Realistic Expectations in The Data-Informed District

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Paper presented at the 2014 annual meeting of the American Educational Research Association, Philadelphia, PA.

Copies of this paper are available at the AERA website.

The authors wish to thank the Spencer Foundation for the grant that funded this study.

Introduction

Much research has been devoted to understanding the ways in which educational data can be used to inform educational practice (e.g., Copland, 2003; Datnow et al., 2007; Little, 2012; Mandinach & Gummer, 2013; Marsh, 2012; Wayman & Stringfield, 2006). In spite of this research base, school leaders often have difficulty implementing these recommended practices (Valli & Buese, 2007; Wayman, Snodgrass Rangel, Jimerson, & Cho, 2010). It is thus useful to examine the reasons why these troubles occur. In this paper, we examine one area that is particularly difficult for school leaders: the implementation of computer data systems.

Over the last decade, the capacity to gather, analyze, and distribute data about students has rapidly increased (B. Tucker, 2010; Mieles & Foley, 2005; Wayman, Cho, & Richards, 2010; Wayman, Stringfield, & Yakimowski, 2004). Accordingly, it has made good sense for many districts to attempt to leverage computer data systems toward supporting student achievement (Burch & Hayes, 2009; Hamilton et al., 2009; Marsh, 2012; Shaw & Wayman, 2012).

Obtaining a data system is relatively easy, but getting people to make the most of out of a system is not. Districts have been quick to invest significant dollars in data systems (Burch & Hayes, 2009), and have hoped for equally significant use of these systems. Unfortunately, increased system acquisition among schools has not necessarily resulted in strong system use among educators (Cho & Wayman, in press; Means, Padilla, DeBarger, & Bakia, 2009; Wayman, Cho, & Shaw, 2009; Shaw & Wayman, 2012).

The research base can be interpreted to suggest that low system use is a result of poor implementation practices. Research on educational technology in general has described how easy it is to oversimplify and underestimate the interactions between technologies and work (Leonardi, 2009; Orlikowski & Barley, 2001; Orlikowski & Iacono, 2001). For example, Brooks

(2011) describes how district leaders can confuse investing in a new technology with actually improving teaching and learning. This same dynamic appears to be playing out specific to computer data systems, where research implies that districts typically invest more in the acquisition of data systems than they do on the subsequent infusion of these systems into work practices (Cho & Wayman, in press; Means et al., 2009; Wayman et al., 2009). Our prior research suggests that, while planners implement computer data systems focusing largely on technological aspects of implementation, they could improve subsequent use by focusing closely on the human aspect of implementation (Cho & Wayman, in press; Cho & Wayman, under review).

Therefore, the aim of this paper is to explore a socially-based data system implementation plan. In doing so, we will examine prior research on data use, data systems, and educational technology to create a plan that is responsive to how educators make sense of data systems and how they adapt to the introduction of a data system into their everyday work. In doing so, we first offer a section that describes common approaches to data system implementation, followed by a section that describes characteristics of a socially-based implementation. Next, we describe our implementation plan, along with supporting research. We end the paper with a final conclusion section.

Common Approaches to Data System Implementation

Data system implementation is often an extension of the approach used to system procurement, where planners focus on technical requirements: what data can be put in the system, how fast will it respond, etc. (Cho & Wayman, under review; Means et al., 2009; Wayman et al., 2004). Sometimes, a committee provides input during system procurement (Cho & Wayman, under review; Wayman & Conoly, 2006), but implementation is largely under the purview of one or a few “champions” (Cho & Wayman, under review; Wayman & Conoly, 2006; Wayman et al., 2009). In fact, research describing good data systems has typically focused on technical aspects (Mieles & Foley, 2005; Wayman et al., 2004). Once the system is bought and/or built, it is introduced to users through a number of training sessions focused on system features and how to run them (Cho & Wayman, in press; Cho & Wayman, under review; Wayman & Jimerson, 2014; Wayman et al., 2009).

In sum, data system implementation typically consists of putting a technically sound system in place, then showing educators how to use it. Unfortunately, this approach does not seem to be producing use commensurate with the resources spent in acquiring and implementing a system. Although studies based on user reports have suggested there are exemplary implementations where widespread use is common (Lachat & Smith, 2005; Wayman & Stringfield, 2006), studies based on system use logs have shown use to be centered around infrequent events, such as benchmark assessments (Tyler, 2013; Wayman et al., 2009; Wayman et al., 2010; Shaw & Wayman, 2012). Further, studies that have examined the relationship between data system use and student achievement have not showed a significant positive correlation (Tyler, 2013; Shaw & Wayman, 2012).

Research suggests some underlying assumptions to this approach that may be responsible for disappointing outcomes. For instance, the implementation approach described above is consistent with a technologically deterministic perspective (Barley, 1990; Brooks, 2011; Orlikowski & Iacono, 2001), whereby the technologies are assumed to automatically improve work, making it faster and more efficient. Technologically deterministic perspectives thus tend to portray technologies as holding pre-determined effects on work. This perspective is evident in the fact that typical approaches to data system implementation focus on training for system features rather than exploring various work-based uses (Cho & Wayman, in press; Cho & Wayman, under review; Wayman & Jimerson, 2014; Wayman et al., 2009). That is, training on system features carries an implicit assumption that once users know how to work the system, everyday uses to support practice will then be obvious.

Similarly, this approach implicitly assumes that users will know the "right" thing to do with these features (i.e., a rational systems perspective; March, 1991). Thus, system planners may have implicitly assumed that implementation work is simply about giving educators access to what planners have decided are the "right tools" for the job. Unfortunately, this approach works well in environments with predictable challenges (e.g., production lines), but may not work well in contexts where workers frequently apply professional judgment (Davenport & Prusak, 1998; Pfeffer, 1997; Weick, 1976). In endeavors such as education, "right answers" are not always obvious or consistent from person to person, and may be influenced by factors such as training, personal experience, and politics (Brown & Duguid, 1991; Carlile, 2002; Eisenhardt & Zbaracki, 1992).

In sum, this research suggests that data systems are typically implemented as though introducing the system will result in changed and improved practice. We suggest that this notion is flawed. Instead, we put forward that technology merely provides the occasion for change – but that the agency for changes lies in people, not technology. In the following section, we will discuss a human-based approach to implementation that we believe holds promise in helping districts, schools, and educators get more out of their data system.

Accounting for the Human Side: A Social Approach to Data System Implementation

We are not suggesting that the technical side of data system implementation is unimportant. Research is clear that it is necessary to ensure that a data system is technologically sound, providing accurate and complete data in a rapid fashion (Means et al., 2009; Mieles & Foley, 2005; Wayman, Cho, & Richards, 2010; Wayman et al., 2004). We forward that once the data system is available, envisioning and habituating its use to support practice is a social matter. Under this approach, implementation does not end with system rollout, in fact, implementation is just beginning. It continues into periods when educators think through how, why, and *whether* a system ought to be used. Accordingly, data system implementation can be considered an extended period of social adjustment (Cho & Wayman, in press).

A socially-based implementation approach bears a number of characteristics. For instance, prior research revealed that educators' views and opinions of the value of a data system to their practice was driven by their notions of data and data use (Cho & Wayman, in press). Thus, we suggest that the system should be implemented such that educators' varied ideas, definitions, and values about data and its practical use mesh with system functionalities. One example would be to contextualize system implementation within problems faced by educators in their current practice (Wayman & Jimerson, 2014; Wayman, Jimerson, & Cho, 2012). Research suggests that educator notions about data often are not well-defined, so another example could include using system implementation to help explore common understandings about data use (Lachat & Smith, 2005; Wayman, Jimerson, & Cho, 2012; Wayman & Stringfield, 2006). Doing so not only allows educators an opportunity to discuss and develop "shared mental models" (Senge, 2006) about data and the data system, but also affords leaders the opportunity to support and shape these understandings.

Second, system implementation should account for the fact that planners' ideas of how the system should be used and how it will support practice are not the only possible ideas. In fact, educators will often have different ideas about the system, resulting in rich diversity of system use (Cho & Wayman, in press). Approaches that acknowledge the potential for such differences emphasize issues such as information flow and adaptation to circumstances as they arise (McDaniel & Driebe, 2001; Rivkin & Siggelkow, 2002; Thomas, Sussman, & Henderson, 2001). Thus, implementation planners could chart the course of implementation, but also anticipate and embrace differing ideas about system use. In doing so, it will be important to establish a variety of methods for eliciting feedback on system use. Some could be as simple as offering easy ways to comment through the system. Others could take advantage of educator-to-educator interaction: research suggests that if information is a resource flowing among people, then relationships with others can be important conduits for ideas and feedback (Burt, 2004; Daly, 2012; Granovetter, 1983). Put another way, educators are probably going to be talking about the system anyway (Wayman, Cho, & Johnston, 2007), so capturing this flow of information helps the organization respond with appropriate implementation activities.

Third, it is important that implementation remains consistent with the tenets of good professional learning. Educators consistently criticize their data-related professional learning opportunities (Means et al., 2009; Wayman et al., 2007; Wayman & Jimerson, 2014), using terms such as “sit and get” and “death by PowerPoint.” In contrast, a literature summary by Wayman and Jimerson (2014) indicates educators benefit from professional learning activities that are collaborative in nature, relevant to their current work, and delivered within their professional context. In light of this research, implementing a data system could be organized within the course of educators’ everyday work and made immediately relevant to the problems they face. This research also implies that long training sessions that focus on system features are ill-advised. Instead, any planned training could deal with information on data or content needed to solve specific problems, and the data system could merely be a support for providing needed data. For example, the data system could be introduced to small collaboratives of teachers, working on a common problem that will immediately impact their practice.

Example of A Socially-Based Data System Implementation

In this section, we offer an example of a socially-based data system implementation plan that draws upon the concepts presented previously. This plan is inspired by an activity described in Wayman, Shaw, & Cho (2010): a central office leader was trying to draw attention to a new data system and sent a problem for each principal in the district to solve, using the new system. Many principals involved teachers in the work, thus generating social activity around the system – and increased use, based in practice.

In the example plan for the present paper, the data system is rolled out to school staff through several small, practice-based learning sessions. Each session focuses on a limited group of data elements to be used in solving a practical, context-based problem, preferably one that participants actually face in their daily practice. In the sessions, educators first learn thoroughly about the properties of the selected data and how such data can be used to inform practice. Then, educators are shown how to access these data from the system in order to examine and address the assigned problem.

Through such consistent practice (i.e., several problems), educators not only will gain familiarity with the data system, but also experience in using it to examine real-world problems. In so doing, educators will be developing routines for integrating the data system into their daily practice.

This example is designed to be conducted with core campus teams, each consisting of a school principal and at least two other school leaders. Focusing initially on campus-level leadership provides a manageable scale for the data system implementation. It also provides principals and other school leaders with experience, skills, and confidence in the process, which they will need when later implementing this plan with their campus faculty. Subsequent phases of this plan could work toward including all staff in the process.

The plan is designed to be repeated multiple times during the year and consists of four steps:

1. Specify a problem
2. Learn about properties and use of data
3. Explore the problem
4. Reconvene to share knowledge

In the following sections, each step is explained in detail, followed by a section describing next steps.

Specify a problem. The first step of this example plan involves the specification of a problem (or a short menu of problems) for principals and their core teams to work on. This could be done in conjunction with principals, but has also been shown to be effective when a central office administrator specifies the initial problem (Wayman, Shaw, & Cho, 2010). Working from a specified problem is a good way for district or school leadership to communicate what they believe is important to focus on in terms of practice and how data serves practice (Cho & Wayman, in press).

In line with tenets of good data-related professional learning (Wayman & Jimerson, 2014; Jimerson & Wayman, in press), this problem should be one that core teams find immediately relevant, thus solving an immediate issue facing them. To these same tenets, the problem should be "small": short in duration (i.e., can be finished in a week or two) and involving only a small amount of data elements (one, two, or three at the most). Finally, since the aim is to familiarize teams with the system being rolled out, the problem should be one that can only be solved using the data system under implementation.

Learn about properties and use of data. Once the problem is specified, support should be provided such that core teams become expert in the properties of the data elements involved (e.g., raw scores vs. scale scores, what an assessment is meant to measure, strengths and weaknesses of qualitative observation). In building this knowledge base through practice, not only is capacity and expertise being built, but core teams will be better able to apply professional judgment and adapt to changing circumstances as they arise (McDaniel & Driebe, 2001; Rivkin & Siggelkow, 2002; Thomas, Sussman, & Henderson, 2001).

Explore the problem. After receiving the problem and gaining expertise around data elements, teams are now sent away to explore the problem collaboratively. This is an important step, because it is where many of the previously-described characteristics of social exchange play out. For instance, it is in this stage that educators collaboratively figure out how they will apply to their own context the information they learn, and determine the changes in practice that will be a good fit (Daly, 2012; Granovetter, 1983). Exploring the problem collaboratively also allows them to converse and share ideas, thus learning each others' perspectives and creating common understandings (Senge, 2006; Jimerson & Wayman, in press; Wayman, Jimerson, & Cho, 2012).

It is during this step that educators get instruction on how to use the data system to access the data they need. To avoid a technologically deterministic approach (Barley, 1990; Brooks, 2011; Orlikowski & Iacono, 2001), however, we recommend that educators only are instructed on how to access data such that they can solve the problem, instead focusing on developing routines around the system that fit their work. Increased familiarity with the system will be realized as this process is repeated numerous times.

Reconvene to share knowledge. After one or two weeks, teams then reconvene to share the work they have accomplished. This step is important for a number of reasons.

First, reconvening reduces isolation and enables teams to share how they related the problem to their own contexts. This exchange of information can introduce creative friction and generate new insights into district-wide practice (Brown & Duguid, 1991; Carlile, 2002; Nonaka, Umemoto, & Sasaki, 1998). Sharing information in this way can also create new relationships between schools that facilitates knowledge exchange (Daly, 2012; McDaniel & Driebe, 2001)

Second, reconvening instills accountability for finishing the problem. Much as Wayman, Midgley, & Stringfield (2006) suggested that peer-to-peer accountability can create positive pressure in collaborative data teams, so can team-to-team accountability.

Third, reconvening enables implementation planners to collect feedback on the implementation process, the data system and the ways that teams worked with the data system. Allowing for such feedback recognizes that implementation is not a fixed, straight line. Rather, it is a meandering line with unpredictable turns. Eliciting feedback enables planners to adapt implementation as it evolves (McDaniel & Driebe, 2001; Rivkin & Siggelkow, 2002; Thomas, Sussman, & Henderson, 2001).

Next steps. After cycling through the above plan once, planners should prepare another problem and set the cycle in motion again. In line with previously discussed characteristics of socially-based implementation, planners can monitor the process and look to relinquish various responsibilities to schools when appropriate. For instance, at some point, school teams should begin specifying problems on their own in Step 1. Also, school leaders should choose when to involve teachers and other building-level staff, in order to implement the system school-wide.

Finally, we note that the example presented here is merely one example of many that can implement characteristics of socially-based data system implementation. In order to fully illustrate these characteristics, we chose an example that was wide in breadth. We recognize, however, that some districts may not be in position to undertake a plan of this size. In those cases, it will still be valuable to tap whichever characteristics the particular context will allow during implementation.

Conclusion

It may not be a surprise that educators have not yet incorporated the use of data systems into their everyday routines. Introducing a new system implies some changes in the ways educators work, so they need to adjust to these new ways of working. Actually, research suggests that educators *have* adjusted, but have done so by using data systems sporadically and mostly outside of their usual practice.

We are hopeful, however, that research such as that presented here can serve as a stepping stone for developing socially-based implementation routines that make data systems more relevant to the work of education. Accounting for the human side of data system implementation holds promise in helping educators leverage 21st-century technology in the quest for more information about their students.

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