Journal for Research in Mathematics Education
2018, Vol. 49, No. 4, 362–372

Editorial

Using Data to Understand and Improve Students' Learning: Empowering Teachers and Researchers Through Building and Using a Knowledge Base

Jinfa Cai, Anne Morris, Charles Hohensee, Stephen Hwang,
Victoria Robison, and James Hiebert
University of Delaware

In our May editorial (Cai et al., 2018a), we explored how collaborations among teacher–researcher partnerships could harness emerging technological resources to address the problem of isolation in the work of teachers and researchers. In particular, we described a professional knowledge base (Cai et al., 2018b) and a mechanism by which that knowledge base could be continuously populated, updated with data and resources that are useful to teachers and researchers, and shared among partnerships thereby enabling them to work on the same instructional problems. In this editorial, we shift our focus to discuss how data on students' thinking and classroom experiences could be leveraged within such a system to improve instructional practice. We will explore how the knowledge base could serve as a tool to (a) gather, process, and analyze data from individual students; (b) increase our understanding of the effects of students' mathematical learning experiences; and (c) help teacher–researcher partnerships understand and improve students' learning.

Developing an Explanatory Theory That Connects Teaching With Students' Learning

An overarching theme of our editorials has been addressing the persistent gap between research and practice in mathematics education. We have acknowledged that if research is to have a greater impact on practice, it must address the problems of practice that teachers grapple with, and it must do so in a way that produces knowledge that teachers can use. The professional knowledge base we have described attempts to do this by engaging teacher–researcher partnerships in collaborative efforts to create and share lessons whose effectiveness is iteratively refined over the course of many cycles of design and implementation. This process is based on the assumption that specific instructional activities can be connected to students' opportunities to learn and the degree to which students are able to take advantage of those opportunities.

This assumption echoes Nuthall's (2004) call, in his critique of research on teaching effectiveness, for "research that actually answers the question of how teaching is related to learning in a way that is comprehensible and practically useful for teachers" (p. 273). Nuthall proposed six considerations that must be taken into account for research on the teaching–learning relationship to produce useful findings. Of these, he considered "complete, continuous data on individual student experience" (p. 296) to be the most critical because this kind of data is fundamental to developing an explanatory theory of how different ways of teaching are related to student learning outcomes. Without data on how students experience and respond to teaching, research cannot fully illuminate the underlying processes that connect the choices made by teachers in the classroom to students' learning.

In his own research, Nuthall (2004) made use of different technologies, including "miniature video cameras with zoom lenses mounted on the ceiling of the classroom" and "miniature individual broadcast microphones" (p. 300), to systematically capture continuous data on each individual student in a classroom. These data allowed him to follow the development of each student's understanding of particular concepts and to trace the origins and consequences of particular misconceptions that students developed during lessons. We agree with Nuthall about the value of collecting continuous data on the learning experiences of each student. We have further extended this view to include collecting continuous data about noncognitive aspects of each student's learning experiences (Cai et al., 2017b).

Challenges to Understanding Students' Learning Experiences

Taking such a broad view of students' learning experiences comes with a cost. In typical mathematics classrooms, teachers (and researchers) face a number of obstacles to collecting continuous data from (and studying) students' mathematical learning experiences. Accessing how all students think about and make meaning of mathematics in the moment would be daunting, to say the least. Teachers often gain insights into students' thinking by talking with students or by examining artifacts of their work. However, keeping track of every student's thinking through an entire lesson or over several lessons is an overwhelming task for a teacher. Collecting so much information about every student, and keeping that information up-to-date, could easily collapse under its own weight. Although Nuthall (2004) found the comprehensive data he collected to be a powerful resource for understanding the cognitive relationships between teaching and learning, he acknowledged that the process of obtaining and processing the data was time-consuming and labor-intensive.

Including noncognitive aspects of students' experiences adds yet more complexity to data collection and processing. For example, comprehensively assessing students' engagement and motivation might require a combination of classroom observation, video analysis, surveys, and interviews (Middleton, Jansen, & Goldin, 2017). Nevertheless, we believe it is worth pursuing the creation and use of technologically aided professional knowledge bases because of the considerable power such knowledge offers for building a usable explanatory theory that connects teaching with students' learning.

In response to the challenges of creating and using large databases and to calls for greater adoption of data-driven instruction (Hamilton et al., 2009), a number of digital tools to collect and manage student data have been created and marketed to teachers and school districts. These tools include digital gradebooks and dashboards, learning management systems, applications that generate assessments, software and online platforms for individual student instruction, and digital remediation tools. Indeed, in a national representative survey of 4,600 teachers in the United States, the Bill & Melinda Gates Foundation (2015) found that "virtually all teachers (93%) regularly use some form of digital tool to guide instruction" (p. 3). However, the same survey revealed that 67% of those teachers were "not fully satisfied with the effectiveness of the data or the tools for working with data that they have access to on a regular basis" (p. 3). The teachers identified key challenges presented by the tools, reaching the consensus that, despite the help of existing digital tools, it remains too overwhelming to collect, analyze, and use data to support data-driven instruction. Current offerings such as digital dashboards that track and display student progress remain subject to the fundamental problem of communicating too much information about too many students at once. Information overload is a very real phenomenon (Ingram, Louis, & Schroeder, 2004). Moreover, the use of the data provided by current digital tools is often constrained by the incompatibility of different technological platforms and inconsistency in reporting the data. Connecting student data from different sources into a single platform often requires much time and effort. Finally, teachers are hard-pressed to react to data effectively and to adjust their instruction based on feedback from digital systems because these systems often do not provide timely information in a usable form. Therefore, it is not surprising that the promise of data-driven instruction has, to this point, not been fully realized.

In the future world we envision, however, it is not difficult to imagine solving the technical difficulties of gathering and managing such complex and large data sets in ways that could provide timely insights in a form that teachers could use on a daily basis. Even today, portable video cameras and audiorecording equipment are ubiquitous in the form of smartphones. In addition, the spread of one-to-one technology initiatives that provide every student in a school district with a laptop or tablet computer means that many students are rarely far from a device that can gather the continuous student data that Nuthall (2004) described. Moreover, the technology to automatically process, transcribe, parse, and filter these data is rapidly developing. Online services already routinely process huge collections of image data, automatically indexing pictures by faces and objects. The presence of these technologies in the classroom can also facilitate the collection of data relevant to noncognitive outcomes and affective factors by making it easier to capture real-time data directly from students using methods such as experience sampling (Zirkel, Garcia, & Murphy, 2015). In other words, the capacity to capture, process, and store comprehensive cognitive and noncognitive data longitudinally for every student either already exists or is on the near horizon. Thus, a critical consideration for our vision is how these kinds of data on students' classroom experience, coupled with detailed student assessment data and teachers' own observations, could enable teachers and researchers to gain insights into students' mathematical learning experiences that have a real impact on practice.

The Power of the Knowledge Base for Collecting, Analyzing, and Using Data

Our vision of the use of data on students' thinking and experiences is based on three assumptions about these data and the relationship between teaching and learning. The first assumption is that conceptual models based on longitudinal data on individual students or groups of students with similar learning profiles, often called learning trajectories, are incomplete without descriptions of instructional activities or learning experiences associated with changes in student thinking and learning. In other words, data on students' experiences must be paired with data on instruction to make connections between teachers' teaching and students' learning. This is a point we have emphasized in our descriptions of how teacher–researcher partnerships could work with a professional knowledge base (Cai et al., 2018a). The second assumption is that teaching can greatly improve students' learning if teachers understand students' thinking and learning experiences. The work of Cognitively Guided Instruction has already provided ample evidence to support this assumption (Carpenter, Franke, Jacobs, Fennema, & Empson, 1998). The final assumption is that a professional knowledge base offers the potential, through the effective application of technology, to provide timely and useful information to teachers about students' thinking and learning in ways that do not further burden them.

What makes this level of student data important? Why would we, as researchers and teachers, want to have this flood of information? What would researchers and teachers actually do with this information? How could the data be collected, analyzed, and used efficiently and productively? In this section, we propose a framework for supporting teacher–researcher partnerships' use of data for instruction. As we indicated in Cai et al. (2017b), we believe that students' learning experiences include both cognitive and noncognitive aspects in both the short and the long term. Thus, data have the potential to be useful to teachers and researchers at different times relative to any individual lesson. We will therefore consider how data can be useful in the moment (during a lesson), in the short term (shortly after a single or multiple lessons), and in the long term (across years).

Table 1 outlines our proposed framework for envisioning the collection, analysis, and use of student data, indicating the kinds of data on students' experiences that could be useful at different points in time. Although not explicitly listed in the table, our first assumption implies that any data on a student's experiences collected within this framework would necessarily be coupled with a description of the instructional activities associated with those experiences. It is also important to note that the data and the tools that support teachers' use of data must work together to avoid the time-consuming, manual aggregation of information often required today (Bill & Melinda Gates Foundation, 2015). Moreover, it remains an

Table 1
Framework for Collecting, Analyzing, and Using Data on Students' Mathematical Learning Experiences

Time frame	Cognitive	Noncognitive
In the moment		
Data	• Students' conceptions and misconceptions • Students' unexpected responses	• Students' engagement with tasks • Students' affect or frustration level • Students' participation in discourse
Goals	• Address, in the moment, particular misconceptions among subgroups of students and provide immediate supports	• Enact supports for students who are disengaged or discouraged • Identify how students are being positioned within the classroom and shape classroom discourse to provide them with a voice
Short term		
Data	• Students' conceptions, misconceptions, and unexpected responses • Students' solution strategies • Students' ways of thinking • Students' insights	• Factors that affect students' engagement with a task • Students' confidence both before and after solving a problem • Classroom norms of participation
Goals	• Identify groups of students with similar conceptions, misconceptions, or ways of thinking to inform the next lesson plan	• Identify groups of students who are experiencing different levels of motivation or engagement with the lesson to inform the next lesson plan
Long term		
Data	• Data across classrooms and research sites	• Connections between affect and achievement
Goals	• Longitudinally examine changes in students' cognitive learning outcomes so that teachers can track the progress of individual students • Develop explanatory theories that connect teaching and learning for particular groups of students	• Longitudinally examine changes in students' affect related to their learning

open question what kinds of information teachers can use effectively, especially while they are actively engaged in instruction. Rather than an exhaustive list, we see this proposed framework as a potential guide for research in this area, providing some examples of the data that could be relevant and the goals for using that data at different time frames.

Data in the Moment

In the classroom, teachers engage in a complex interaction with students wherein they continuously assess their students' responses and make pedagogical decisions in the moment based on those assessments, their own knowledge, and their instructional plan. What data would be useful in the moment to help teachers make these decisions more effectively as they teach? How could those data be presented to teachers in such a way that it is not just another distraction or demand on their time?

Suppose that all students were equipped with a tablet device onto which they recorded their mathematical work as they would on paper. The device's handwriting recognition algorithms would read and process the data, and the data would be uploaded to the knowledge base for analysis, resulting in immediate feedback provided to teachers about each student's understanding and strategy use. For example, a teacher–researcher partnership could identify potential attributes of interest for each instructional task that they stored in the knowledge base. These attributes would be "dimensions of reasoning or understanding in a given domain" (Izsák & Templin, 2016, p. 20) that would be needed to complete the task. The system would provide feedback about students' performance with respect to those attributes. Developments in diagnostic classification models (de la Torre, Carmona, Kieftenbeld, Tjoe, & Lima, 2016) and computer adaptive testing (Chang, 2015) as well as advances in technology could contribute to designing a system to assess students' mathematical thinking in such ways. This combination of technology and psychometrics would give teachers a window into each student's understanding and allow them to use students' responses to immediately inform instruction.

As another example of using data in the moment, the system of data collection and analysis could provide the teacher with an initial clustering of student responses to a task based on similarities along particular attributes. Different categories of student responses could be easily compared to illustrate different strategies or to address misconceptions. As a third example, if a task involved drawing a diagram, the system could classify the students' pictures and present the main types to the teacher in a side-by-side comparison. If the teacher was working with a well-designed lesson and this allowed him or her to see that the students had used only two of four expected responses, the teacher could adjust the remainder of the lesson to focus on the two responses that students generated (or find a way to bring out the other two responses).

Many kinds of data on students' noncognitive learning experiences could also inform in-the-moment teacher decision making. For example, students could rate their confidence level before and after working on a particular problem. Research has shown that students' confidence for solving a particular problem is highly correlated with their success in solving the problem (Pajares, 1996; Zimmerman, 1995). Information about how confident students are when approaching a task could signal teachers that less confident students might need additional support to engage in productive struggle with the task. With respect to student engagement and participation in classroom discourse, a system could monitor each student's talk and process it on the fly to produce classroom "heat maps" indicating which students are contributing to mathematical discussions and which students are silent. If a teacher were equipped with such visualizations, he or she could quickly gain important insights into which students are being positioned as mathematically powerful and which students are playing more passive roles (Esmonde & Langer-Osuna, 2013; Herbel-Eisenmann, Meaney, Bishop, & Heyd-Metzuyanim, 2017). This would then allow the teacher to shape the classroom discourse to give all students an opportunity to have a voice. Similarly, the system could report in-the-moment data on student frustration based on image and voice analysis, helping the teacher judge when students are productively struggling with a task versus when students are becoming too frustrated. Another possibility is a tablet device equipped to collect data to determine how engaged the students are with a task or to which aspects of the task they are attending. This could also involve on-the-fly voice analysis or other technologies such as eye tracking. Real-time displays of these data could, again, be provided to teachers for their use in the moment.

Of course, many teachers already gather some information of this type through their own observation in the classroom. Noticing what students do and listening to what they say is a powerful tool, as expert teachers have long recognized. But no teacher (and no researcher) has the time or resources to collect and make sense of these data for every student during every lesson. The difference in the type of system that we describe is that data from every student would be gathered simultaneously and automatically, and the system itself would surface those data that would be most helpful at any given moment to support teachers' pedagogical decision making—a just-in-time resource for instruction.

Data in the Short Term

In our framework, analyzing and using data in the short term refers to using data reflectively after a lesson or unit has been taught to inform subsequent instruction with the same students. Data recorded in the knowledge base on each student's strategy use, conceptions and misconceptions, and affective responses to a lesson could guide teachers and researchers as they decide what needs to be addressed in the next lesson and what new concepts are feasible for students given their current understanding. Similarly, teachers and researchers could access students' performance on previous instructional tasks to help them predict how those students would think about tasks in the next lesson. For example, following a lesson introducing exponential growth and graphs of exponential functions, the knowledge base would contain data on the kinds of graphs students produced. If some students produced graphs that did not show equal growth factors over equal intervals (perhaps producing linear graphs or graphs with irregular growth factors), the system could alert the teacher and researcher of this development and make predictions about how those students would engage with the next lesson's tasks, allowing the teacher and researcher to plan how to address the misconception in the next lesson.

Such data would also reveal individual students' learning progressions in the unit. The data could be used to identify students who had difficulty with particular concepts in the unit. The system could then spotlight clusters of students who were experiencing similar difficulties, perhaps identifying those clusters in another type of heat map display, so that the teacher and researcher could plan how to address those difficulties. Data on noncognitive aspects of students' experiences could also be used by the teacher and researcher to build targeted noncognitive supports into the next lesson. For example, the teacher and researcher could look specifically at students who were not participating much during a given lesson and check that they still were engaged and not "falling through the cracks." Or the system could highlight productive and unproductive classroom norms, allowing the teacher and researcher to plan for supports in subsequent lessons that would promote productive norms and discourage unproductive ones. By analyzing these kinds of data from the lessons in a unit, the system could help teacher–researcher partnerships to identify key aspects of how each student's affect and cognitive aspects of learning mutually influence each other.

Data in the Long Term

The professional knowledge base that we have described (Cai et al., 2018b) would provide teachers and researchers with a powerful tool suitable for a variety of needs ranging from large scale (across classrooms or schools) to small scale (across particular groups of students or individual students). Teachers and teacher–researcher partnerships will likely want to study data from their own classroom or a few classrooms in which students are trying to achieve the same learning goals. Moreover, with access to longitudinal data on each student's mathematical thinking, teachers and researchers could become increasingly familiar with how their students think about certain concepts and, ultimately, could begin accurately predicting how particular students will respond. By connecting classroom data sets from teachers who have used the same instructional task or sequence of tasks, the system could begin to make useful connections between students' understanding and conceptions and their subsequent learning experiences with those tasks. These connections would generate an explanatory theory of the kind envisioned by Nuthall (2004), a theory that would predict how other students will respond to the activity and, along with data from the teacher's own classroom, enable a kind of data-based planning not previously possible. This kind of long-term use of data could have a strong impact on equity by affording teacher–researcher partnerships the ability to tailor implementation to create similar learning opportunities for all groups of students.

Teacher–researcher partnerships might also be interested in studying students who respond in different ways to hypothesized cause-and-effect relationships between a task and student learning. Learning more about these local cause-and-effect relationships would allow tweaking of the explanatory theory, as well as tweaking of the instructional activity for future implementation. Moreover, these data could aid the planning of follow-up activities to build on students' thinking as revealed by the data. Fundamentally, the long-term work of teaching (conducted by teachers and teacher–researcher partnerships) would not lie in redesigning activities (i.e., curriculum development) but in studying tendencies of students and making systematic incremental improvements in teaching and learning that, over time, accumulate into big improvements.

Researchers would likely have a special interest in accumulating long-term data on a sequence of tasks that develop a particular learning goal or network of goals. Teacher–researcher partnerships at different sites might use different tasks or sequences of tasks for a particular mathematical topic, and the data on students' experiences with different tasks and sequences would help shed light on the more promising sequences of tasks for maximizing students' learning. Stepping back and looking at larger data sets (across more students and connected sequences of activities) would allow building more ambitious explanatory theories based on models of students' thinking or learning trajectories that provide new insights into how students with different backgrounds develop their thinking connected to particular kinds of instructional tasks. The knowledge base would open new possibilities for formulating and testing both local and more general theories about cause-and-effect relationships between teaching and learning. These explanatory theories could, for example, specify relationships that are contingent on the development of particular prerequisite knowledge.

With respect to teaching, and specifically the pedagogical decisions that teachers make as they teach, the system could collect data across research sites about the different kinds of in-the-moment decisions that teachers make when confronted with unexpected situations in a given task or lesson. Over time, collecting and analyzing those data along with the student outcomes that followed particular pedagogical choices could help populate the knowledge base with information on what kinds of decisions are best for students' learning on the topic. The same kind of analyses could be conducted on the effects of using particular planned questions, follow-up responses to students' anticipated solution strategies, and practice exercises after the concept was developed. Were the predicted outcomes confirmed, or are changes to the predictions warranted? As data are collected across multiple classrooms with diverse groups of students, explanatory theories can be refined to guide the planning of instruction that reaches more and more students.

The Roles of Teachers and Researchers

If we assume the existence of a system that could efficiently collect, analyze, and share data on student experiences linked to instructional activities to create usable knowledge bases, we are confronted with the fact that teachers and researchers are likely to play quite different roles. We have already described some of the radical changes in the work of teachers and researchers in this new system in this and earlier editorials (Cai et al., 2017a, 2017b, 2017c). In our next editorial, we will further explore these new roles and consider how we might move from our present reality to this future reality.

References

Bill & Melinda Gates Foundation. (2015). *Teachers know best: Making data work for teachers and students.* Retrieved from http://k12education.gatesfoundation.org/resource/teachers-know-best-making-data-work-for-teachers-and-students-2/

Cai, J., Morris, A., Hohensee, C., Hwang, S., Robison, V., & Hiebert, J. (2017a). A future vision of mathematics education research: Blurring the boundaries of research and practice to address teachers' problems. *Journal for Research in Mathematics Education*, *48*(5), 466–473. doi:10.5951/jresematheduc.48.5.0466

Cai, J., Morris, A., Hohensee, C., Hwang, S., Robison, V., & Hiebert, J. (2017b). Clarifying the impact of educational research on students' learning. *Journal for Research in Mathematics Education*, *48*(2), 118–123. doi:10.5951/jresematheduc.48.2.0118

Cai, J., Morris, A., Hohensee, C., Hwang, S., Robison, V., & Hiebert, J. (2017c). Making classroom implementation an integral part of research. *Journal for Research in Mathematics Education*, *48*(4), 342–347. doi:10.5951/jresematheduc.48.4.0342

Cai, J., Morris, A., Hohensee, C., Hwang, S., Robison, V., & Hiebert, J. (2018a). Building and structuring knowledge that could actually improve instructional practice. *Journal for Research in Mathematics Education*, *49*(3), 238–246.

Cai, J., Morris, A., Hohensee, C., Hwang, S., Robison, V., & Hiebert, J. (2018b). Data in a brave new world: Reducing isolation to amplify the impact of educational research on practice. *Journal for Research in Mathematics Education*, *49*(2), 118–124. doi:10.5951/jresematheduc.49.2.0118

Carpenter, T. P., Franke, M. L., Jacobs, V. R., Fennema, E., & Empson, S. B. (1998). A longitudinal study of invention and understanding in children's multidigit addition and subtraction. *Journal for Research in Mathematics Education*, *29*(1), 3–20. doi:10.2307/749715

Chang, H.-H. (2015). Psychometrics behind computerized adaptive testing. *Psychometrika*, *80*(1), 1–20. doi:10.1007/s11336-014-9401-5

de la Torre, J., Carmona, G., Kieftenbeld, V., Tjoe, H., & Lima, C. (2016). Diagnostic classification models and mathematics education research: Opportunities and challenges. In A. Izsák, J. T. Remillard, & J. Templin (Eds.), *Psychometric methods in mathematics education: Opportunities, challenges, and interdisciplinary collaborations* (*Journal for Research in Mathematics Education* Monograph No. 15, pp. 53–71). Reston, VA: National Council of Teachers of Mathematics.

Esmonde, I., & Langer-Osuna, J. M. (2013). Power in numbers: Student participation in mathematical discussions in heterogeneous spaces. *Journal for Research in Mathematics Education*, *44*(1), 288–315. doi:10.5951/jresematheduc.44.1.0288

Hamilton, L., Halverson, R., Jackson, S. S., Mandinach, E., Supovitz, J. A., & Wayman, J. C. (2009). *Using student achievement data to support instructional decision making* (NCEE 2009-4067). Washington, DC: National Center for Education Evaluation and Regional Assistance, Institute of Education Sciences, U.S. Department of Education.

Herbel-Eisenmann, B., Meaney, T., Bishop, J. P., & Heyd-Metzuyanim, E. (2017). Highlighting heritages and building tasks: A critical analysis of mathematics classroom discourse literature. In J. Cai (Ed.), *Compendium for research in mathematics education* (pp. 722–765). Reston, VA: National Council of Teachers of Mathematics.

Ingram, D., Louis, K. S., & Schroeder, R. G. (2004). Accountability policies and teacher decision making: Barriers to the use of data to improve practice. *Teachers College Record*, *106*(6), 1258–1287. doi:10.1111/j.1467-9620.2004.00379.x

Izsák, A., & Templin, J. (2016). Coordinating conceptualizations of mathematical knowledge with psychometric models: Opportunities and challenges. In A. Izsák, J. T. Remillard, & J. Templin (Eds.), *Psychometric methods in mathematics education: Opportunities, challenges, and interdisciplinary collaborations* (*Journal for Research in Mathematics Education* Monograph No. 15, pp. 5–30). Reston, VA: National Council of Teachers of Mathematics.

Middleton, J., Jansen, A., & Goldin, G. A. (2017). The complexities of mathematical engagement: Motivation, affect, and social interactions. In J. Cai (Ed.), *Compendium for research in mathematics education* (pp. 667–699). Reston, VA: National Council of Teachers of Mathematics.

Nuthall, G. (2004). Relating classroom teaching to student learning: A critical analysis of why research has failed to bridge the theory-practice gap. *Harvard Educational Review*, *74*(3), 273–306. doi:10.17763/haer.74.3.e08k1276713824u5

Pajares, F. (1996). Self-efficacy beliefs in academic settings. *Review of Educational Research*, *66*(4), 543–578. doi:10.3102/00346543066004543

Zimmerman, B. J. (1995). Self-efficacy and educational development. In A. Bandura (Ed.), *Self-efficacy in changing societies* (pp. 202–231). New York, NY: Cambridge University Press.

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. doi:10.3102/0013189X14566879