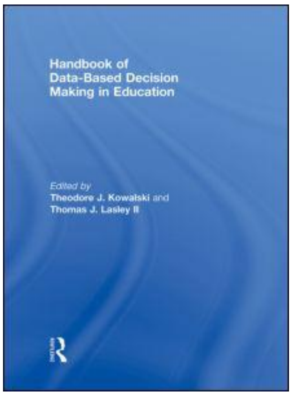

Handbook of Data-Based Decision Making in Education

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Swimming in the Depths

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Swimming in the Depths

Educators' Ongoing Effective Use of Data to Guide Decision Making

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Educators are awash with data. Classroom teachers calculate student grades using the data they collect: attendance, participation points, test scores, and homework completion. School administrators track different data in their daily work: discipline referrals, average daily attendance, school budgets, and expenses related to extracurricular programs. At the district level, data are more departmentalized: with the Personnel Department calculating salaries, benefits packages, and retirement accounts; those in Instruction tracking expenditures on curricular materials and professional development, and Special Services keeping tabs on students receiving additional assistance, completing annual reports to document compliance with a variety of laws. With all these data, one might expect to find educators confident in their data acumen. Sadly, the opposite is more likely to be the case. As a public spotlight is focused on AYP-based school performance data, teachers and administrators all too often are caught floundering in the depths, as waves of data threaten to drown them.

Our work with school leaders (building and district administrators, as well as teachers studying for their administrative licenses) has highlighted three main findings.

1. The educators we have worked with have little training in the meaningful use of data beyond the scope of a single classroom. Although they are familiar with the use of total scores and percentiles to calculate grades, their knowledge does not extend beyond these rudimentary skills.
2. Basic statistics offer meaningful insights to educators who understand how to use them. Simple concepts such as measures of central tendency and variance, standard error, domain sampling, and rank can help educators make more informed decisions.

3. Introduction to these measurement concepts is not sufficient. For educators to move beyond basic familiarity to actual comfort in using data to guide instructional decision making requires a transformation in their approach to schooling. This transformation requires ongoing mentoring and forced practice to move into educators' working knowledge.

In this chapter, we first locate our studies in the research literature on data-based decision making before introducing the dual theoretical lenses through which we view the adoption of new practice: cognitive dissonance (Festinger, 1957) and self-efficacy (Bandura, 1982, 1993, 1997). We then describe our findings from two studies documenting educators' increased ability to use data to make instructional decisions before concluding with suggestions based on our research for those who work in this area. It is our hope that this chapter will provide some guidance to others involved in the effort to help educators gain the skills they need to be able to swim rather than drown in the sea of data in which they work.

The Focus on Data in School Improvement

The Center for Research on Evaluation, Standards, and Student Testing (CRESST; Mitchell, Lee, & Herman, 2000) suggests that

> Data-based decision-making and use of data for continuous improvement are the operating concepts of the day. School leaders are expected to chart the effectiveness of their strategies and use complex and often conflicting state, district, and local assessments to monitor and ensure progress. These new expectations, that schools monitor their efforts to enable *all* students to achieve, assume that school leaders are ready and able to use data to understand where students are academically and why, and to establish improvement plans that are targeted, responsive, and adaptive. (p. 22)

However, research literature on data-driven decision making to guide instructional practices is still limited. Early research in this area was conducted in the 1980s (Popham, Cruse, Rankin, Sandifer, & Williams, 1985), but as a whole, this area of research did not gain momentum at the classroom or school level because complex, easy to access data systems were not readily available and were not being used in school systems until recently. Today, however, more school systems and states have the capacity to collect, analyze, and share data with all stakeholders in an efficient and timely manner (Ackley, 2001; Thorn, 2002). This trend has been further accelerated by legislated requirements of No Child Left Behind (NCLB; U.S. Department of Education, 2001) to use data to improve school performance (Hamilton, Stecher, & Klein, 2002).

In the 2002 publication, *Leading Learning Communities: Standards for What Principals Should Know and Be Able to Do*, the National Association of Elementary School Principals (NAESP) included among its six performance standards for principals: "Use multiple sources of data as diagnostic tools to assess, identify, and apply instructional improvement" (p. 2). Five strategies accompanying the standard on data use encourage principals to

> consider a variety of data sources to measure performance; analyze data using a variety of strategies; use data as tools to identify barriers to success, design strategies for improvement and to plan daily instruction; benchmark successful schools with similar demographics to identify strategies for improving student achievement; and create a school environment that is comfortable using data. (p. 7)

Principals are expected to use data by first beginning with a "global question" or issue, then breaking down the issue into its component parts for analysis to make reasoned decisions on subsequent steps (Streifer, 2002). Killion and Bellamy (2000) suggest

> without analyzing and discussing data, schools are unlikely to identify and solve the problems that need attention, identify appropriate interventions to solve these problems, or know how they are progressing toward achievement of their goals. Data are the fuel of reform. Because data abound, schools must become data savvy. (p. 1)

Jandris (2001) describes data-driven decision making as an integral part of the continuous improvement process guided by quantitative and qualitative data drawn from the classroom, the school, the district, and state sources. For a variety of reasons, however, schools continue to struggle with meaningful use of schoolwide data.

Establishing Data-Driven Decision-Making Practices in Schools

One barrier to implementing a data-driven decision-making culture is the need for parents, teachers, administrators, district leaders, and school boards to know what to do with the data once they are collected (Bernhardt, 1998, 2003; Cromey & Hanson, 2000; Killion & Bellamy, 2000; Lambert, 2003). A further barrier is an integrated, well-conceived systems approach to data-driven decision making. This includes an accessible data storage system, benchmarking, planning, personnel evaluation, and professional development showcasing the interdependency of inputs, processes, and outcomes under scrutiny (Streifer, 2002).

Holcomb (1999) identifies eight key school improvement activities involving staff that increase student achievement, with three relating specifically to data. The activities that focus on data collection, analysis, interpretation, and decision making described by Holcomb are:

(a) identifying significant, meaningful data to compile for the school;
(b) interpreting the data, requesting more data, and identifying areas of concern; and
(c) discussing and analyzing data evidencing progress with implementation and goal attainment.

Holcomb (1999) and Schmoker (2001) both maintain that all instructional staff should be involved in data analysis and goal setting.

The lack of formal training on how to evaluate programs and student data and how to apply assessment information or the new data-mining tools to the school improvement process is a serious challenge, as is the lack of an established, coherent process for using data in ways that support ongoing, continuous systemic improvement in schools (Cromey, 2000; Paige, 2002; Schmoker, 2001; Streifer, 2002). Focused acts of improvement founded in well-conceived data-driven decision-making processes will help superintendents and school board members, as well as their constituents, gain confidence in their school improvement initiatives (Bernhardt, 1998). The key to meaningful use of educational data lies in the verb: *use.* All too often, educators collect data without clear understanding of how to analyze them (Creighton, 2001), a practice which must be confronted directly (Beghetto & Alonzo, 2006).

Professional Development is a Key to Data Use

There may be reasons why schools do not effectively make the most of their data. In some schools and districts, data analysis is not a high priority (Van der Ploeg & Thum, 2004). Some state education departments may put little emphasis on schools gathering data for improved student performance and thus provide little incentive for districts and schools to devote time, money, and staff resources to utilizing data in new ways to increase student performance. School-based educators may fear data analysis; others may not fear data analysis yet may not have received adequate training to gather and disaggregate data or to establish and maintain databases. Although educational reformers suggest that teachers should embrace data as a way to make their jobs easier and more rewarding (Kinder, 2000; Wiggins, 1993), practice often lags far behind theory in the reality of everyday schooling.

The North Central Regional Educational Laboratory (NCREL) suggests that professional development is central to any attempt to improve the way student achievement is assessed in schools. For the greatest effect on continuous school improvement, a school leader or a district evaluator with a solid grounding in the use of data who is familiar with the school vision (Van der Ploeg & Thum, 2004) should conduct this professional development. Professional development can bring rigor to the use of data-driven decision making. Educators do not need advanced degrees in statistics to begin gathering data and analyzing them in ways that benefit their schools and students; they need professional development training focused on the facets of data-driven decision making.

Professional development and role modeling focused solely on effective data-driven decision-making practices, however, is not enough. Training must also include supports targeted at increasing the educators' efficacy around data-driven decision making. Feelings of self-efficacy and cognitive dissonance play a complementary role in getting educators to use skills gained from professional development activities in their classrooms and schools. Successful performance raises self-efficacy, while failures lower self-efficacy (Bandura, 1977, 1997). Cognitive dissonance research suggests the impact of failure is exacerbated even more when people are sure they put forth their best effort to accomplish a task that they believe to be important. The potential negative impact of failure when educators are learning how to use data to inform their instructional decisions implies that educators in professional development situations need opportunities to participate in data-driven initiatives in safe and successful contexts prior to expecting them to use their skills in the real world.

The importance participants place on professional development opportunities focused on data-driven decision making is also key. If consonant feelings toward data use are unattainable, the efforts at training are wasted, as the person will never fully support the practice (Festinger, 1957). It is evident then that educators participating in professional development activities focused on data-driven decision making must believe data are worthwhile. Without this basic belief, it is unlikely that they will persist in their effort to master the skills required to become competent users of school data, impacting the effectiveness of professional development initiatives.

The lack of substantial and relevant professional development has been a barrier to many initiatives. Wayman (2005) asserts this to be a characteristic also found in many data initiatives. Armstrong (2003) supports this claim, suggesting that a crucial characteristic of a data-driven district is professional development, without which no data initiative involving teachers and technology can be sustainable. Professional development alone, however, is not enough. The support of school leadership and their modeling of data use are essential (Lachat & Smith, 2005; Wayman, 2005). Research conducted by Lachat and Smith (2005) stressed that data use is strongly influenced by the leadership practices of the principal. Their findings further suggest that data use is also influenced by the shared leadership of other administrators and teacher leaders in the school.

Cognitive Dissonance, Self-Efficacy, and the Use of Data

Success in data use goes beyond professional development that trains a person to use a few new skills or strategies in their practice. Data initiatives must also address human behavior; a belief system related to data use, and feelings of efficacy toward applying the new skills. Psychologists and educational researchers turn to theories to better understand human behavior. Two theories from the work of cognitive and social psychologists are particularly relevant to our interest in moving educators to use data to guide their instructional decisions: cognitive dissonance and self-efficacy.

Cognitive Dissonance: The Motivator Behind Behavior Change

Cognitive dissonance, a psychological theory first published by Festinger (1957) in *A Theory of Cognitive Dissonance*, refers to discomfort felt because of a discrepancy between what one already knows or believes, and new information or interpretations. Cognitive dissonance occurs when there is a need to make informed instructional decisions, yet at the same time develop or expand our thoughts to accommodate new ideas. Cognitive Dissonance Theory has encouraged many studies focusing on a better understanding of what determines an individual's beliefs, how individuals make decisions based on their beliefs, and what happens when their beliefs are brought into question. This theory deals with pairs of cognitions defined as "any knowledge, opinion, or belief about the environment, about oneself, or about one's behavior" (Festinger, 1957, p. 3).

Of primary concern are those pairs of elements that are relevant to each other. If two cognitions are, in fact, relevant to one another, they are classified as either *consonant* or *dissonant* cognitions (Festinger, 1957). Consonant cognitions occur when elements of knowledge follow from one another without conflict. Dissonant cognitions occur when one element of knowledge is followed by the opposite of the element. It is these dissonant cognitions that are most applicable to our understanding of educators' use of data to guide instructional decision making.

According to Festinger's theory, the existence of dissonant cognitions produces an uncomfortable feeling, which motivates an individual to lessen or to eliminate the dissonance. "The strength of the pressure to reduce the dissonance is a function of the magnitude of the dissonance" (Festinger, 1957, p. 18). The number of dissonant beliefs and the importance associated with each belief are two factors that affect the magnitude of the dissonance and the motivation to work toward consonance. The theory, because it is so broad, is relevant to many different topics, including data-driven decision making (Harmon-Jones & Mills, 1999).

Self-efficacy: A Force that Maintains Momentum for a Change

Self-efficacy, a major construct of Social Cognitive Theory (Bandura, 1982, 1993, 1997), refers to a person's judgment about being able to perform a particular activity. It can be conceptualized as a person's *I can* or *I cannot* belief. Unlike self-esteem, which reflects how individuals feel about their worth or value, self-efficacy reflects how confident people are about performing specific tasks. Because self-efficacy is specific to the task being attempted, high self-efficacy in one area may not coincide with high self-efficacy in another area. And, although self-efficacy indicates how strongly people believe they have the skills to do well, there may well be other factors that keep them from succeeding.

Bandura's theory of self-efficacy has important implications with regard to motivation. Bandura's basic principle is that people are likely to engage in activities to the extent that they perceive themselves to be competent at those activities. With regard to education, this means that learners will be more likely to attempt, to persevere, and to be successful at tasks for which they have a sense of efficacy. When learners fail, the failure may occur because they lack the skills to succeed or because they have the skills but lack the sense of efficacy to use these skills well.

Applying these two psychological theories to educators' use of data, we build from Festinger's (1957) view that educators need to have the motivation to move toward consonance, the desire to use data, and the understanding that it is a necessary component in the decision-making process. To this understanding, we add the patina of efficacy. Bandura (1977, 1993) believed that those using data to inform their instruction must have both the knowledge to perform the tasks and the feelings of efficacy to actually enact those skills. In spite of the endorsements for data-based decision making as a critical school reform initiative, there appears to be inadequate preparation of how to use the data-driven decision-making process effectively and accurately.

Empirical Studies: Bridging the Gap Between Administrators and Data

This chapter, then, addresses the critical questions of how best to address this need. In two studies which built upon each other, we tested the effectiveness of professional development focusing on basic statistics with an emphasis on the use of student performance data to guide instructional decision making. In both studies, we sought to create dissonance in our participants as a mechanism for motivating awareness of a need to change their approach to using data, then built on their knowledge through structured group and individual assignments to increase their sense of efficacy in data manipulation, analysis, and use. The chapter contains information and findings from two studies varied in setting (the first took place in the Pacific Northwest of the United States, the second in western Canada) and participants (the first study involved 31 individual preservice administrators from a range of schools and districts throughout a region enrolled in an administrative licensure program; the second included teams of three from five suburban schools, each comprised of a principal and two lead teachers), but provided complementary results. Because the studies were so closely linked and the findings so congruent, we present them both together in this chapter.

In both cases, we found that participants began with quite rudimentary knowledge of basic statistics and measurement principles and ended with much greater skills in this area. In all cases, educators in our studies both before and after receiving the intervention reported greater knowledge of and comfort with interpreting graphs and charts compiled by others than constructing their own graphs—or selecting relevant data to display graphically. Their efficacy toward data manipulation and use, however, was directly related to the degree to which they had experienced success in analyzing their own school data during the course of the study. We found that the participants who had received the most regular feedback (whether from the instructor in the first study or from organized peer groups in the second study) exhibited the greatest growth in skill as well as efficacy over the course of the study. In fact, this finding from Study 1 led us to select school-based data teams as a critical organizing component of Study 2. We now move to a discussion of the two studies.

Methods

The studies in this chapter both used a pre-test, post-test design. In Study 1, a two-day intervention (workshop on measurement principles, basic statistics, and the use of data to guide instructional decision making) was preceded by a pre-test and followed by two guided assignments and a post-test. There were 31 participants in the treatment group, 16 participants were female, the mean age was 39 ($SD = 9.8$) and participants had an average of 10 years' teaching experience ($SD = 6.5$). Participants were a convenience sample of educational leaders in generally equivalent stages of their careers. At the time of the study, they were all participating in an administrative training program seeking further opportunities for leadership in their district. In the six months between pre- and post-test, three follow-up interviews were conducted with each of four participants, who represented different levels of skill and efficacy, based on performance on the pre-test and a survey to measure efficacy delivered prior to the intervention. Two high-skilled participants (one demonstrating low efficacy for data use, the other high efficacy) and two low-skilled participants (also demonstrating opposite extremes on the efficacy scale) were selected for follow-up interviews.

In Study 2, the two-day intervention was followed by six months of bi-weekly coaching and peer support group meetings. Five teams made up of three people each were involved in both the training and the coaching/peer support groups. Coaching sessions included mini-lessons and scenarios involving data as well as question and answer sessions and collaboration on school data projects with a data expert. Peer support groups were established within school teams and met at the school site: one administrator and two lead teachers from each school participated, representing one elementary school, two middle schools, and two high schools. Principals volunteered themselves and their staff to be part of the study. Each school principal chose the two teachers who would make up their team. There were 15 participants in the second study; seven participants were male. The mean age of the group was 46.2 ($SD = 7.4$) and the average years of teaching experience was 18.4 years ($SD = 8.6$).

The Intervention: Teaching Basic Statistics and Measurement Principles

The intervention was delivered through a three-part seminar using computer-based training modules to teach how to use school data to make informed decisions regarding instructional practices. The modules covered the following three topics: (a) distribution and percentile rank, (b) cut scores and standard error of measurement, and (c) domain and skill sampling. Content for the training modules was based on the type of knowledge and skills identified by Schmoker (2003), Creighton (2001), and Bernhardt (2003) as being of critical importance to educators. Each lesson was accompanied by small pre-tests intended to induce dissonance in participants by presenting the information in a context that illustrated why the knowledge would be useful for school leaders to possess while highlighting their unfamiliarity with the type of knowledge being presented (see Figure 18.1). These small pre-tests were not intended to be used to measure intervention effectiveness but rather to be part of the intervention itself. To measure intervention effectiveness, we used overall pre- and post-tests in conjunction with efficacy surveys, interviews, and focus groups.

Task: From each selection of three **bold** words, choose the word that fits the sentence best.

1. Imagine student scores are arranged in rank order from lowest to highest. Next, the scores are divided into 100 equally sized groups or bands. The lowest score is in the **[1st percentile/0 percentile/1st percentage]**. The highest score is **[the 100th percentile/the 99th percentile/100 percent]**.
2. If you were going to compare two or more sets of data using box-and-whisker plots, first you would need to look at the **[boxes/percentiles/whiskers]** to get an idea whether or not they are located in about the same place. Next compare the **[mean/median/mode]** to find out how the data are separated into two equal parts. Then study the lengths of the boxes to determine whether or not the **[variability/predictability/scattering]** as measured by the quartiles, are about the same. It may be that the data sets are very similar, but with a different spread of data. Check the pattern of **[outliers/skewness/predictability]** in each data set to find the scores furthest from the middle.

Figure 18.1 Examples of module questions designed to create cognitive dissonance in participants.

Measuring the Effectiveness of the Intervention Overall pre- and post-tests sampled all content presented in the three modules of the training sessions. These three-part tests were organized into three levels of cognitive demand: identification, evaluation, and application. The *identification* section required participants to match data analysis terms with their definitions. The *evaluation* section required participants to read one to two sentence scenarios and then to choose the appropriate type of analysis to use from a given list. Participants also provided a rationale for their data analysis choice. The *application* portion consisted of three scenarios accompanied by data sets (see Figure 18.2). Based on information provided in the scenarios, participants analyzed data and explained their decisions based on their analysis. All three sections sampled participants' content knowledge of distributions, percentile rank, cut scores, standard error of measurement, and domain and skill sampling.

Initial and exit surveys used Likert-type scale questions to address perceptions, confidence, and efficacy in data analysis, interpretation, and decision making. Open-ended questions had respondents describe their current ability and understanding of assessment, data, data collection, data analysis, data interpretation, and data-based decision making. On the exit survey, additional questions asked participants to share their perceived area of greatest growth and their biggest fears about using data-driven decision-making practices in their school.

Case studies (Study 1) or focus groups (Study 2) helped us interpret the quantitative results. In the first study, four of the 31 participants were purposefully selected to participate in the case studies. In Study 2, all participants participated in the focus groups. Interview participants were interviewed three times over a six-month period. In the replication study, we conducted three 20-minute focus groups with each of the five participating groups (September, November, and February). The interview questions evolved from session to session; however, the same questions were asked of each participant. Questions focused on participants' feelings of efficacy and confidence regarding analysis, interpretation, and decision making using data.

Data Analysis This chapter used three different types of data: a series of test results, surveys, and interviews. Each type of data required its own data analysis procedures. Test results were analyzed using repeated measures analysis of variance (ANOVA). Likert-type survey questions were analyzed by counting the frequency of answers in each response category. Survey results were used to describe the sample and

> Scenario 1: Central Elementary school is an urban school in the Pacific Northwest with an enrollment of 300 students in grades K-5. The staff members at Central have decided to report the year-end average math scores in each grade. They plan to collect these data annually, to demonstrate growth in these areas each year. Further, the teachers want to find out how their individual students in each grade compare to other students in the school and district.
>
> The principal and her head teacher decide to explore the district math assessment to provide each of the grades with the appropriate information. The fourth grade data are given below.
>
> <*note to reader: this scenario is followed by a table of data, an accompanying spreadsheet, and series of tasks requiring application of knowledge*>

Figure 18.2 Example of an application scenario prompt presented to participants.

determine subjects' perceived abilities in data-based decision making prior to the intervention and how their perception changed over time. Interview transcripts were analyzed to evaluate the degree to which participants' sense of efficacy, confidence, and comfort level increased as a result of the intervention.

Results

Results in this chapter indicate that the seminar on the use of data increased participants' knowledge of measurement and data analysis as well as their feelings of efficacy toward the use of data to inform instructional decisions at their schools. Our second study, in which we included peer support groups and more structured, peer-mediated learning activities resulted in greater increases in knowledge but perhaps more importantly, given the role of efficacy in people's willingness to persist in using new knowledge, these additional supports also resulted in greater gains in participants' feelings of efficacy toward the use of data in their school settings.

Gains in Test Performance In Study 1 participants experienced growth in all three areas. On average, participants grew on the identification section, going from a mean of 5.17 ($SD = 2.93$) on the pre-test to a mean of 10.41 ($SD = 3.28$) out of 15 on the post-test. Their gain on the interpretation section was equally noteworthy, moving from a mean of 2.93 ($SD = 2.39$) on the pre-test to a mean of 7.66 ($SD = 3.72$) out of 16 on the post-test. On the third and most challenging section of the tests, participants' learning was even more impressive. On the pre-test, the mean score on the application section of the test was a low 1.14 ($SD = 1.03$) out of 23 possible points. In contrast, participants scored a mean of 4.00 ($SD = 4.65$) on the post-test. Improvement from pre- to post-test was statistically significant on all three sections (Identification, $F(1,28) = 76.58$, $p < .0001$; Analysis, $F(1,28) = 54.29$, $p < .0001$; Application, $F(1,28) = 11.40$, $p < .0001$).

Similarly, in Study 2 participants' growth in performance was dramatic on all three sections of the tests. On average, participants more than doubled their scores from pre- to post-test on the identification section, going from a mean of 5.87 ($SD = 3.46$) on the pre-test to a mean of 12.80 ($SD = 1.86$) out of 15 on the post-test. Scores on the interpretation section grew from a mean of 3 ($SD = 2.45$) on the pre-test to a mean of 11.73 ($SD = 2.66$) out of 16 on the post-test. On the third section participants' learning was most impressive. On the pre-test, the mean score on the application section of the test was only 1.33 ($SD = 1.04$). On the post-test participants scored a mean of 14.00 (SD = 6.18) out of 23, a dramatic increase indeed. Improvement from pre- to post-test was statistically significant on all three sections (Identification, $F(1,14) = 92.67$, $p < .0001$; Analysis, $F(1,14) = 102.06$, $p < .0001$; Application, $F(1,14) = 61.56$, $p < .0001$). Growth in both studies was marked, but was more pronounced in Study 2 in all three sections of the test.

Changes in Self-Reported Efficacy Survey findings supported test results. Frequency counts on the survey indicated that educators felt they were overwhelmingly better able to apply their knowledge of data analysis and interpretation after the intervention. Participants reported an increase in confidence to analyze, interpret, and make decisions as a result of the training and practice received as part of the intervention. The most significant reported increase in confidence in the first study, from 32% to 64.5%, was found in respondents' confidence in explaining to others why a certain approach to analyzing data was used. In the second study, one of the most significant increases in confidence, from 27% to 87%, was in participants' overall ability to work with student learning data.

In addition, participants in both studies reported an increase in frequency of interpreting student data. The most significant increase, from 32% to 65% in the first study, occurred when respondents were asked by school personnel to interpret district data. Respondents in the second study also exhibited an increase in interpreting district data; however, the most dramatic increase in interpreting data, from 20% to 87%, was in interpreting school data. Twice the number of respondents in the first study and four times the number of respondents in the second study indicated they were asked to interpret data since participating in the seminar. Counts also demonstrated an increase in feelings of efficacy to interpret and use data between the initial survey and the exit survey. When respondents were asked if they considered themselves as someone who has a lot of experience using student learning data to make instructional decisions, responses in both studies more than doubled from the initial questionnaire to the exit survey. Clearly, test scores and survey responses alike indicate that professional development modules on data analysis and interpretation can result in enhancements of educators' skill and sense of efficacy related to data-based decision making.

Case Studies and Focus Groups Enhance the Overall Interpretation of Improvement To further understand the quantitative findings in this chapter, case studies and focus groups were conducted following the intervention. In the first study we conducted case studies of four participants over six months. In the second study, during the six months that followed the intervention, focus groups were conducted of five teams of educators concurrently as the coaching and peer group meetings occurred. Case studies and focus groups focused on educators' confidence, ability, and willingness to analyze, interpret, and make decisions using data in their respective schools.

Initially, all respondents agreed that the two-day training seminar did increase their ability to analyze assessment data. An elementary participant recounted in her first interview, "as we went through the training, I would say by the second day I felt really confident, like 'Oh, I get this' . . . and I felt confident in how to use it and how to really analyze it and really understand what does it tells, what data tells you." However, participants reported not liking analysis, citing a lack of time and confidence, concern over making mistakes, frustration with complex statistical programs such as EXCEL, and challenges posed by limited and/or unreliable data. All respondents discussed their personal lack of confidence and avoidance of data analysis. A high school participant with high pre-test scores and higher reports of efficacy explained, "Data analysis is easy, it is math. The real problem, to make, to choose the analysis to do and to, to know the choice was right. Good quality, reliable data better than . . . chapter ending tests is also important."

A further interview session supported the respondents' resistance to analyze data. During this session, participants' reported confidence to analyze data appeared to have lessened since the first focus group two months prior. In fact, the high school participant who had expressed the most confidence in her initial survey and earned the highest pre-test score seemed to be losing ground two months after the intervention. "I think it would be great if there was one person that the district had that was . . . kind of the data person," she explained. "If there was someone that their job was to be the data person, and they could come and sit down with the department and analyze the data for us and make sense out of the numbers, and say, look at it in numbers and just say [this is] where your kids are at, they [are] this far away from the average or from grade level . . . I think that would be a great service." Halfway through the study, although participants had demonstrated the ability to analyze data on several previous occasions, they still lacked confidence in their ability to fill that role in their schools. All participants echoed the sentiments expressed by the high scorer quoted above in wishing that somebody else in their district would analyze their data for them.

Knowing that new skills require repeated practice to master, in the second study we built additional structured opportunities for participants to engage in data analysis as part of their peer data teams. The final interviews were scheduled after all teams had completed assignments related to identifying, gathering, and analyzing data from their school. In this focus group, it was clear that participants' confidence level had increased. A middle school participant from the first study stated, "I'm much more confident; I'm probably at that dangerous level where I know just enough to be dangerous and not enough to really know what I am doing. But I can follow the directions on the training website." This increased confidence, however, did not necessarily translate to independent application. One elementary participant explained that unless she is forced to analyze data, or if she could work with a group of very competent colleagues, she would not voluntarily analyze data. Another elementary participant, like the others interviewed, reported that she would prefer to either collaborate on the analysis portion of data-driven decision making or have someone, more practiced and less likely to make errors, analyze her school data. Most seemed fearful of making errors and not catching them if they were to attempt data analysis on their own.

Despite this concern about analyzing data on their own, participants reported that they felt confident in their ability to interpret data analysis. Further, all participants indicated that they thought it was much easier to interpret a chart or graph than to make sense of raw numerical data reported by the state on student assessments. A middle school participant captured the essence of all interview participants, stating, "By putting stuff in charts, it really is for someone who's not a real data person a much, much easier way to look at it . . . and there's almost no explanation needed." When participants were asked about interpreting graphs and charts, they all suggested that they did not feel they had to be an expert with statistics or data to interpret a graph.

Participants were asked to describe any opportunity they had to interpret data and how they felt about their interpretation skill. An elementary participant stated, "Right now, we collect a lot of data. I see eyes glaze over real quickly when we talk about analysis, but I was really afraid of EXCEL, and I am not afraid of EXCEL [anymore]. I can't make it do a lot for me, but for the kind of stuff I'm doing, like standard error and standard deviation, and mean, median stuff, and graphs, I can do that and I can explain it to my staff so their eyes don't glaze over as quickly."

During the second interview, all participants suggested they were making decisions using data; however, their level of confidence varied. Both a high school participant and an elementary participant suggested that their schools were collecting too much data and were not spending enough time looking at the data or making decisions from them. They also suggested that even if people knew what the data meant, their practices in the school would be unlikely to change. It appeared that the schools, in both cases, were collecting data for the sake of collecting data and that no one was using the data to make instructional decisions. An elementary participant said,

> They're collecting a ton of information about what is being done in the building, where the kids are at in each building, we have been collecting data, since September, in math, reading, science, what materials each building has, what protocols each school uses. All this and we are still not at any decision-making process at this point. We practice at our meetings with you, but this seems to be where the discussion ends. More people need to be able to join in the conversation to make an impact. This is a problem if the school wants to change, make changes to instruction, this is taking too long. I think they're afraid of what to do next so they are just going to keep collecting data.

All participants seemed to be at different stages in their confidence as a result of many different situations in their schools. Amount of data collected, length of time since training, collegial acceptance of data use, and time were issues affecting their confidence.

All participants continue to express their willingness, ability, and confidence to make decisions using instructional data in the final interviews and focus group sessions.

Discussion

The central purpose in this chapter was to examine the impact of training in measurement statistics and follow-up coaching on educators' ability to use data to make instructional decisions. Quantitative measures suggested training was effective, while qualitative measures such as interviews and surveys identified facets that worked, did not work, and helped pinpoint where additional support and practice were needed to enable educators to use data to guide their instructional practices.

Training increased participants' ability to use data to inform decision making. However, all sources of data support the finding that participants had the lowest feelings of efficacy with analysis and were most hesitant to explore their new abilities in this area. Although participants followed instructions to use data and were more confident to work in a collaborative group after the intervention, they were still not confident about analyzing data independently, nor did they feel confident and equipped with the right tools to make decisions that went beyond their immediate classroom or team.

Focus group participants claimed that once data were collected, people did not seem to know what to do next. Festinger (1957) would say this is where cognitive dissonance exists: Educators know to collect data but are uncomfortable with the next steps, and therefore, until something interferes with their current situation, there is no motivation to move forward, toward cognitive consonance, even if educators know they should use data to inform their practice.

Clearly, the training session conducted was useful and applicable to participants; however, educators must get beyond collecting data to actually using their data to inform instruction. Independently, most participants were very hesitant to use data. As individuals, participants did not indicate strong confidence in their analysis skills, nor did they have confidence in the decisions they made from the results of their data analysis. They were quick to cast their decisions aside and revert back to "gut-level" decisions rather than those based on data. Their own school colleagues could easily crumble their confidence simply by asking them to explain why they made a specific decision rather than choose what appeared to be an equally viable alternative.

In groups, participants were much more confident and willing to take risks. They would challenge each other to defend the analysis used or the decision made, particularly if two group members differed on their analysis or final decision. They would explore more than one way to analyze the same data set, or they would use different data sets to confirm a theory or to support a decision. Each of the five groups reported out to either its staff or its parent council as a group, whereas not a single individual demonstrated a willingness to present to peers or parents. A middle school teacher explained, "If I share our data and decisions with staff, and they ask me questions, and I'm not sure of the answer one of my group members will step in and respond and then I can build on their answer if they leave out some details. My team has me covered and I am more confident." To further explain the risks one middle school group took, data from a group of struggling readers were analyzed over a three-month period, then the middle school team took its information to the school board in an effort to seek further support and funding for a reading program. Interestingly, in most groups the participants were quick to defer to the school principal when a final decision was necessary. Three of the five school principals said this left them in a slightly uncomfortable position. However, as they were responsible for all decisions in the school anyway, they felt their decisions supported by data would be much easier to explain and defend should the need arise.

Focus groups indicated that participants in this study felt overwhelmingly successful at interpreting data. All shared their feelings of efficacy and their increased ability to interpret data. Participants also stated that using data displays such as box and whisker plots, charts, and graphs assisted them in interpreting and explaining data. They further conveyed that they would, without hesitation, continue to interpret the types of data and graphic displays in which they were trained. In examining these feelings of success and efficacy toward interpretation of data through the lens of cognitive dissonance and efficacy, an interesting pattern emerges. Festinger (1957) proposed that two cognitions are in question: interpretation and application. Both need to be relevant and somewhat consonant to determine an individual's success. Participants established that they had limited cognitive dissonance and high efficacy in interpreting data, suggesting that they knew data interpretation was important and that they were able to apply the skills successfully. As a result, most participants suggested they would incorporate interpretation into their educational practice.

Bandura recommended that efficacy be increased by providing people with small tasks with which they can be successful, that simultaneously build on a specific competency (1997). Interpretation of data is a skill introduced in elementary mathematics when students are asked to interpret bar graphs or pie charts in relation to problem solving or fractions. A typical American adult has engaged in the interpretation of graphs since elementary school. Therefore, when contemplating data interpretation, participants' efficacy should be high and their dissonance should be low given their exposure and experience with this particular skill.

Streifer (2002) extended this point by advocating that one of the barriers to a data-driven decision-making model is, in fact, an integrated, well-articulated systems approach to the process. This systems approach must build on the strengths and efficacy of educators (Bandura, 1993) and offer collaborative training rather than individual experiences in data use (Wayman, 2005). At the same time, the systems approach needs to ensure that all parts of the decision-making model are addressed and understood so that educators can move from cognitive dissonance toward cognitive consonance and strong feelings of efficacy. A well-articulated system of data use, with supports, would assist participants in effectively using data. It is apparent from this study that training alone will not suffice. Our initial study resulted in improved test scores, indicating greater knowledge, yet no change in participants' efficacy, suggesting limited potential for changing their actual behavior. In Study 2, we increased the supports offered to participants by introducing small school data teams and bi-weekly data team meetings with a data expert. These enhancements to the intervention appeared to improve its overall effectiveness, particularly in the area of efficacy. The ongoing coaching and peer group meetings encouraged people to use data and created a safer environment for participants to take risks and apply their new skills to the task at hand.

Bandura (1977) advises that people need to feel success in order to increase efficacy with data use. Wayman (2005) and Lachat and Smith (2005) highlight collaboration in using data as an idea to increase teacher efficacy, suggesting that data initiatives are more successful if teachers work together. If data use is to cause change in our schools, Killion and Bellamy (2000) note that educators need to discuss data and be able to explain why they make the decisions they do with the data they have. Educators must become savvy in data use if school improvement is to result from data use. Our findings certainly support these assertions, as the more collaborative Study 2 resulted in greater changes in participants' knowledge as well as efficacy, compared to Study 1.

It is important to note, however, that although participants in this study were successful with analysis, interpretation, and decision making on a post-test and discussed their successes with using data in focus groups and coaching sessions, it was less clear if they were able to return to their schools and actually use data to inform their decisions beyond what was done in the coaching sessions. The findings of Lachat and Smith (2005) highlight the importance of teacher collaboration in analyzing data and making decisions set around a clearly defined goal or question. This chapter demonstrates that educators worked collaboratively through the training sessions and throughout the coaching and peer group meetings. Collaborating on data analysis and decision making required participants to engage in conversation. This conversation, while it required extensive time, helped move participants toward cognitive consonance as they articulated their personal views to their team and listened to the perspectives of others.

Suggestions for Future Research

Given the exploratory nature of the studies in this chapter, several suggestions for future research are in order. With regard to the training session, it is certainly warranted to replicate this type of training across different groups of educators so that findings can be further generalized. If training sessions are effective, it is important to determine how much educators' abilities in analysis, interpretation, and decision making increase based on the training. Moreover, long-term application and on-site use of data were not addressed in this chapter, but it is of great interest because of a central belief that improving teachers' ability to analyze, interpret, and use data to make decisions leads to better outcomes in the classroom (Cromey, 2000; Popham, 1999). Examination of teachers' change over time in their use of data to inform their instructional practices, in both ability and efficacy, should be an essential part of similar future research into the application of data-driven decision making.

Conclusion

This chapter describes an effort through two different studies to provide direction and clarification for research in helping educators use data to make informed instructional decisions. Although the findings in this chapter should be viewed as exploratory, they suggest that this type of training and ongoing coaching can influence content knowledge and effectiveness in using data to make informed instructional decisions. In the current climate of educational accountability, further research in the effective and appropriate use of data-driven decision making can help address issues regarding curriculum and instruction effectively.

Improving district and school leaders' ability to develop effective internal accountability systems using data-driven analysis may assist them not only in finding the answers to their school performance questions and creating new knowledge about their schools, but may also assist them in engaging the entire community in a level of detailed, objective, purposeful reflection (Fuhrman, 1999). It is our hope that our findings may serve as an indication of what is possible. Educators can be taught how to gather, analyze, and interpret data from their schools and districts without requiring large allocations of time or resources to the efforts. In the two studies reported here, participants spent a total of 12 hours attending a seminar on measurement principles and data analysis. They then completed additional independent (Study 1) or small group (Study 2) assignments which required them to apply their new learning to their own school data. These extended assignments were particularly effective in enhancing participants' comfort with data analysis when they were completed as part of small collegial teams, providing support along the way.

The findings in this chapter suggest that modest interventions, such as the lessons used in our studies reported here (available free of charge from www.cbmtraining.com) can offer educators a life preserver when it comes to negotiating the waves of data which wash over them in their daily school lives. Basic knowledge of measurement principles and data analysis, especially when coupled with ongoing peer support and coaching, can help school leaders stay afloat even in the most tempestuous seas.

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