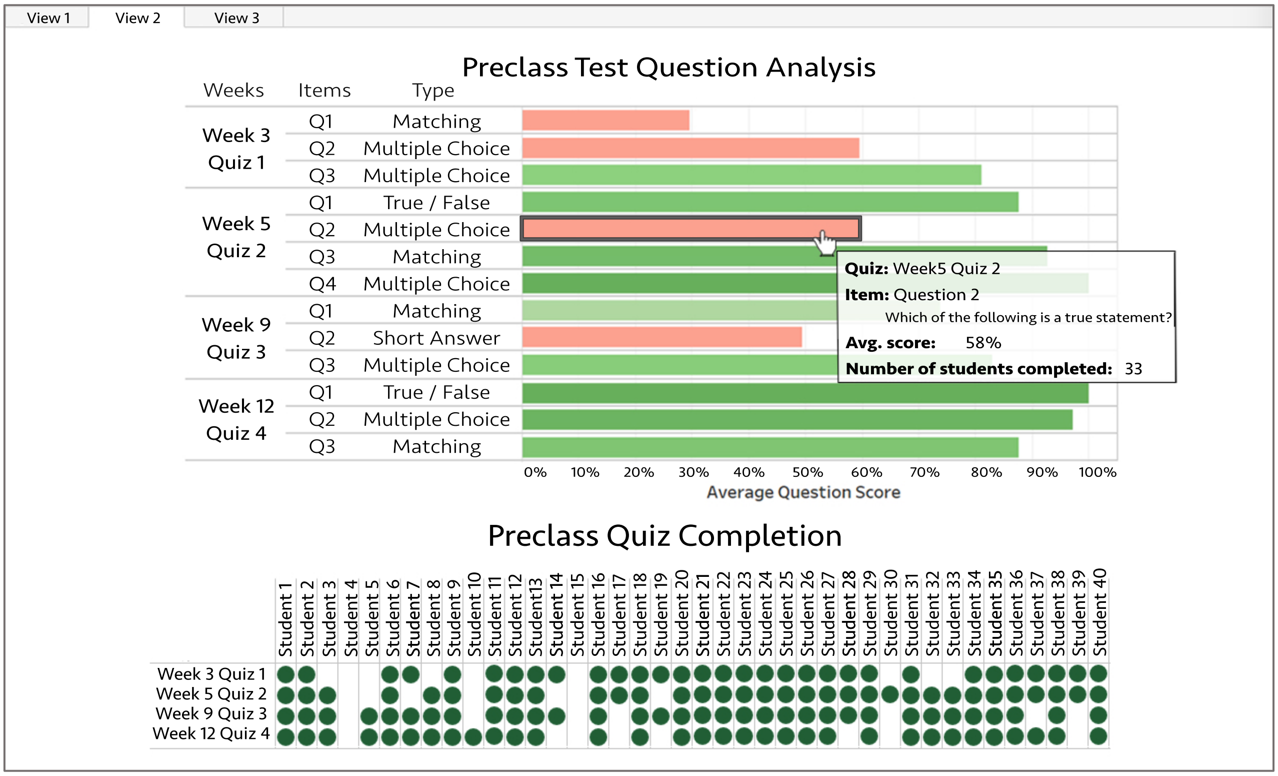

Figure 4. Example dashboard view of quiz results.

4.3. Participants and Courses

All five instructors in the pilot project run by ITLAT agreed to participate in the research (see Table 1).

Table 1. Course and Participant Profiles

Case	Discipline	Course Mode	Course Size and Format	Teaching Experience	Analytic Experience
IN1	Science	Weekly face-to-face	Mid-size lecture (~40 students) Team-teaching	> 25 years	Novice
IN2	Social Science	Blended (weekly online sessions plus two face-to-face meetings)	Large lecture (~75 students) Individual teaching	> 15 years	Proficient
IN3	Humanities	Weekly face-to-face	Small seminar (~20 students) Individual teaching	> 30 years	Proficient
IN4	Science	Weekly face-to-face	Mid-size lecture (~40 students) Team-teaching	> 10 years	Novice
IN5	Social Science	Weekly face-to-face	Small seminar (~20 students) Individual teaching	> 20 years	Novice

4.4. Data Collection

Retrospective interviews were conducted with the five instructors immediately following the semester using the dashboard. While collecting data at multiple points during the semester would have been desirable, it was decided in consultation with ITLAT that doing so would have placed an excessive burden on instructors who were already devoting a great deal of time to their participation in the pilot project through creating use cases and implementing the tool. Before conducting the interviews, the researchers obtained IRB approval at their institution. Ethical considerations taken into account included obtaining informed consent and protecting participant identity. Individual interviews, lasting one hour, took place in-person or virtually via video conferencing. A semi-structured interview format was used to allow for follow-up of interesting topics emerging throughout the interviews. The protocol began with an initial set of questions about teaching background, technology skills, and expectations for the dashboard. The main part of the interview asked instructors to load the dashboard and then walk through their process of use following a series of prompts that asked them about 1) what they looked at in the analytics, 2) how they made sense of the information provided, 3) any instructional decisions made based on this, and 4) whether they checked the impact of their decisions in the analytics. This process was repeated for each of the views individual instructors had available to them, each

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time using the relevant visualizations to concretize their responses. A final set of questions elicited overall reflections on their analytics use, including any challenges encountered. All interviews were audio-recorded and transcribed.

4.5. Data Analysis

Interview transcripts were analyzed using the constant comparative method (Gibson & Brown, 2009). This is an inductive approach in which the goal is to identify salient emergent themes with robust support. In this qualitative analysis paradigm, support includes not simply the number of times an idea is mentioned nor how many people mentioned it, but also how strongly it was emphasized and how important it seemed to the participants. Rigour in this method relies on credibility and dependability as evidenced by the trustworthiness of the analysis process and presentation of its results, rather than traditional measures of inter-rater reliability (Guba, 1981). The three phases of the data analysis process used in this study are described below; all phases were conducted collaboratively with extensive consultation between the two researchers.

4.5.1. Phase 1: Identifying Possible Relevant Ideas

Each researcher worked line-by-line through each of the transcripts, noting possible statements that might be relevant to the research questions. Each line of the transcript was constantly compared to previous lines as well as to already-identified ideas to create a set of consistent labels. At the completion of each transcript, the two researchers shared and integrated all labels to create a combined list of possible relevant ideas linked to supporting transcript segments.

4.5.2. Phase 2: Developing Ideas into Themes

The researchers reviewed each of the ideas from phase one, merging similar ones, grouping related ones, and discarding ones that were not sufficiently substantiated in or across the transcripts. The linked transcript segments were used to ground all decision-making about themes in the actual comments of participants. Groups of related ideas were coalesced into proposed themes, allowing for possible sub-themes within each larger class.

4.5.3. Phase 3: Confirmation and Consolidation of Themes

Each proposed theme and subtheme was re-examined by looking at the linked transcript segments and reconsidered in connection with each of the other themes and the research questions. Through ongoing review and line-by-line reading, the grouping of ideas and labelling of each theme and sub-theme was progressively revised until a stable set was arrived at. The final consolidation resulted in twenty themes that address the five research questions.

5. Findings & Discussion

The twenty themes that emerged in response to the five research questions are summarized in Table 2 with sample supporting quotations from the interviews. In the interests of space, the themes are presented and discussed in relation to the prior literature, in groups organized by research question.

Table 2. Summary of Emergent Themes

RESEARCH QUESTIONS AND EMERGENT THEMES	SAMPLE SUPPORTING QUOTES
RQ1. How Do Instructors Ask Questions of the Analytics?	
T1. Approaching the analytics based on existing areas of curiosity	*"I remember just scanning across and then seeing who didn't look at the slides"* (IN1 p. 6)
T2. Developing questions through interacting with the analytics	*"Now that I've seen the data, I probably would have asked different questions [than I did in the initial use case]"* (IN2 p. 7)
RQ2. How Do Instructors Interpret the Analytics?	
T3. Getting oriented and focused attention to the analytics	*"I had a look at all the students, and there was a huge disparity in terms of how much different students had been looking at all the materials"* (IN5 p. 6)
T4. The need for absolute or relative reference points	*"I'm really not sure [what this means] because I don't know what normal is"* (IN4 p. 13)
T5. Examining changes in overall student engagement over time	*"It looked like there was a bit of an upward curve over the course of the semester"* (IN3 p. 8)
T6. Triangulating the analytics with additional information about students	*"I know these students too because I've taught them in our [other course], the same cohort of students. So I know students that are not high performers"* (IN2 p. 11)
T7. Using the course context to explain or question the analytics	*"[Students] definitely wouldn't [access the materials more at this point]. The [readings] are pretty boring"* (IN5 p. 24)
T8. Inconsistent attribution of analytic results	*"The students didn't read the things or didn't learn the material? I assigned too much"* (IN1 p. 20)
T9. Data interpretation was affective as well as cognitive	*"I was pleasantly surprised that students for the most part thought that they were learning a good deal"* (IN3 p. 8)

RESEARCH QUESTIONS AND EMERGENT THEMES	SAMPLE SUPPORTING QUOTES
RQ3. How Do Instructors Respond to the Analytics?	
T10. Taking actions via whole-class scaffolding	*"I would get a nice bar chart and then I'd use these analytics in my teaching… I would show the class how they responded"* (IN2 p. 16)
T11. Taking actions via targeted scaffolding	*"I didn't say to students 'you're not spending enough time in [the LMS].' Instead, I just said 'you seem to be disengaged. You've missed a few classes'"* (IN3 p. 10)
T12. Taking actions via revising elements of the course design	*"This [wonderful] paper has been accessed zero times. So maybe that needs to be replaced by something else"* (IN5 p. 19)
T13. Adopting a wait-and-see posture	*"It's the first time I'd seen it. I didn't feel all that confident to act on it. I just wanted to wait and see how it developed"* (IN5 p. 17)
T14. Reflecting on pedagogical strategies and knowledge	*"That's what I really would like to take this further; how can we actually study this from a perspective of not just 'what do they click on?' and 'how do they respond to this question?' but 'where are they in their progress?' and 'are they doing things that are reflective?'"* (IN2 p. 20)
RQ4. How Do Instructors Check the Impact of Actions Taken in Response to the Analytics?	
RQ5. What Are Other Important Aspects of Instructors' Process of Analytics Use?	
T15. Wrestling with questions of transparency around analytics	*"If you are looking in [on] students, you should really tell them. You should say, 'we're checking your behaviour'"* (IN5 p. 5)
T16. Potential value of collaborative interpretation	*"It might need to be more of a collaborative process. Let's look at the data together to try to answer [the questions]"* (IN2 p. 8)
T17. Analytics seen as useful but not essential	*"[They are] good to have but not a must have yet"* (IN4 p. 17)]
T18. Disconnection between information structure and pedagogical concerns	*"They are in alphabetical order by first name, which is not usually a way that you think of students, because there are many students with the same first name"* (IN2 p. 10)
T19. Misalignment between instructors' uses and system timing	*"Sometimes I'd look [on] Monday evening, but the data that I got then was usually very partial because students keep later hours than professors do"* (IN3 p. 6)
T20. Experiencing a learning curve in analytics use	*"I'm no expert by far. But I've tried to use it more and more. It's definitely a growing skillset for me"* (IN1 p. 2)

5.1. RQ1: How Do Instructors Ask Questions of the Analytics?

Despite the theoretical importance of having questions to drive sense-making of analytics (Dyckhoff et al., 2012) and as initiators of the cycle of teacher inquiry (Hansen & Wasson, 2016), in the current study, instructors did not always come to the data with precisely formed questions to answer. Rather, they often came with **a general area of curiosity (Theme 1)** that guided their analytics use in an exploratory fashion. Similar to Tarmazdi et al. (2015) and Xhakaj et al. (2017), common curiosities related to how students interacted with the materials provided, specifically a desire to verify (or refute) assumptions instructors had made about what their students were doing outside of class and if there were students with particularly low levels of activity. For example, *"I want to know how much students really engage with the materials that we provide"* (IN5 p. 3). In addition, instructors expressed curiosity about which materials students chose to engage with, suggesting that this could be taken as an indicator of what they *"were regarding as essential"* (IN3 p. 14). Beyond coming to the analytics with existing areas of curiosity, instructors also **developed more specific (or entirely new) questions through their interactions with the data (Theme 2)**. Questions often arose from identifying an interesting potential relationship in the data or from disambiguating between possible explanations for the initial patterns they observed. For example, *"[To understand their low performance on this quiz] I probably would want to look at the data or the access of [specific course materials] to match up 'is it that they didn't look at the content?' or 'is it that we have to rewrite the questions?'"* (IN1 p. 13). Reflection on data leading to question generation is an aspect of analytic sense-making suggested theoretically by Verbert et al. (2013) and designed for by Molenaar and Knoop-van Campen (2018). This paints a picture of question generation in analytics use as part of an ongoing iterative process in which data interpretation acts both as an opportunity to close and open paths around the cycle of teacher inquiry (Avramides et al., 2015; Sergis & Sampson, 2017).

5.2. RQ2: How Do Instructors Interpret the Analytics?

The seven themes that related to how instructors interpret data can be conceptualized as composed of two complementary, but conceptually distinct, activities: reading the data to identify the noteworthy patterns and explaining their meaning for the teaching and learning context.

5.2.1. Reading the Data

The current study found that in reading the data, instructors engaged in the two previously identified activities of **getting oriented** and **applying focused attention (Theme 3)**; however, different to prior work (e.g., van Leeuwen et al., 2017), focused attention was found to be a possible first entry point into the analytics. Specifically, some instructors used focused attention to a specific piece of information in the analytics as a "way in" to the data that allowed them to get oriented and then expanded

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their view outwards. For example, *"I remember this being one of the first things I saw... that coloured bubble and size on their actual use of the pieces in [the LMS]"* (IN1 pp. 5–6). This practice of finding an accessible entry point to the data that related to instructors' existing areas of curiosity was previously noted by Molenaar and Knoop-van Campen (2018). Whether instructors begin by getting oriented to the analytics as a whole or with a specific area of focus within them may depend on the specifics of how an analytics view is organized in terms of layout design and information arrangement; thus both activity sequences should be considered as possibilities.

Another important aspect of reading the data is **the need for absolute or relative reference points (Theme 4)** to make sense of the data. Instructors noted that as they did not always have a sense of what "normal" was to use as a baseline, zero (representing a clearly problematic situation) was one of the few absolute reference points available for use and then often employed. For example, *"There were just quite a few students who were still at absolute zero in terms of how often they'd accessed the site"* (IN5 p. 14). The lack of absolute reference points led to the common use of relative reference points to make sense of the data. Specifically, instructors made comparisons across students. For example, *"We are able to see that there's individual variation, right? Like not everyone accesses or spends the same amount of time on those materials"* (IN4 p. 9). There are dangers, however, in using the activity of other students as the sole standard for comparison without some external sense of how much activity is required or desired. In a class with low overall engagement, even students doing more than average may not be doing enough (Wise, Vytasek, Hausknecht, & Zhao, 2016). In addition, instructors often made **comparisons of overall student engagement across time (Theme 5)**, a view on the data that instructors have previously suggested would be useful to them (Bakharia et al., 2016). For example, *"You can see in the beginning of the class, [most students] were pretty good [while later on] some individuals were not consistent [in participating in the activities]"* (IN1 p. 12). These findings imply that helping instructors to learn and apply appropriate context-relevant reference points is an important area for future work.

5.2.2. Explaining Patterns

The second activity of data interpretation involved examining the meaning of the patterns identified by explaining (or questioning) their implications related to the course. Instructors commonly **triangulated the analytic data with other sources of information (Theme 6)**, such as classroom observations, to confirm their interpretation. For example, *"The one that tracked the number of minutes per week that a student was doing a reading, that was correlating very early in the semester with some students who were also having attendance issues. It looked like they were both missing classes and not doing as much of the reading as other students were when they were attending"* (IN3 p. 10). When this did not occur, conflicting information sources could lead them to question the analytics and/or hesitate to take action. For example, *"There was a point about four weeks [in] where it looked suddenly like everybody had stopped doing anything [online]. This doesn't seem right because in class conversation they were referring to specific things in the reading"* (IN3 p. 17). This positions analytics as one part of a larger information ecosystem available to instructors, rather than a single authoritative representation, and suggests that analytics can act not only to increase instructor confidence (van Leeuwen, 2015), but in certain circumstances to decrease it as well.

When analytic interpretations were supported by triangulation with additional data, similar to Dazo et al. (2017) and Herodotou et al. (2017), instructors **used their contextual knowledge of the course and their students (Theme 7)** to explain what these results might mean. In addition, in this study instructors were found to **make inconsistent attributions to potential underlying causes (Theme 8)**. In many cases, in explaining the results, instructors referred to the structure of the course or particular features of the course materials. For example, *"It's interesting that not everyone is taking some of these quizzes. These aren't required at all. There's no participation grade. There's no incentive"* (IN4 p. 11). But at other times, instructors would describe similar results as being due to the choice of the students or the instructors themselves. For example, *"They think about how little to do in the exam rather than during the running of the course [trying to] engage with the stuff and think about the material"* (IN5 pp. 13–14) and *"[It's my fault]. I assigned too much"* (IN1 p. 20). During this process, instructors sometimes considered different possible attributions of why a particular pattern was observed (e.g., a reading may have not been accessed because it was difficult, irrelevant, or assigned during a very busy point in the term) and then select the best choice guided by their experience and craft knowledge (Molenaar & Knoop-van Campen, 2018). In many cases, however, instructors were not explicit about the process through which they came to decide why a certain pattern was observed. Overall, the process of root cause attribution was relatively opaque, highlighting an area in which further work is needed.

5.2.3. Affective Aspects

Finally, it is important to highlight that instructors' process of interpreting data involved more than just cognitive processing of patterns; it also commonly **provoked affective response (Theme 9)** such as surprise, disappointment, or joy. When observing a lower level of activity than expected, instructors sometimes felt disheartened: *"I see 37 views, which is a little depressing to me, that [most of] my students haven't watched it"* (IN2 p. 15), but often indicated that they would hear the "bad news" and learn about the student activity rather than remain in the dark: *"Zero percent looked at some of the screencasts. It took hours to* *make*. *But, it's better than thinking the wrong thing"* (IN5 p. 19). Surprise was also used to describe situations in which the analytics changed their interpretation of something they had observed in class: *"[The low levels of accessing the resources] were a surprise to me because I thought they were meant to come prepared for each of these classes, and they often asked questions and they all seemed to be really engaged"* (IN5 p. 14). While emotional responses to analytics have been noted previously in the literature (e.g., Park & Jo, 2015; Wise, Zhao, & Hausknecht, 2014), exploration of their impact and how analytics designs might take them into account remains an area requiring further attention.

5.3. RQ3: How Do Instructors Respond to the Analytics?

Instructors responded to the analytics in one of three kinds of ways: taking various kinds of actions, adopting a "wait-and-see" posture, and reflecting on larger issues in their pedagogy.

5.3.1. Taking Action

Instructors in the current study engaged in three kinds of actions in response to the analytics, all well-documented in the literature. **Whole-class scaffolding (Theme 10)** as a form of orchestration (Molenaar & Knoop-van Campen, 2018; Tan et al., 2018) was often framed in terms of devoting more attention to explaining specific concepts that were difficult for students. For example, *"I [could] even adjust sometimes on the fly during the semester if it seems like students are not learning what they are hoping to learn in the class, or not learning what I think I want them to be learning in the course"* (IN3 p. 4). This use of analytics can be seen as a kind of formative assessment supporting responsiveness and continuity in the learning process (Dazo et al., 2017). However, it is important to note that this (and many other forms) of whole-class scaffolding depends on students moving through a course in the same way. The instructor of a large distance course in which students do not follow exactly the same learning pace in accordance with the course schedule, for example, might not feel it appropriate to provide whole-class scaffolding in this way (Tempelaar, Rienties, & Nguyen, 2017). This highlights the importance of taking the course context into account in understanding pedagogical responses to analytics.

In contrast, **targeted scaffolding (Theme 11)** as a form of orchestration (Tarmazdi et al., 2015) involves focusing attention on particular students. As observed previously, these were usually students who seemed to be disengaged or struggling (Herodotou et al., 2017). Instructors highlighted that the analytics not only helped them to identify such students, but to do so (and take action) sooner. For example, *"I intervened with them a bit earlier than I might have otherwise as they hadn't missed so many classes"* (IN3 p. 10). This may be due to an increase in confidence about the situation based on the analytics that spur instructors to act (van Leeuwen, 2015). In terms of how the analytics were referenced in these orchestration actions, instructors felt comfortable sharing class-level analytics with students, describing this as a powerful form of evidence to support their actions in whole-class scaffolding. However, instructors were hesitant to use individual-level analytics as evidence in scaffolding targeted at individuals. For example, *"I would still find it probably quite [bold] to single out people and take them apart and say, 'I've noticed that you're not looking at the stuff and keeping up with the material'"* (IN5 p. 13; also see contrast between quotes for Theme 10 and 11 in Table 2). This indicates that social norms around privacy and surveillance manifest differently in these two situations, which is an important distinction to be aware of for learning analytics designers.

The third kind of action described was **revising the course elements (Theme 12)** as a form of learning design (Lockyer et al., 2013). Again, attention seemed focused on identifying low levels of activity or performance (in this case with respect to particular materials or online activities), leading instructors to consider how they could change the course design to stimulate greater engagement or success. In some cases, the changes related to the structure of the course. For example, *"There may be an option to get the quizzes out of being a separate activity or to have them be part of the video to make it more engaging"* (IN4 p. 14). In other cases, the revisions involved the content itself. For example, *"It tells us we might need to look at a question again. For example, 'is this written well?' or 'do we need to change the question?'"* (IN1 p. 12). These kinds of analytics use align well with Lockyer et al.'s (2013) category of checkpoint analytics (revising course design based on *if* students accessed particular resources or not), while revisions based on process analytics (indicating *how* students completed particular tasks) was less prominent. This may be due to the relative salience of access versus process information provided in the dashboard and/or the fact that access information may offer an easier entry point to analytics use from which to inform course design.

Across all three kinds of actions, there was a tendency to take a deficit perspective, taking action based on students *not* engaging with the materials or materials *not* receiving attention. A similar pattern of focusing on an absence of activity was described previously by Herodotou et al. (2017). While identifying students needing support is an important and valuable use of analytics, a focus only on the bottom end of activity and engagement limits the extent to which analytics can contribute to success for all students. Considering the ways in which the use of analytics to identify students who may need additional challenges or who are showing growth over time and can be encouraged is an important area for future work.

5.3.2. Adopting a Wait-and-See Posture

While each of the actions described above was mentioned by instructors in the current study, such references were often to actions they were considering taking in the future, rather than ones they had actually completed. In place of action, participants tended to adopt **a holding pattern of wait-and-see (Theme 13)** in which they deferred actions to the future when more data would be available (Herodotou et al., 2017). This response seemed to emanate from a lack of certainty either due to a missing reference point for comparison (e.g., "is a certain level of student activity acceptable or too low?") or absence of triangulating information (e.g., "it doesn't look like they are doing the work online but in class things seem fine"). For example, *"I'm really not sure [what this means] because I don't know what normal is"* (IN4 p. 13). A compounding factor was a *"reluctance to making real-time changes"* (IN4 p. 17) to a course based on the partial data available early in the term without having seen what common complete patterns (through the end of the term) look like (c.f. Wise et al., 2014). This was often tied to the newness of using the analytics (see Theme 20); for example, *"It's the first time I'd seen it. If I had confidence [to act on the data], then I probably would have acted"* (IN5 p. 17). This suggests that providing access to full data from prior courses could potentially offer instructors useful reference points for comparison of both individual data points and trends over time.

5.3.3. Reflection on Pedagogy

The final response to the analytics observed was **reflection on pedagogy (Theme 14)**; a new and interesting response to analytics that has not received much attention in the literature (c.f. Molenaar & Knoop-van Campen, 2018). This suggests that changes stimulated by the analytics can, at times, be much greater than the simple course "adjustments" commonly discussed (see Theme 10–12) and spark deep consideration of an instructor's larger teaching practices, student learning, and course design. The ability of analytics to contribute to fundamental shifts in how instructors think about their teaching and themselves as teachers is a valuable leverage point for pedagogical change and an important component of the teacher inquiry cycle (Cochran-Smith & Lytle, 1999). In this study, for one instructor it was a transition to see course design decisions as something with concrete, testable impact on student behaviour (the start of an iterative stance towards course design). For example, *"Now I think I would refocus to figure out how I can directly design it in a way, when I have the data, 'how am I going to respond as soon as I have that data?'"* (IN2 p. 21). For another it was a reconsideration of what "participation" means in the modern technologically enhanced university classroom. For example, *"I'm thinking about how I formally assess class participation and what it really consists of. I'm wondering if that's the best way to gauge this level of engagement and if there are other ways that I can think about what really constitutes participation"* (IN3 p. 16). Such reflections indicate the potential of analytics to support instructors in engaging in a deep inquiry process that reshapes their pedagogical knowledge and fosters their professional growth (Avramides et al., 2015; McKenney & Mor, 2015).

5.4. RQ4: How Do Instructors Check the Impact of Actions Taken in Response to the Analytics?

In contrast to the first three phases of analytics use, no themes emerged in relation to the final phase of checking impact. Given the low levels of action taken in response to the analytics in the current study, it is not surprising that attempts to check impact were rare. One instructor, however, did describe a few examples of how the instructor monitored the analytics over time to see if there was a change in student engagement based on the action taken. For example, *"There was a student here, for instance, who you can see the first couple of weeks wasn't really doing that much, and then we had a talk about the performance and then it improved quite a bit in the weeks after that"* (IN3 p. 22). While the findings from this study are limited, lack of checking impact has also not been reported in previous studies in which substantial action was taken (Herodotou et al., 2017; Molenaar & Knoop-van Campen, 2018). Thus, this aspect of analytics use remains an area of potentiality more than actuality.

5.5. RQ5: What Are Other Important Aspects of Instructors' Process of Analytics Use?

5.5.1. Questions of Transparency

An important finding that emerged in this study was how **instructors wrestled with questions related to transparency in analytics use (Theme 15)**. This was a very important issue for some instructors, while of less concern for others. For instructors who wrestled with transparency, there were multiple competing issues at play. One tension was between the obligation to let students know what data was being collected and/or how it was being used and the concern that this would elicit gaming behaviour. These contrasting views were often both held by the same instructor. For example, *"If you are looking in [on] students in that way, you should really tell them. You should say, 'we're checking your behaviour'"* (IN5 p. 5) and *"Once [students] know about it, it becomes much less informative for us, because they then can just start playing the system"* (IN5 p. 27). A second tension related to the appropriateness of sharing analytics directly with students at the class- but not individual-level, as described in Section 5.3.1. Equally important is how the analytics are positioned as a "third object" meditating the teacher–student relationship (Wise et al., 2016). For instance, while Tan et al. (2018) shared analytics as an object for collective whole-class reflection, some instructors in this study described the potential use of showing class-level analytics to students as proof that they knew what was happening outside the classroom walls. For example, *"I could say, 'I have access to the data, you can't tell me that you are accessing [the material]'"* (IN1 p. 19). In both of the examples above, instructors and students are positioned in adversarial roles, with data as an authoritative source of external truth. This can be problematic in two ways. First, setting up analytics as a tool that instructors and students use against each other places them in opposition, an unproductive position from which to foster change effectively. Second, the positioning of analytics as "fact" ignores important decisions made in the creation of analytics as well as the possibility for noise and uncertainty (Kitto et al., 2018). Future work should continue to explore ways in which analytics can be positioned as a shared resource for interpretation and action that instructors and students can use together as allies in the pursuit of better learning.

5.5.2. Potential Value of Collaborative Interpretation

An additional finding in this study suggests **collaborative interpretation of analytics (Theme 16)** as a promising area for exploration. Professional development efforts at the secondary level have long recognized the importance and added value of teacher learning communities for fostering sustained instructional improvement (Borko, 2004; Darling-Hammond & Richardson, 2009). In the current study, evidence for the potential of collaborative interpretation came from two sources. First, during the interviews, instructors explicitly expressed a desire to engage with colleagues around the data. For example, *"Having a user group community would be really helpful. We [can] build a community and it becomes part of our vocabulary"* (IN4 p. 17). Second, in every interview, the process of walking through and describing their analytics use seemed to support instructors in further developing their understanding of the data. For example, *"Well here it does correlate. That's interesting, I hadn't really noticed that [before this conversation during the interview]"* (IN3 p. 21). Beyond simple description, dialogue (in this case with the interviewers) around the analytics to support the process of interpretation added additional value. For example, *"You [the interviewer] have given me some feedback on a different way to reflect on it, which is great"* (IN1 p. 13). While fostering trusting groups that engage in critical examination of teaching practices together is no simple matter (McLaughlin & Talbert, 2006), the introduction of learning analytics with community-level support can allow instructors to clarify questions around data interpretation, draw collective insights, and share ideas about effective actions to be taken in response (Rienties et al., 2016).

5.5.3. Barriers to Integrating Analytics into Regular Teaching Practices

While instructors found the access to student data offered by the dashboard interesting, the majority did **not yet consider the analytics an essential tool for teaching (Theme 17)**. There was a general sense that receiving improved information about one's students should be beneficial, even though exactly how was not yet clear. For example, *"I think it's definitely useful. You know it's hard to argue that any data that's this detailed and fine grained is not useful"* (IN5 p. 18). Seeing analytics as a "nice to have" rather than a "must have" was often attributed to a variety of challenges that made it difficult for instructors to connect the information provided with their core teaching practices. One critical challenge that appeared multiple times was that **analytic information was often organized in the ways that differed from how instructors thought about their courses (Theme 18)**. For example, *"The sequence of the [information] is not intuitive to me because I would think the first thing I want to see is 'did they [do task A], then how many people clicked on [task B], then did they [complete task C]?'"* (IN2 p. 18). This highlights the need for human-centred learning analytics that involves end-users not just in the beginning of the design process but also iteratively throughout the development cycle (Holstein, Hong, Tegene, McLaren, & Aleven, 2018). Ongoing input is important because, as observed in the current work, gaining access to data once the tool was made available concretized, shifted, or generated new questions for instructors. In addition, some instructors were challenged by **misalignment between the timing of when instructors wanted to use the analytics and the cycle on which the data refreshed (Theme 19)**. For example, *"Whatever they had done [on] Thursday morning wouldn't appear till Friday morning. So it would look like students weren't doing a particular reading in the numbers that I would hope, but then by the time the full data became available it turned out they actually had"* (IN3 p. 6). Updating the data daily in the middle of the night was a technical requirement due to the large number of distinct systems and the amount of data involved, but it limited the usefulness of the analytics for instructors who generally wanted to check the dashboard right before class and see what students had done up to that minute. This highlights the argument made by Ferguson et al. (2016) that analytics development needs to be attentive to actionability and how "analytics connect with education and the changes that administrators, teachers and students want the tools to make in order to support their everyday learning, teaching and assessment work" (p. 9). In addition to these specific challenges, overall instructors **experienced a relatively steep learning curve (Theme 20)** since this kind of data-informed decision-making had not previously been a part of their teaching routine. For example, *"Just the fact that you can see this fine grain level of engagement. That's a completely new way of looking at student data"* (IN5 p. 25). Despite the challenges, once instructors found some entry point into the tool, they seemed to invest in working through their lack of comfort or experience with data: *"I'm not an expert by far, but I've tried to use it more and more. It's definitely a growing skillset for me"* (IN1 p. 2). This suggests that it can be useful to think about progressively advanced analytics use, offering accessible starting points with trajectories for growth.

5.6. A Model of Instructors' Analytics Use

Synthesizing the findings discussed above yields a model of instructors' process of analytics use (Figure 5). The model details multiple activities embedded within the two-part structure of sense-making and pedagogical response, some or all of which may occur for any given instructor. Compared to the original template for inquiry, there is substantial elaboration and expansion of the activities involved. Of particular note, the model offers multiple possible starting points (existing questions, areas of curiosity, interactions with the data) and includes question generation as an ongoing part of analytic sense-making. It also makes a conceptual distinction between identifying noteworthy patterns in the data and figuring out what they mean for a learning situation, and incorporates affective considerations into these activities. Finally, it offers alternative possible responses to taking immediate action. It is important to note that the intent of this model is not to suggest a lock-step process by which all instructors in all contexts use all different kinds of analytics in the same way, but to make available a set of useful categories for activities instructors commonly engage in when using analytics, some combination of which are likely to occur in any particular situation.

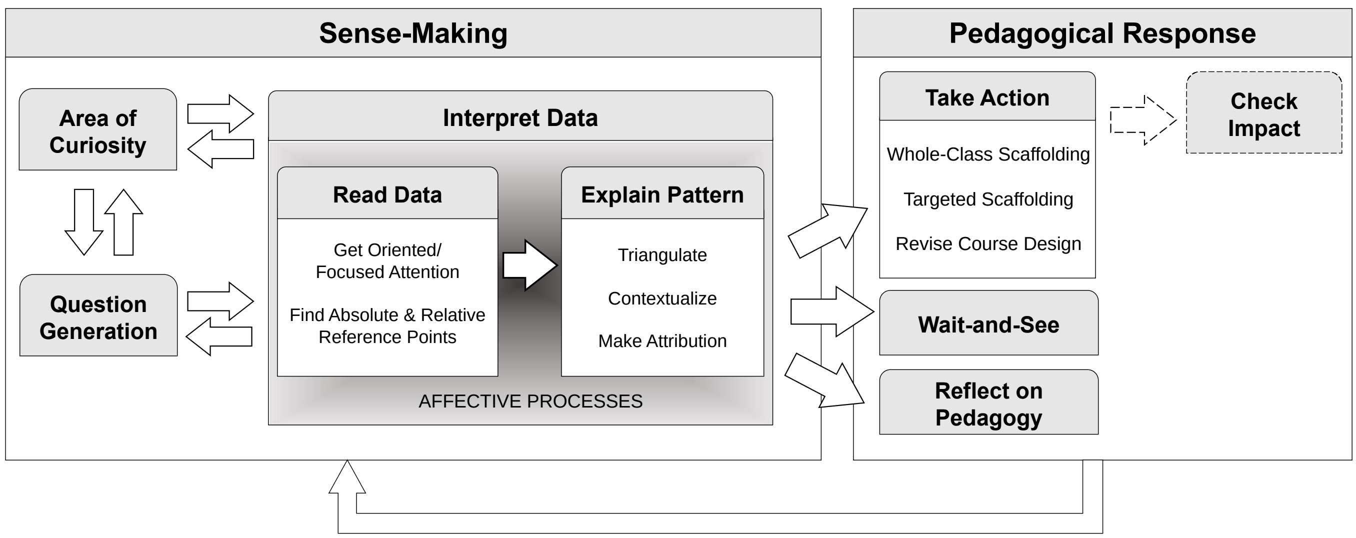

Figure 5. A model of instructors' process of analytics use.

6. Implications

6.1. Implications for Learning Analytics Design

The question of how to translate instructor excitement and enthusiasm for analytics into effective use is a pressing one (Dazo et al., 2017). Many of the challenges that appeared in this study mirror issues well known in the fields of human–computer interaction and usability that can be addressed through the practices of human-centred design (e.g., Maguire, 2001; Steen, 2011). Our field would do well to draw on these existing literatures, which offer both design principles and processes that can usefully inform the development of learning analytics. For example, some projects have begun to foster clearer connections between analytic data and instructors' teaching concerns by incorporating local instructors' ongoing involvement throughout multiple design cycles (Holstein et al., 2018). As well, the focus of this special section on human-centred learning analytics design reflects a move in the field to recognize analytic tool creation as the design of a socio-technical system rather than solely a technical one. Below, we contribute to this effort by suggesting a list of specific design considerations arising from this study that can guide analytic developers in thinking ahead to instructor practices of use during the design process. Not every consideration will make sense for every analytic design; however, the kinds of considerations (specifically focusing on the expected activity patterns of the end-users at the beginning of the design process) are an important class of issues that should be taken into account when building analytics for instructors.

6.1.1. Learning analytics should be designed to align with instructors' pedagogical practices

- *Organize information from the perspective of instructors, not data structures*. Instructors often think in different categories (e.g., weeks of a class, sets of associated activities) than those by which data comes to analytic developers (Bakharia et al., 2016). This can be addressed by explicitly eliciting instructor conceptualizations of how they think about their course and teaching elements as part of the design process. Attention to this issue may also raise the need for (re)considering learning design before analytics are built so that the two can be aligned (Lockyer et al., 2013).
- *Align timing of system and instructors' practices*. In the current study, the timing of the system data refresh limited the usefulness of the analytics for instructors who accessed the dashboard immediately prior to class. While constant data

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updating for the entire system may not be realistic, allowing instructors to update their data on demand in situations of need could be one way to address this.

6.1.2. Learning analytics should be designed to support processes of use

- *Embed support for question generation and maintenance*. A key element of the value proposition for analytics use is that the data answers important questions on which people can take action. But such questions often emerge (or are refined or reshaped) through examination of the data and may not be retained across sessions of use. Analytic tools can be designed to support this process by including features to aid in the generation and maintenance of questions (and perhaps answers). For example, a question area associated with a visualization could offer a set of editable, tailorable questions with add, delete, and edit functions that provide flexibility of use. Questions can be maintained across sessions of use, annotated with answers that instructors find in the data, or tagged for future follow-up.
- *Incorporate visual aids to find entry points to the analytics*. Another important consideration is how to facilitate entry points with which instructors can orient themselves to the analytics. The current study showed that rather than beginning with an overview and then digging in, instructors often begin with some part of the analytic that they can make sense of and then work outwards. Visual aids could be incorporated into analytics to support this process; for example, in a large matrix of data (e.g., Figure 3) toggleable tools that highlight information by rows or columns could help users focus their attention on finding certain kinds of patterns.
- *Help instructors to find and work with reference points for data interpretation*. Providing access to similar data from prior terms or overarching trends from similar courses or tools for making comparisons across time can provide high-level relative reference points (Bakharia et al., 2016). Absolute reference points may be elicited through a process of guided reflection through which instructors articulate their expectations for class activity, engagement, or performance in terms of the metrics available.
- *Embed flags for later decisions to take action and check impact*. Wait-and-see is a pattern of delayed response that requires instructors to remember to return to check on a situation at some future date. Rather than relying on instructor memory, analytics design can support this process by offering features that let instructors mark and/or annotate a pattern they observe in the data for future follow-up. Similarly, when action is taken, analytic features can be used to create externalized reminders to check the impact of the action.

6.1.3. Learning analytics should be designed to support sharing and conversations

- *Support analytics sharing and conversations by offering de-identified views*. Sharing analytics with other instructors to engage in a process of collaborative interpretation or with students as an object for discussion and reflection raises potential privacy concerns. One way to facilitate the use of analytics as a mediational object (Wise, 2014) is by making it easy for instructors to switch to a view in which student identities have been removed or hidden.

6.2. Implications for Learning Analytics Implementation

In addition to rethinking learning analytics design in the context of instructional practices, it is also important to consider ways to help instructors in the process of translating analytic information into actionable insights for their teaching (Wise & Vytasek, 2017). The most critical element of such support is to help instructors link pedagogically meaningful questions, data-informed answers, and appropriate responsive action together. While these connections can be seeded through initial orientation or training sessions, the professional development literature is conclusive in showing that ongoing networks of support are more effective in supporting change than short-term information delivery (Darling-Hammond & Richardson, 2009). Thus, ongoing support for learning analytics use is an important aspect of implementation. Such support can take various forms, including providing examples of how other instructors have used analytics to gain insight into their classes and/or inform their teaching. More powerful, however, is the opportunity for instructors to interact around the meaning and implications of their own data. For example, in our own university, we have worked with ITLAT to introduce a pedagogical analytics coach who sends out periodic emails with ideas for data-based questions to ask, offers one-on-one sessions to think through an instructor's analytics with them, and runs collaborative workshops for groups of related instructors. In these sessions, instructors are coached through the sequence of asking questions, finding answers, and deciding on actions; they are also able to share common challenges and strategies they have developed for analytics use. In the long term, such contextualized and connected support can not only support individuals in using analytics, but can also cultivate local communities of practice to help universities move towards a culture of data-informed teaching.

6.3. Limitations and Future Research

This study's main limitations relate to the sample and the use of retrospective data collection. All five instructors who had access to the dashboard in its initial roll-out participated in the study. This was a small sample of uniformly experienced teachers; however, there was diversity in course subject matter and instructor experience in using analytic data. In addition, the dashboard under study was designed by one institution to offer particular visualizations of certain kinds of data from the university's learning management system. For these reasons, no claim is made that the model presented here represents a generalized process of instructor analytics use across different contexts where diverse instructors use other kinds of analytics. Instead, the model offers a set of useful categories for activities commonly involved in instructor analytics use that may appear in different configurations in distinct situations. In this way, it offers a conceptual schema for future study and support of instructor analytics use. Future work can help validate, refine, and expand the model to be useful for a broader set of contexts, participants, and analytic tools. In addition, the findings of this study are based on retrospective reflection from the instructors, rather than a real-time study of use-in-the-moment. Future studies can attempt to triangulate reflective data with log-file records, experience sampling methods (Zirkel, Garcia, & Murphy, 2015), and, potentially, classroom observations. Balance must be sought between specificity and timeliness of data collection and the intrusion or burden it causes for instructors. In addition, as analytic action becomes more prevalent, future work can examine the ways in which students respond to and interact with instructors' analytics use.

7. Conclusion

This study unpacked the situated practice of five university instructors' use of learning analytics to inform their teaching. Findings reaffirmed that the translation from information to insight to action is not a straightforward one (Molenaar & Knoop-van Campen, 2018) and that if impactful analytics adoption is to occur, instructors must see this new technology as addressing centrally important issues related to their teaching (Cuban, 2001). The study further elaborated on the activities of instructor analytics sense-making and pedagogical response, synthesizing the findings into a model that offers a clear starting place to frame future work in the area. It is important to continue to conduct such studies of analytics use in-situ at the same time that we continue to improve the analytic tools available (Kitto et al., 2018). A better understanding of the practices (and challenges) instructors engage in when using analytics in their teaching supports processes of human-centred learning analytics design and the creation of systems of support for analytics use, thereby improving actionability and impact. Together these efforts help build towards data-informed instruction as a regular teaching practice to support student learning and educational success.

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References

Ali, L., Hatala, M., Gašević, D., & Jovanović, J. (2012). A qualitative evaluation of evolution of a learning analytics tool. *Computers & Education, 58*(1), 470–489. https://dx.doi.org/10.1016/j.compedu.2011.08.030

Avramides, K., Hunter, J., Oliver, M., & Luckin, R. (2015). A method for teacher inquiry in cross-curricular projects: Lessons from a case study. *British Journal of Educational Technology*, *46*(2), 249–264. https://dx.doi.org/10.1111/bjet.12233

Bakharia, A., Corrin, L., de Barba, P., Kennedy, G., Gašević, D., Mulder, R., Williams, D., Dawson, S., & Lockyer, L. (2016). A conceptual framework linking learning design with learning analytics. In *Proceedings of the 6th International Conference on Learning Analytics and Knowledge* (LAK '16), 25–29 April 2016, Edinburgh, UK (pp. 329–338). New York: ACM. http://dx.doi.org/10.1145/2883851.2883944

Borko, H. (2004). Professional development and teacher learning: Mapping the terrain. *Educational Researcher, 33*(8), 3–15. https://dx.doi.org/10.3102/0013189X033008003

Borko, H., & Shavelson, R. J. (1990). Teacher decision making. In B. F. Jones & L. Idol (Eds.), *Dimensions of thinking and cognitive instruction* (pp. 311–340). Mahwah, NJ: Lawrence Erlbaum Associates.

Cochran-Smith, M., & Lytle, S. L. (1999). The teacher research movement: A decade later. *Educational Researcher*, *28*(7), 15–25. https://dx.doi.org/10.3102/0013189X028007015

Cuban, L. (2001). *Oversold and underused: Computers in the classroom*. Cambridge, MA: Harvard University Press.

Darling-Hammond, L., & Richardson, N. (2009). Research review/teacher learning: What matters. *Educational Leadership*, *66*(5), 46–53.

Dazo, S. L., Stepanek, N. R., Chauhan, A., & Dorn, B. (2017). Examining instructor use of learning analytics. In *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (CHI EA '17), 6–11 May 2017, Denver, Colorado, USA (pp. 2504–2510). New York: ACM. http://dx.doi.org/10.1145/3027063.3053256

Dillenbourg, P. (2013). Design for classroom orchestration. *Computers & Education*, *69*, 485–492. https://dx.doi.org/10.1016/j.compedu.2013.04.013

Dyckhoff, A. L., Zielke, D., Bültmann, M., Chatti, M. A., & Schroeder, U. (2012). Design and implementation of a learning analytics toolkit for teachers. *Journal of Educational Technology & Society*, *15*(3), 58–76.

Ferguson, R., Brasher, A., Clow, D., Cooper, A., Hillaire, G., Mittlemeier, J., Rienties, B., Ullman, T., & Vuorikari, R. (2016). Research evidence on the use of learning analytics: Implications for education policy. In R. Vuorikari & J. Castano-Munoz (Eds.), *A European framework for action on learning analytics*. Luxembourg: Joint Research Centre Science for Policy Report. http://dx.doi.org/10.2791/955210

Gibson, W., & Brown, A. (2009). *Working with qualitative data*. Los Angeles, CA: Sage.

Greller, W., & Drachsler, H. (2012). Translating learning into numbers: A generic framework for learning analytics. *Journal of Educational Technology & Society, 15*(3), 42–57.

Guba, E. G. (1981). Criteria for assessing the trustworthiness of naturalistic inquiries. *Educational Technology Research & Development, 29*(2), 75–91. https://dx.doi.org/10.1007/BF02766777

Hansen, C. J., & Wasson, B. (2016). Teacher inquiry into student learning: The TISL heart model and method for use in teachers' professional development. *Nordic Journal of Digital Literacy*, *11*(1), 24–49. http://dx.doi/10.18261/issn.1891-943x-2016-01-02

Herodotou, C., Rienties, B., Boroowa, A., Zdrahal, Z., Hlosta, M., & Naydenova, G. (2017). Implementing predictive learning analytics on a large scale: The teacher's perspective. In *Proceedings of the 7th International Learning Analytics and Knowledge Conference* (LAK '17), 13–17 March 2017, Vancouver, BC, Canada (pp. 267–271). New York: ACM. http://dx.doi.org/10.1145/3027385.3027397

Herodotou, C., Rienties, B., Verdin, B., & Boroowa, A. (2019). Predictive learning analytics "at scale": Towards guidelines to successful implementation in higher education based on the case of the Open University UK. *Journal of Learning Analytics*, *6*(1), 85–95. https://doi.org/10.18608/jla.2019.61.5

Holstein, K., Hong, G., Tegene, M., McLaren, B. M., & Aleven, V. (2018). The classroom as a dashboard: Co-designing wearable cognitive augmentation for K–12 teachers. In *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (LAK '18), 5–9 March 2018, Sydney, NSW, Australia (pp. 79–88). New York: ACM. https://dx.doi.org/10.1145/3170358.3170377

Kitto, K., Buckingham Shum, S., & Gibson, A. (2018). Embracing imperfection in learning analytics. In *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (LAK '18), 5–9 March 2018, Sydney, NSW, Australia (pp. 451–460). New York: ACM. http://dx.doi.org/10.1145/3170358.3170413

Lockyer, L., Heathcote, E., & Dawson, S. (2013). Informing pedagogical action: Aligning learning analytics with learning design. *American Behavioral Scientist, 57*(10), 1439–1459. https://dx.doi.org/10.1177/0002764213479367

Maguire, M. (2001). Methods to support human-centred design. *International Journal of Human–Computer Studies*, *55*(4), 587–634. https://dx.doi.org/10.1006/ijhc.2001.0503

McKenney, S., & Mor, Y. (2015). Supporting teachers in data-informed educational design. *British Journal of Educational Technology, 46*(2), 265–279. https://dx.doi.org/10.1111/bjet.12262

McLaughlin, M. W., & Talbert, J. E. (2006). *Building school-based teacher learning communities: Professional strategies to improve student achievement* (Vol. 45). New York: Teachers College Press.

Molenaar, I., & Knoop-van Campen, C. (2018). How teachers make dashboard information actionable. *IEEE Transactions on Learning Technologies*. (Early Access). http://dx.doi.org/10.1109/TLT.2018.2851585

Mor, Y., Ferguson, R., & Wasson, B. (2015). Learning design, teacher inquiry into student learning and learning analytics: A call for action. *British Journal of Educational Technology*, *46*(2), 221–229. https://dx.doi.org/10.1111/bjet.12273

Park, Y., & Jo, I. H. (2015). Development of the learning analytics dashboard to support students' learning performance. *Journal of Universal Computer Science, 21*(1), 110–133.

Rienties, B., Boroowa, A., Cross, S., Kubiak, C., Mayles, K., & Murphy, S. (2016). Analytics4Action evaluation framework: A review of evidence-based learning analytics interventions at Open University UK. *Journal of Interactive Media in Education, 2016*(1), 2. http://dx.doi.org/10.5334/jime.394

Rust, F. (2009). Teacher research and the problem of practice. *Teachers College Record*, *111*(8), 1882–1893.

Sergis, S., & Sampson, D. G. (2017). Teaching and learning analytics to support teacher inquiry: A systematic literature review. In A. Peña-Ayala (Ed.), *Learning analytics: Fundaments, applications, and trends* (pp. 25–63). Cham, Switzerland: Springer. https://dx.doi.org/10.1007/978-3-319-52977-6_2

Siemens, G., Gašević, D., Haythornthwaite, C., Dawson, S., Shum, S. S., Ferguson, R., Duval, E., Verbert, K., & Baker, R. S. (2011). *Open learning analytics: An integrated & modularized platform*. [Concept paper]. Society for Learning Analytics Research.

Spillane, J. P. (2012). Data in practice: Conceptualizing the data-based decision-making phenomena. *American Journal of Education, 118*(2), 113–141. https://dx.doi.org/10.1086/663283

Steen, M. (2011). Tensions in human-centred design. *CoDesign, 7*(1), 45–60. https://dx.doi.org/10.1080/15710882.2011.563314

Tan, J. P-L., Koh, E., & Jonathan, C. R. (2018). Visible teaching in action: Using the WiREAD learning analytics dashboard for pedagogical adaptivity. Paper presented at the American Educational Research Association Annual Conference (AERA 2018), 13–17 April 2018, New York, NY, USA. Retrieved from the AERA Online Paper Repository. http://dx.doi.org/10.302/1321813

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

Tempelaar, D. T., Rienties, B., & Nguyen, Q. (2017). Towards actionable learning analytics using dispositions. *IEEE Transactions on Learning Technologies*, *10*(1), 6–16. http://dx.doi.org10.1109/TLT.2017.2662679

van Harmelen, M., & Workman, D. (2012). Analytics for learning and teaching. *CETIS Analytics Series*, *1*(3), 1–40.

van Leeuwen, A. (2015). Learning analytics to support teachers during synchronous CSCL: Balancing between overview and overload. *Journal of Learning Analytics*, *2*(2), 138–162. https://dx.doi.org/10.18608/jla.2015.22.11

van Leeuwen, A., van Wermeskerken, M., Erkens, G., & Rummel, N. (2017). Measuring teacher sense making strategies of learning analytics: A case study. *Learning: Research and Practice*, *3*(1), 42–58. https://dx.doi.org/10.1080/23735082.2017.1284252

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist*, *57*(10), 1500–1509. https://dx.doi.org/10.1177/0002764213479363

Wise, A. F. (2014). Designing pedagogical interventions to support student use of learning analytics. In *Proceedings of the 4th International Conference on Learning Analytics and Knowledge* (LAK '14), 24–28 March 2014, Indianapolis, IN, USA (pp. 203–211). New York: ACM. http://dx.doi.org/10.1145/2567574.2567588

Wise, A. F., Knight S., & Ochoa, X. (2018). When are learning analytics ready and what are they ready for? *Journal of Learning Analytics*, *5*(3), 1–4. http://dx.doi.org/10.18608/jla.2018.53.1e

Wise, A. F., & Vytasek, J. (2017). Learning analytics implementation design. In C. Lang, G. Siemens, A. F. Wise, & D. Gašević (Eds.), *Handbook of learning analytics* (pp. 151–160). Beaumont, AB: Society for Learning Analytics Research. http://dx.doi.org/10.18608/hla17.013

Wise, A. F., Vytasek, J. M., Hausknecht, S., & Zhao, Y. (2016). Developing learning analytics design knowledge in the "middle space": The student tuning model and align design framework for learning analytics use. *Online Learning*, *20*(2), 155–182.

Wise, A. F., Zhao, Y., & Hausknecht, S. (2014). Learning analytics for online discussions: Embedded and extracted approaches. *Journal of Learning Analytics*, *1*(2), 48–71. https://doi.org/10.18608/jla.2014.12.4

Xhakaj, F., Aleven, V., & McLaren, B. M. (2017). Effects of a teacher dashboard for an intelligent tutoring system on teacher knowledge, lesson planning, lessons and student learning. In E. André, R. S. Baker, X. Hu, M. M. T. Rodrigo, & B. du Boulay (Eds.), *Proceedings of the 18th International Conference on Artificial Intelligence in Education* (AIED 2017), 28 June–1 July 2017, Wuhan, China (pp. 315–329). Cham, Switzerland: Springer. http://dx.doi.org/10.1007/978-3-319-61425-0_69

Zirkel, S., Garcia, J. A., & Murphy, M. C. (2015). Experience-sampling research methods and their potential for education research. *Educational Researcher*, *44*(1), 7–16. https://dx.doi.org/10.3102/0013189X14566879