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A Framework for Understanding Community Colleges' Organizational Capacity for Data Use: A Convergent Parallel Mixed Methods Study

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Abstract

This convergent parallel design mixed methods case study of four community colleges explores the relationship between organizational capacity and implementation of data-driven decision making (DDDM). The article also illustrates purposive sampling using replication logic for cross-case analysis and the strengths and weaknesses of quantitizing qualitative data in a mixed methods design. The findings suggest that community colleges' organizational capacity for data-driven decision making is a function of human and social capital, but not physical capital. Methodologically, the data analyses suggest that researchers considering quantitizing qualitative data should consider an exploratory sequential design to better understand the phenomenon under study before reducing qualitative data to numbers.

Keywords

data-driven decision making, capital, mixed methods, case study, quantitizing

Despite the heavy emphasis on student outcomes in community colleges and the expectation that colleges make decisions based on evidence to improve outcomes, research on data use in postsecondary education is still scant. Much of the literature and the most recent advances in understanding and framing research on data-driven decision making (DDDM) is focused on K–12 (see Coburn & Bueschel, 2012; Coburn & Turner, 2011; Turner & Coburn, 2012); research on the use of data is less developed in the postsecondary sector. This article advances our understanding of DDDM in the field of postsecondary education by presenting a theoretically driven framework for DDDM capacity to explore the relationship between organizational capacity and implementation of DDDM at four community colleges participating in an initiative to improve student success.

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I used a mixed methods approach because, by drawing on existing literature from a different educational sector and trying to gain a fundamental understanding of the influences on DDDM in community colleges, I asked confirmatory and exploratory research questions. These questions were (1) What factors influence the organizational capacity for data-driven decision making at community colleges? and (2) Do these factors account for the extent of DDDM in the community colleges in this study? Since mixed methods research enables ''researchers to simultaneously ask confirmatory and exploratory questions, thus verifying and generating theory in the same study'' (Teddlie & Tashakkori, 2009, p. 152), together, the qualitative (QUAL) and quantitative (QUAN) data shed light on the relationship between capacity and the extent of data use to inform decisions at four community colleges. Since case studies are not inherently quantitative or qualitative, they present a unique opportunity to draw on mixed methods. Furthermore, through this study, I endeavored to treat research as a creative process in which methodologies and methods follow from research questions and are combined when and where appropriate (Christ, 2009, 2010; Jang, McDougall, Pollon, Herbert, & Russell, 2008).

This article begins with an overview of the mixed methods research on the sampling and analytic strategies that informed the research design before summarizing the relevant literature on the organizational influences on DDDM, paying special attention to theories of capital. Then I present the conceptual framework that shaped the convergent parallel mixed methods design (Creswell & Plano Clark, 2007, 2011) within a multiple-case study approach (Yin, 2008). The empirical findings are then presented, followed by a discussion of the methodological insights resulting from this study.

Mixed Methods Research on Sampling and Integrative Analytic Strategies

This study contributes to the literature on sampling methodologies in mixed methods (Collins, 2010; Sharp et al., 2011; Teddlie & Tashakkori, 2009) by presenting a convergent parallel mixed methods design (Creswell & Plano Clark, 2007, 2011) that uses Yin's (2008) replication logic to inform case selection in a multiple case design. Yin (2008) and others have suggested that such a design is more robust than a single case design because of the ability to select cases according to a ''replication logic'' instead of a sampling logic. Using replication logic requires that each case be ''carefully selected so that it either (a) predicts similar results (a *literal replication*) or (b) predicts contrasting results but for predictable reasons (a *theoretical replication*)'' (Yin, 2008, p. 47). This requires a theoretical framework that leads to propositions about the ''conditions under which a particular phenomenon is likely to be found (a literal replication) as well as the conditions when it isn't likely to be found (theoretical replication)'' (Yin, 2008, p. 50). To that end I provide a conceptual framework depicting the influences on DDDM in community colleges and three related propositions.

I invoke Jang, McDougall, Pollon, Herbert, and Russell's (2008) integrative analytic strategies and Sandelowski, Volis, and Knafl's (2009) discussion of quantitizing by presenting an integrative analytic approach for a convergent, parallel mixed methods study using quantitized data. To emphasize the theoretical and methodological contributions of this article, I present a visual display of the framework, consistent with Maxwell (2005), and a diagram of the study, similar to those presented by Jang et al., Christ (2009, 2010), and Onwuegbuzie and Dickenson (2008) to illustrate the mixed methods research design.

The Capacity of Educational Organizations for Data-Driven Decision Making

I identified four commonly addressed organizational influences on DDDM in the literature: (a) leadership, (b) faculty, (c) institutional research (IR) capacity, and (d) information technology (IT) capacity. All contribute to an organization's ability, or capacity, to use data to inform its operations. After further reflection, I grouped these four factors according to two underlying constructs relating to the notion of capital, human capital and physical capital, to recognize the ways in which capital may be used to achieve new goals.

Capital

Bourdieu (1986) and Coleman (1988) suggest that all forms of capital can be used to achieve desired goals; this article draws upon human and physical capital to examine the capacity to achieve new goals, such as improved student outcomes, through DDDM. Human capital is defined as the skills and knowledge that an individual possesses (Becker, 1993; Rosen 1989). It is possible for individuals to increase their human capital by enhancing their skills and knowledge thereby developing the ability to ''act in new ways'' (Coleman, 1989, p. S100). Discussions of human capital frequently focus on the role of education and training in developing an individual's knowledge and skills (Becker, 1993). Organizations care about human capital because it represents the knowledge of the organization. Human capital is the accumulated skills and knowledge of an organization (Hitt & Ireland, 2002); in this study human capital is the commitment, the skills, and the knowledge of the leadership, the faculty, and the IR staff to cultivate a culture of data use and to know how to collect data, how to use data, and how to promote its use in decision making throughout a community college.

Physical capital has historically been defined as what is made by humans and is ''embodied in tools, machines, and other productive equipment'' (Coleman, 1988, p. S100). Goodwin (2003) refers to physical capital as produced capital, distinguishing it from natural capital (i.e., natural resources) used in the creation of physical capital. Although recent works have sought to elucidate the distinctions in human production, for example, parsing out produced capital from intellectual and structural capital (see Ordonez de Pablos, 2004), this article focuses on physical capital.

Leadership, Faculty, and IR Staff as Human Capital

Leadership. The importance of leadership in new initiatives and reform efforts is cited widely in organizational and reform literature (Abbott, 2008; Allen & Kazis, 2007; Freed & Klugman, 1997; Young, 2006). Examples abound in which leaders are the agents of data use. For example, Abbott (2008) argues that ''leadership is the engine that moves an educational organization to readiness [for DDDM]'' (p. 264), and Allen and Kazis (2007) suggest that ''leaders can drive their systems and messages toward the use of data across the college'' (p. iii).

Leadership as human capital has not been addressed in the DDDM literature, but it is well established in business research. For example, Hitt and Ireland (2002) suggest that leaders are responsible for managing a firm's resources, including human and social capital ''to develop capabilities that can be leveraged in ways to create competitive advantages'' (p. 3). Thus, leadership, in light of human capital, is the idea that leaders have the skills and knowledge to develop, support, and promote new initiatives resulting in desired outcomes.

Faculty. Faculty support of educational reforms is important because colleges are examples of shared governance (Mortimer & Sathre, 2010; Tierney, 2008). Recent research suggests that faculty should be active participants, even drivers, in the development of new initiatives at community colleges [name deleted to maintain the integrity of the review process]. Research on governance explores faculty culture and faculty's view of participation in their institution (Peterson & White, 1996; Smart, Kuh, & Tierney, 1997; Tierney, 2008), but empirical research specifically on the role of faculty in DDDM is lacking. Tierney (2008), for example, indicates the importance of understanding faculty culture in relation to decision making and knowledge. Framing faculty support as human capital for the purposes of this article also calls attention to the significant store of education existing within faculty. By definition, colleges are large repositories of human capital because of the extensive amount of formal schooling faculty have had and the amount of ''on-the-job training'' that faculty have given their longevity on campus, which results in significant tacit knowledge about how their college functions.

IR staff. In order for leaders to promote the use of information and data, their organizations must first collect meaningful data and provide access to them. Thus, IR is important to DDDM capacity. Research underscores the importance of a distinct IR office (i.e., staff with responsibility for collecting, analyzing, and disseminating research) to ensure the reliability of the data and to facilitate access to the data (Allen & Kazis, 2008; Morest & Jenkins, 2007; Petrides, McClelland, & Nodine, 2004). This perspective views IR capacity primarily as a function of staffing. The national average of IR staff in a sample of all types of postsecondary educational institutions was two Full-Time Equivalent (FTE) (Volkwein, 2009). A similar analysis of community college IR offices found an average of three (FTE) (Huntington & Clagett, 1991). This study captured the IR capacity by comparing the number of full-time equivalent staff at the case study colleges who performed the IR function with the national average.

IR and IT Infrastructure as Physical Capital

Investment in effective and user-friendly information systems is among the most important steps in promoting DDDM (Datnow, Park, & Wohlstetter, 2007; Mandinach & Honey, 2008). The IR and IT infrastructure includes software, hardware, network connectivity, and the structure, access, and ease of use of databases that house the data required for DDDM. For the purposes of this study, the infrastructures that support IT and IR are framed as physical capital. Although Goodwin (2003) suggests that technology may be categorized as both ''embodied in produced capital [and] disembodied, potentially enhancing the productivity of many different inputs used in production'' (p. 9), she acknowledges that technology is generally thought of in terms of produced capital. Because they both have to do with the underlying technology required for gathering, storing, and disseminating data and information, in this article IR and IT infrastructures are discussed as one entity in relation to physical capital.

Breadth and Depth of Data Use as Organizational Capacity

To capture the organizational capacity for DDDM, I developed the constructs of breadth and depth of data use, mirroring Goodman, McLeroy, Steckler, and Hoyle's (1993) concepts of extensiveness and depth. Goodman et al. address the institutionalization of health promotion programs in which the level of institutionalization is measured by the extensiveness of the program across dimensions of the organization and by degrees of depth. The concepts of breadth and depth presented here break down the college into functional subunits rather than dimensions. Breadth of DDDM refers to the use of data, evidence, and/or research across academic and administrative areas at the college. For the purposes of this study, the areas of interest within the colleges are four subunits: faculty, academic affairs, student services, and business functions. The concept of breadth is also consistent with Huber's (1991) concept of breadth of organizational learning. Huber suggests that the more organizational components, or subunits, that have knowledge, the more easily accessible that knowledge is to the organization, and therefore, the range of possible actions the organization can pursue is greater.

Depth of DDDM refers to the use of data and research for purposes that appear more substantive than symbolic. The use of the word *appear* is deliberate; substantive data use can be difficult to capture. In an effort to gauge the extent of data use, the indicators of data use that this study employs are outcomes or process oriented, instead of input oriented, because the former imply more substantive than symbolic uses of data.

Conceptual Framework

Using a mixed methods multiple case study (Yin, 2008) I developed a framework to depict the relationship between human and physical capital, and the extent of DDDM where extent was captured by the breadth and depth of data use at a college (Figure 1). Propositions, rather than hypotheses, play an important role in case studies by bounding the research and developing a framework that later becomes the vehicle for generalizing to new cases (Yin, 2008). This generalization to new cases reinforced the fundamental structure of this study—that is, the reliance on replication logic to inform sampling and to permit the development of theory. Proposition 1 illustrates a literal replication in which the cases are selected to predict similar results and Propositions 2a and 2b illustrate theoretical replication in which the cases are selected to predict contrasting results for predictable reasons (Yin, 2008).

Proposition 1: Colleges with more human and physical capital will display greater breadth and depth of data use than will colleges with less capital.
Proposition 2a: Colleges with more human and physical capital in different states with similar external influences to use data will display similar breadth and depth of data use.
Proposition 2b: Colleges with less human and physical capital in different states with similar external influences to use data will display similar breadth and depth of data use.

These propositions and Figure 1 depict a unidirectional relationship in which capital influences DDDM capacity. It is possible that the relationship is not unidirectional and that the breadth and depth of data use reinforce or act on the human and physical capital that exists within an organization; however, in this study, I did not examine that relationship.

Methods

Overview of the Study Design

This research empirically examined the influences on DDDM capacity in four case study community colleges located in two states through a convergent parallel design mixed methods study (Creswell & Plano Clark, 2011) to understand what factors influence the organizational capacity for DDDM at community colleges and whether the identified factors account for the extent of DDM in the community colleges in this study. Replication logic informed the case study selection through a three stage sampling process; then the data in the QUAL and QUAN strands were collected in the same phase, and the results of the two strands were combined through data merging and transformation. This approach was not for the purposes

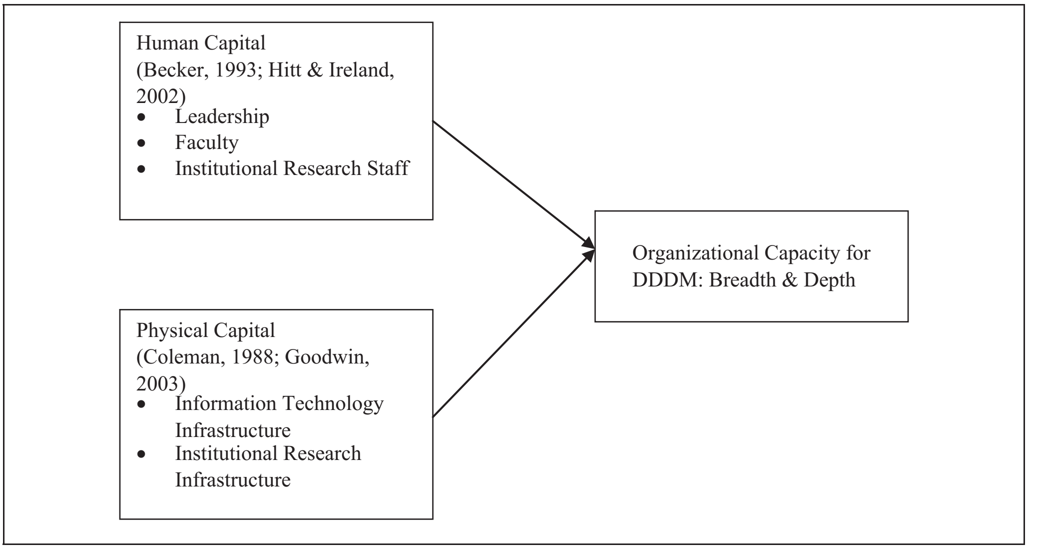

Figure 1. Community college organizational capacity for data-driven decision making.

of comparing results, a common reason for conducting a parallel design; instead, I included transformed data in the convergent analysis process (Creswell & Plano Clark, 2011) to gain a more complete understanding of the phenomenon of DDDM at the participating community colleges (Figure 2).

Validity criteria for QUAL and QUAN as well as mixed methods and case study research are addressed throughout the methods descriptions. To begin, design suitability (Teddlie & Tashakkori, 2009) is addressed through this discussion of the research design, which illustrates the appropriateness of a convergent parallel design for the research questions. The selection and data collection procedures described earlier were implemented to ensure consistency with the stated design approach: a convergent, parallel mixed methods case study, thereby achieving design fidelity (Teddlie & Tashakkori, 2009).

Case Study and Participant Selection

Using a concurrent nested mixed methods sampling design (Onwuegbuzie & Collins, 2007; Teddlie & Tashakkori; 2009; Teddlie & Yu, 2007) combined with Yin's (2008) purposeful multiple case study replication logic the case study and participant selection were conducted in three stages. First, states were selected based on two criteria. The states were located in higher education accrediting regions that, at the time of the study, were characterized as moderate pressure as the accrediting agencies had well-established guidelines about the use of data and evidence (Biswas, 2006). The states had passed performance funding legislation that required colleges to collect and report performance and outcomes data in order to receive a percentage of their funds. These two criteria established a moderate pressure environment for colleges to be data driven; this is consistent with a critical case sampling approach (Patton, 2002), in which we can expect that if DDDM is occurring in community colleges, it is most certainly occurring in community colleges within states with external pressure.

In the second stage, after one western state and one southern state were selected, two community colleges were chosen from each state with the intent to achieve literal and theoretical

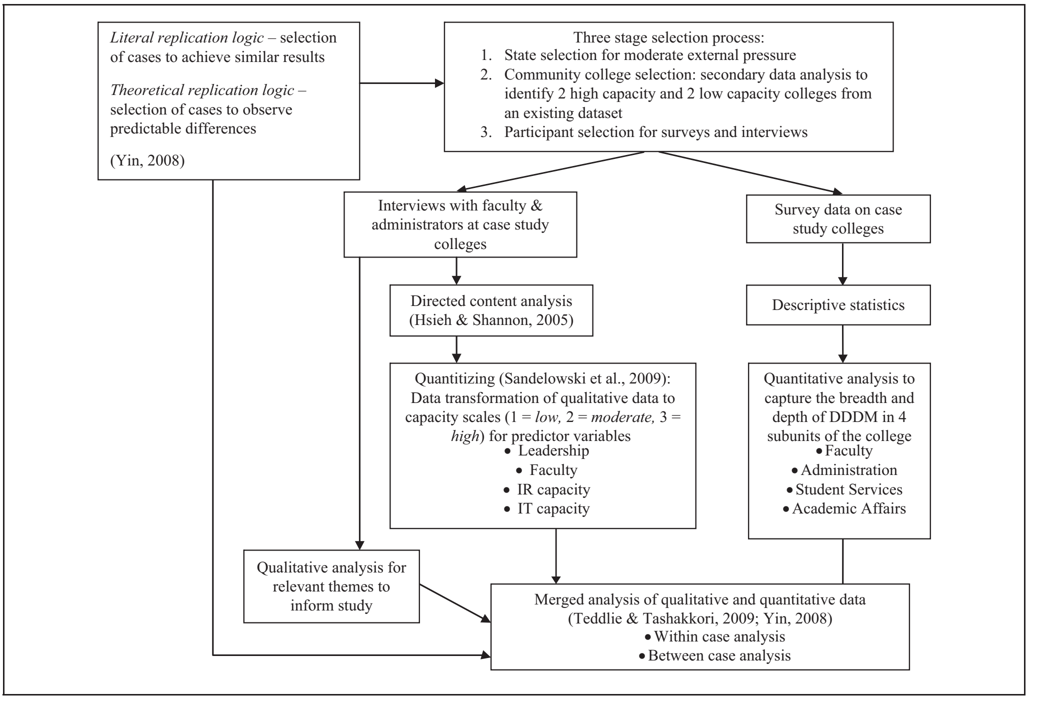

Figure 2. Mixed methods convergent parallel design and analytic procedures.
Note. DDDM = data-driven decision making.

replication. The colleges were drawn from an existing data set of 41 colleges ranked in descending order and grouped into thirds based on existing research on their capacity for data use from an evaluation that captured the colleges' ability to (1) analyze outcomes and plan strategies and (2) evaluate and assess outcomes. One college from the top third and one from the bottom third in each state were then selected as a way to achieve maximum variation sampling. Two high-capacity and two low-capacity colleges allowed for literal and theoretical replication between the western and the southeastern states, and comparison between high- and low-capacity colleges within each state. College capacity was verified after collection and analysis of the data. Results suggested that the criterion validity for the initial selection was poor. Heeding Yin's (2008) caution that case studies should have a feedback loop that informs research design to avoid ''being accused of distorting or ignoring the discovery, just to accommodate the original design'' (p. 58), data on the actual capacity were then used to set up the theoretical and literal replication. The replications were based on the same logic used at the outset of the study: The greater the internal capacity for DDDM, the greater the expected breadth and depth of the DDDM at the college.

In the third stage of sampling, I purposively selected participants for the QUAL and QUAN strands of the study. All full-time administrators (i.e., anyone at the assistant/associate director level and above) at the four colleges were invited to participate in the survey. Due to the relatively large number of faculty at some of the participating colleges, a single-stage sampling procedure was used to reduce the number of faculty who were invited to participate in the survey down to 150 randomly selected faculty at colleges with faculties larger than 150. To encourage a high response rate the survey employed an adaptation of the Tailored Design Method (Dillman, Smyth, & Christian 2009). Final response rates ranged from a low of 41%

for College A1 and a high of 80% for B1 with 151 faculty and 120 administrators participating from the four case study colleges.

The interview participants (n = 38) were selected purposively (Maxwell, 2005; Miles & Huberman, 1994). Using a form of criterion-based sampling (Patton, 2002), interviewees were selected based on their role at their college and ability to provide insight about data use for the purposes of developing a rich understanding of the experience of data use. At each college I interviewed senior administrators, administrators explicitly involved in collecting and/or using data on students at the college, and faculty. The selection of faculty began purposively, and then I used a snowball approach (Patton, 2002) in which I asked faculty to recommend other faculty they thought I should speak with.

Data Collection

Quantitative strand: Survey data. I used 8 questions from a 101-item survey designed for the larger research study out of which this article developed. Consistent with Fink's (2013) recommendations for improving the validity of a survey, the instrument was developed in consultation with experts on community college reform and subsequently field tested with three community colleges. The variables of interest for the analysis presented in this article were Likert scale questions that elicited the extent of a college department's use of data for academic program planning, long-term planning, budgeting, and identification of areas needing improvement on a 1-to-7 scale from *not at all* to *a lot* (see Table 1). The extent of data use was examined within and across the four subunits of each case study college. The survey also captured information on the respondents' role, title, and functional area at the community college so that the respondents could be grouped into four subunits: faculty, academic affairs, student services, and business functions. This grouping enabled me to examine data use by subunit rather than just at the level of the individual.

Qualitative strand: Interview data. I employed semistructured interview protocols to encourage consistency across interviews and colleges while allowing for new ideas to emerge through participant's ability to influence the narrative (Kvale, 1996). The semistructured approach permitted both the researcher and the participants to make meaning of their experiences with DDDM, a structure that Seidman (2005) suggests supports validity. In-depth interviews are useful for answering research questions that require an understanding of ''what past events brought about the current situation'' (Rubin & Rubin, 2004, p. 47), thus the line of questioning asked about the development of and influences on DDDM at the college and participants experiences. The interview protocols also included questions about a specific example of using data to inform decision making, drawing on critical incident technique (Flannigan, 1954). Through the interviews, the context and culture of data use emerged enabling a better understanding of why individuals were using data and how they saw their data use connected to the factors relating to human and physical capital. The interviews were fully transcribed to facilitate analysis.

Data Analysis

Overview. Consistent with a parallel design, I began by analyzing the QUAN and QUAL data independently. Descriptive statistics from the survey data were reviewed and correlations from the variables of data use were calculated to examine relationships among the variables (see Table 2). The qualitative interview data were analyzed with a directed content analysis approach (Hsieh & Shannon, 2005) to understand how participants understood and used DDDM and what

Table 1. Extent and Perceptions of Data Use.

College and Functional Area	n	Extent of data use[a]				Those who agree that	
		Program planning (M)	Long term planning (M)	Budgeting (M)	Identifying areas needing improvement (M)	Leadership has commitment to DDDM	IR office is adequately staffed
College A1							
Academic Affairs	21	5.7 (1.15)	6.0 (1.17)	5.4 (1.62)	5.6 (1.6)	26%	71%
Student Services	6	5.2 (1.47)	5.14(1.77)	6.0 (1.73)	5.3 (1.6)	38%	29%
Business Functions	7	5.0 (1.29)	5(1.55)	5.0 (1.67)	5.2 (1.47)	30%	60%
Faculty	50	4.8 (1.71)	4.66 (1.81)	4.3 (2.12)	5.0 (1.77)	13%	33%
College A2							
Academic Affairs	15	5.4 (1.5)	5.47 (1.51)	5.8 (1.74)	5.3 (1.63)	67%	100%
Student Services	2	6.5 (0.71)	6.5 (0.71)	7.0 (0)	7.0 (0)	100%	50%
Business Functions	2	4.0 (0)	5 (1.41)	5.0 (1.41)	4.5 (0.71)	50%	100%
Faculty	43	5.6 (1.25)	5.56 (1.33)	5.1 (1.8)	5.6 (1.38)	58%	78%
College B1							
Academic Affairs	6	6.7 (0.52)	6.67 (0.52)	5.8 (1.94)	6.5 (0.55)	78%	13%
Student Services	10	5.8 (1.14)	6.0 (1.05)	5.4 (1.88)	5.7 (1.49)	91%	40%
Business Functions	3	6.7 (0.58)	6.67 (0.58)	6.7 (0.58)	6.7 (0.58)	88%	67%
Faculty	32	5.8 (1.48)	5.88 (1.36)	5.7 (1.51)	5.8 (1.41)	88%	45%
College B2							
Academic Affairs	7	5.3 (0.95)	6.17 (1.33)	5.5 (1.76)	5.4 (1.27)	86%	83%
Student Services	9	5.6 (1.67)	6.13 (1.13)	6.1 (0.78)	6.0 (1.1)	100%	56%
Business Functions	8	5.4 (0.53)	5.75 (0.89)	5.9 (0.83)	5.8 (1.04)	100%	57%
Faculty	13	6.3 (0.97)	5.46 (2.03)	5.4 (1.89)	5.8 (1.83)	50%	73%

[a]Scale: Not at all (1), Some (4), A lot (7).

Table 2. Item Correlations.

Use of Data	PP	LTP	B	NI
Use of data for program planning (PP)	1.00			
Use of data for long-term planning (LTP)	0.79	1.00		
Use of data for budgeting (B)	0.66	0.76	1.00	
Use of data to identify areas needing improvement (NI)	0.67	0.71	0.68	1.00

influenced those perceptions and behaviors. After the data were analyzed separately, I conducted further analyses using a parallel and conversion mixed data analysis approach (Teddlie & Tashakkori, 2009) which included quantifying the qualitative data (Sandelowski et al., 2009; Teddlie & Tashakkori, 2009), creating a set of scales to enable the mixed analysis of the data and constructing scales of breadth and depth from the survey data. This process, which demonstrates the analytic adequacy (Teddlie & Tashakkori, 2009) of the research, is discussed in detail in the next section to address the frequent critique that mixed methods studies fail to transparently present the mixing of strands (Creswell & Plano Clark, 2011; Mertens, 2011).

QUAN analysis. In order to understand the extent of DDDM at each college, I developed a set of scales to capture the breadth of data use across a college and the depth, understood as the extent of data use at a college. The scales were based on four Likert-scale survey questions regarding the frequency of use of data for the purpose of (a) program planning, (b) long-term planning, (c) budgeting, and (d) identification of areas at the college in need of improvement.

The development of the scales of breadth and depth of DDDM began with a reliability analysis to see if respondents answered consistently across all of these items. Cronbach's alpha, a measure of internal consistency, for the survey responses to these items was .90, indicating high consistency across items and providing evidence for an underlying construct (''What Statistical Analysis,'' 2009). The correlations ranged from .60 to .79, indicating that these items are at least moderately correlated (see Table 2). Three items were highly correlated: the correlation between use of data for long-term planning and program planning was .79; the correlation between long-term planning and the use of data for budgeting purposes was .76; and the correlation between long-term planning and the use of data to identify areas needing improvement at the college was .71.

Using the Kruskal–Wallis test, I found a statistically significant difference ($p < .0001$) between the colleges in the use of data based on the four variables comprising the study's constructs of breadth and depth. These analyses suggest that the variables designating the extent of the breadth and depth of data use are highly correlated with each other, are capturing similar ideas, and demonstrate a statistically significant difference among the colleges in their data use.

My next step was to develop the scales. The responses to questions about frequency of data use were averaged for each of the four subunits within the college and then, based on this average, the four subunits were broken down into quartiles. Depth in each subunit was captured by the quartile in which the subunit fell. Depth for the entire college was captured by averaging the quartiles for each subunit. Breadth of DDDM at the college captures the number of subunits that fall above the second quartile. The number of subunits across a college (from 1 to 4) that used data at least above the minimum threshold (above the bottom two quartiles) represents the breadth of data use at the college (see Table 3). Breadth ranged from minimum, moderate, extensive, to complete.

Table 3. Breadth Scale.

Scale	Definition
Minimal	College has one area that exceeded the minimum threshold in two of the four subunits.
Moderate	College exceeded the minimum threshold in two of the four subunits.
Extensive	College exceeded the minimum threshold in three of the four subunits.
Complete	College exceeded the minimum threshold in all four subunits.

Note. The four subunits are faculty, business functions, student services, and academic affairs.

QUAL analysis. The analysis of interview data began with a careful reading of the interview transcripts, by college and by functional area within the college, to capture the general attitudes, perceptions of, and influences on interviewees' use of data and their departments' use of data at their college. Coding was done using both a priori coding and emergent approaches. The a priori coding facilitated the quantitizing of the qualitative data using a directed content analysis approach (Hsieh & Shannon, 2005) to understand the influence of DDDM.

Quantitizing is the assignment of numerical values to qualitative data (Sandelowski et al., 2009). Although quantitizing qualitative data may be used to better understand the phenomenon under study and to make sense of the data, in this case the data were quantitized to ''transform qualitative data into numerical data that can be analyzed with other existing quantitative data to answer research questions or test hypotheses involving predictor and dependent variables developed from both strands'' (Sandelowski et al., 2009). Quantitizing can strip qualitative data of their meaning degenerating into a variance theory mental model in which assumptions about linear relationships between variables obfuscate the complex and rich information gathered through qualitative research (Maxwell, 2010); however, Sandelowski et al. (2009) suggest that using numbers in qualitative research enables the analysis of data in new ways to permit greater understanding. Since the QUAL data were also analyzed inductively, nothing was lost, and in fact, more understanding was gained through the ability to compare the quantitative and quantitized data (Jang et al., 2009).

Content analysis is the first step in the process of quantitizing qualitative data (Sandelowski et al., 2009). Qualitative content analysis is defined as a research method for ''the subjective interpretation of the content of text data through the systematic classification process of coding and identifying themes or patterns'' (Hsieh & Shannon, 2005, p. 1278). This approach, which uses theory deductively in the analysis of data, is consistent with the approach I took to theoretical replication (Yin, 2008), including employing the use of predictions to explore relationships and to support and extend theory (Hsieh & Shannon, 2005). The structured approach taken by this analysis process began with defining the a priori codes (see Table 4) using definitions developed from the existing literature, the propositions, and conceptual framework I presented earlier. These ordinal codes captured the relative differences in leadership, faculty support, IT capacity, and IR capacity.

To increase the trustworthiness and validity of the study, I developed and adhered to a coding scheme and employed interrater reliability (Hsieh & Shannon, 2005; Ryan & Bernard, 2003). A research assistant and I both coded a subset of the transcripts using the a priori codes (see Table 4). When there was a difference, we discussed what led to the difference in coding and I made a decision about whether to adapt my coding. The percentage of dual-coded text that were coded the same was 85%; Neuendorf (2002) suggests that agreement above 70% is reliable and above 80% is highly reliable.

Table 4. Qualitative Scales of Capacity.

	Leadership	Faculty	IR Capacity	IT Capacity
Low	The college's leadership says it is committed to DDDM, but other administrators or faculty did not confirm this statement.	Faculty do not perceive data as particularly important and do not feel that faculty should use data.	IR office consists of less than the national average FTE of IR personnel.	Manages computers and network but has minimal involvement with the college's information systems. There are no reporting capabilities, nor is there a data warehouse.
Moderate	The college's leadership says it is committed to DDDM, and other interviewees concur, stating that the college's leadership models the use of DDDM.	Faculty acknowledge the importance of data at the college and express general support for DDDM at the college.	IR office consists of the national average FTE of IR personnel.	Low + manages the information systems and/or has limited reporting capabilities. There is no data warehouse.
High	The college's leadership has made formal changes to the college's budget or operations to support DDDM.	Faculty report that faculty at the college act as data consumers and/or generators and can provide relevant examples.	IR office consists of more than the national average FTE of IR personnel.	Moderate + reporting system tied into a dashboard and/or a data warehouse.

Note. DDDM = data-driven decision making; FTE = ; IR = institutional research.

Table 5. Predictor and Dependent Variables for Case Study Colleges.

	Predictor Variables					Dependent Variables		
College ID	Leadership	Faculty	IR Cap.	IT Cap.	Total Cap.	Breadth	Depth	Total
A2	2	2.7	3	2	9.7	3	3	6
A1	1.8	2.3	3	2	9.1	2	2.5	4.5
B1	2.3	2.5	1	2	7.8	4	3.8	7.8
B2	2.2	2	1	2	7.2	3	3	6

Note. IR Cap. = institutional research capacity; IT Cap. = information technology capacity. The table is ordered by total capacity. Scale for predictor variables: Low (1), Medium (2), High (3). Scale for dependent variables: Minimum (1), Moderate (2), Extensive (3), Complete (4).

Merged analysis. After the independent analysis of QUAL and QUAN data, and quantitizing the qualitative data, the last step was to analyze the data jointly through within and between-case analyses (see Table 5) descriptively. With only four cases the quantitative analytic approaches were limited.

The within-case analysis brought together the qualitative and quantitative data through the examination of the relationship between the predictor and dependent variables. The between-case analysis compared the relationship between predictor and dependent variables and through the analysis of the qualitative data to ascertain, and possibly better explain, the differences in extent of data use at the colleges. Because the merged analysis did not consistently support the propositions, I also returned to the qualitative data and inductively analyzed the data for emergent themes by looking for repetition of concepts (Ryan & Bernard, 2003) not readily apparent from the directed content analysis.

Results

Analyses of the survey data suggested that the colleges and functional areas within the colleges all use data at least to some extent to inform decisions relating to program planning, long-term planning, budgeting, and the identification of areas needing improvement. Within each college the extent of data use for the purposes of program planning, long-term planning, budgeting, and the identification of areas needing improvement varied by functional area as did perceptions that the college's leadership has made a commitment to DDDM and that the IR office is adequately staffed. Between colleges, College A2 demonstrated the greatest difference of means of extent of data use between each functional area when compared with other functional areas across the case study colleges. This was important to note because it suggests that data use occurred in pockets in the organization, but that data use was not institutionalized across the organization. College B2 demonstrated the smallest difference of means of extent of data use between the functional areas; it was also the smallest college in the study.

College B2 also had the greatest extent of data use for purposes of program planning and long-term planning among the four colleges. College A2 had the greatest extent of data use for the purposes of budgeting and identifying areas needing improvement. College A1 consistently demonstrated a lower extent of data use than the other colleges. Across the four case studies, the survey participants at College B1 were most likely to agree that the leadership of their college has made a clear commitment to DDDM. Conversely, they were least likely to agree that their IR office is adequately staffed.

Breadth and Depth of DDDM

Having examined the extent of data use in the previous section I now turn to the breadth and depth of DDDM—the dependent variables in this study. The breadth of data use at the four case study colleges varied; College A1 had two functional areas that used data at least at the minimum threshold, while all the subunits of college B2 used data at least at the minimum threshold (see Table 5). Depth also varied by colleges: College A1 had the least use of data across all four subunits (2.4), and College B1 had the greatest (3.8). Colleges A2 and B2 fell between the other two colleges in both breadth and depth of data use. To answer the question of what accounts for the observed breadth and depth of data use in the cases I now turn to the qualitative data starting with the results of the directed content analysis and then move to a discussion of the findings from the inductively analyzed interview data.

Findings From the Directed Content Analysis

The four case study colleges varied in their organizational capacity. College A2 had the overall greatest total capacity, and College B2 had the overall least total capacity (Table 5). Colleges B1 and B2 had the greatest leadership support while Colleges A2 and B1 had the greatest faculty support. It is also immediately obvious that there are differences between the four colleges that appear to be aligned according to state. For example, colleges in State A had the greatest IR capacity and colleges in State B had the least IR capacity. Table 5 also shows that the range is from 1.8 at College A1 to 2.2 at College B2. Direct presidential leadership for DDDM was strongest at Colleges A1 and A2. Table 2 also highlights the lack of variation in IT capacity across the colleges. Although all the colleges stored their data in an Enterprise Resource Planning (ERP) system and used a dashboard to report from the ERP, none had a reporting system tied into a dashboard or a data warehouse.

Findings From the Merged Analysis

The merged analysis brings together the qualitative data, (i.e., the predictor variables) with the quantitative data (i.e., the dependent variables). Quantitizing the qualitative data enabled a descriptive examination of the relationship between the predictor variables and the dependent variables. The propositions stated earlier suggested that human and physical capital are positively associated with the breadth and depth of DDDM; that is, as the total capacity increases, the total breadth and depth increases. However, this research shows that total capacity was not positively associated with the total breadth and depth of DDDM (see Table 5). Total breadth and depth was positively associated with human capital: College B1 had the greatest human capital and breadth and depth, followed by Colleges A2 and B2, and finally, College A1 had the least human capital and the least breadth and depth. To make sense of this, themes from the inductive data analysis approach are discussed in the next section.

Themes From the Interviews

Two main themes and a limitation emerged from the interviews that were not captured by the directed content analysis. The first theme was the importance of a collaborative culture and the second was the perceptions faculty voiced regarding their value and contribution to their college's use of data. Challenges in accessing and using data also emerged as limitations to DDDM at the participating colleges.

Theme 1: A collaborative culture. The importance of a collaborative culture manifested in two ways: broad leadership involvement in using data that extended beyond the president and creativity in providing access to data and research. Conceptions of the involvement of leadership in DDDM proved important and are congruent with the quantitized data. For example, College A1 scored the lowest on the leadership scale despite the president's assertion of being very interested in DDDM and citing one of the college's main accomplishments as ''how we use data and how we provide data to our instructional areas.'' In particular, the president noted that although the college has had ''lots of data'' for many years,

> we weren't really using it for analyzing . . . [we] needed to understand what the numbers mean and how can we use them to improve retention rates and graduation rates . . . how to create data analysis rather than data.

The president was confident that college personnel now understand what the numbers mean and are using data to analyze and target areas needing improvement.

The development of data-driven decision making at College A1 was attributed to the current and former presidents who were characterized as the ''driving force behind implementing the culture [of evidence] here'' (A1_Admin_2). Despite the president's assertion of being data-driven at College A1, perceptions among the interviewees of the commitment to DDDM by the college leadership overall were mixed. Respondents thought that the president was very committed to DDDM, but perceptions about other administrators' commitment were less clear. The president's commitment to the use of data was not necessarily carried through by the senior leadership. Despite the assurance by the president and the interviewees that the president was data-driven, the interviewees were unable to suggest changes that were made to the college's budget and/or operations to support the use of data. College A1 interviewees suggested that while the president may have supported DDDM, a broad commitment had not been cultivated among other leaders.

Similarly, the College A2 president asked, ''How else do you make decisions? I mean, how else can you make a decision that is based on what the college really needs? How do you make that determination without data?'' This president required all budget requests be tied to the college's program review process and improvement planning process; however, once again, changes made to the budget and/or operations of the college to support DDDM were unclear.

In contrast, at Colleges B1 and B2, direct presidential support and involvement were not evident although broad support was high; these two colleges relied more heavily on the support of other senior leaders, such as vice presidents and deans. For example, at College B1 the president was seen as ''hands-off'' even though there was an expectation of data use at the college. Instead, support for DDDM came from the vice president of student services and was evident through comments made by interviewees and through examples of decisions that were made on the basis of data. One administrator explained:

> [Everything] is tied in, like our budgets are tied into the institutional goals, which are tied into student outcomes. You may have heard about the Chancellor's expectations at the system level . . . We take that in, create our goals around that, and then our budgets tie into that, and it's all pretty well defined. (B2_Admin_2)

The idea of a collaborative culture also emerged in the creativity some colleges displayed in providing access to data. Although College A1 had the greatest IR capacity in terms of staffing, it struggled with providing broad access to data and information. In contrast, at College B1, the college with the greatest total breadth and depth of data use, the college had a distributed approach to data analysis that involved faculty and administrators from around the college in the institutional research process:

> Our goal was to have at least someone from every division that could at least help the institutional researcher with preliminary gathering of the data and then certainly pull researcher in. [The institutional researcher is] fantastic and has helped us analyze what we have. (B1_Admin_4)

The IR office itself was short staffed, but the college developed approaches to involve more people from around the college in the work of data gathering and analysis.

Theme 2: Faculty perceptions of their contribution to DDDM. The interview data also suggest a second theme not captured by the quantitized data: that faculty perceptions of their value and contribution at the college influence the extent of data use at the participating community colleges. Quantitizing faculty support captured the extent to which faculty perceived data and DDDM was important, not the perceptions of their own role and relevance in the data-driven efforts at their college. At Colleges A1 and B2, colleges with the least faculty support, faculty expressed concern with the administration's use of data and how the administration had not involved them in DDDM. Echoing others, one professor explained how it feels to be confronted with data on poor student outcomes:

> I think it's absolutely one of the most harmful things that could happen to a faculty member: to be pummeled with statistics of how it's not working when I don't know one faculty member who isn't giving 100% and more. (A1_Faculty_2)

In contrast, faculty at Colleges A2 and B1 did not raise these concerns. An administrator described faculty and administrators' collaboration:

> I think the spark has to come from administrators, in that we convey to faculty the [accreditation] requirements . . . But I think the success comes from the faculty. I don't care how much the administrator would really be an advocate and preach and remind and all that; until [data use] finds its way to the level of instruction, all we're doing is counting beans because I think that the real differences in the institution will come from the faculty. (B1_Admin_1)

Limitation: Challenges. A limitation also emerged through the inductive qualitative analysis that was encountered by all colleges but was not evident in the quantitized data: the challenges of access to and use of data. This reinforces the idea that the IR capacity is more complex than simply the number of FTE dedicated to IR. Interviewees at Colleges A1 and B2, spoke of impediments to DDDM:

> My biggest problem is not the data; it's having the time to mine it and actually go through it carefully. It's not lack of data, it's lack of time. Because you can get a ton of data and just trying to go through it all and do a reasonable job of getting your hands around it will kill a lot of time. (B2_Admin_3)

The interviewees also discussed the challenges of working with an ERP for data collection and analysis that was never designed for broad use or to support longitudinal analyses. For example, the following comment echoed others from interviewees at all four colleges:

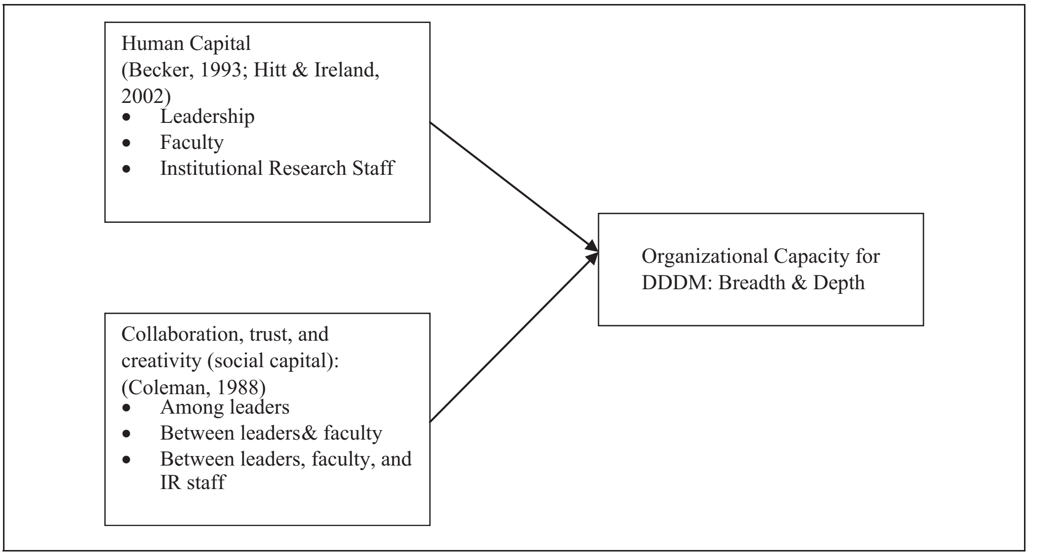

Figure 3. Revised framework of community college organizational capacity for data-driven decision making.
Note. DDDM = data-driven decision making; IR = institutional research.

> Our folks are reporting off of this transactional database, and transactional databases are really not designed or optimized for reporting purposes. The data's not organized in a format that's consistent with users' abilities to peruse and harvest data from that database. (A1_Admin_1)

These examples highlight the challenges experienced by the colleges that were not captured in the directed content analysis.

Discussion

Framing commonly discussed influences on DDDM in the K–12 research as forms of capital and thus recognizing that they are resources that can be developed and can be used to achieve other goals furthers our understanding DDDM in postsecondary education. Although forms of physical capital are prevalent in the literature, this empirical study suggests a framework of DDDM organizational capacity in community colleges that does not include physical capital (see Figure 3). Human capital and social capital, but not physical capital, were found to influence the organizational capacity for DDDM at the participating community colleges and to account for the extent of DDDM at the colleges.

To review, the three propositions that guided this research and the relevant findings are

> **Proposition 1:** Colleges with more human and physical capital will display greater breadth and depth of data use than will colleges with less capital.
> **Proposition 2a:** Colleges with more human and physical capital in different states with similar external influences to use data will display similar breadth and depth of data use.
> **Proposition 2b:** Colleges with less human and physical capital in different states with similar external influences to use data will display similar breadth and depth of data use.

Proposition 1 held true within the two states, but not across them. In particular, in both states the college with more capital displayed greater breadth and depth of data use than the lower capacity college, but this difference did not hold in comparisons of colleges across states. The quantitized data do not support Propositions 2a and 2b. The total capacity of the colleges, as defined by human and physical capital, was greater at the two colleges in the western state than at the two colleges in the southeastern state, but the breadth and depth were comparable with or less than the breadth and depth of the southeastern colleges. The low-capacity college in the west displayed less breadth and depth of data use than did the low-capacity college in the southeast despite having a greater total capacity.

Initially, these findings suggested there may be a state influence differentiating the overall capacity in the two sets of colleges. Support for the first proposition, which was based on literal replication, but not the second propositions, which were based on theoretical replication compelled me to deepen my analysis of the data to revisit the initial propositions, as Yin (2008) suggests. Quantitizing the qualitative data enabled a clear pattern to emerge—the relationship between human capital and breadth and depth. On identifying that pattern, I returned to the qualitative data and found ways in which the quantitized data obscured possibly important insights such as the complexity of leadership, faculty perceptions of their role in DDDM initiatives, and the challenges of using data that have nothing to do with the size of the IR staff or the available technology.

The results of this study contribute to a new framework (see Figure 3), which requires additional empirical examination. As outlined by Yin (2008), the theory generated by case study research contributes to a theoretical framework that may be applied to other cases. Human capital remains in the new framework, as defined at the outset of this study, but a broader conceptualization of leadership, faculty involvement in DDDM, and creativity and distributed access to research are added. Prior research on DDDM was not helpful here because, although the importance of leadership, IR and IT are widely noted in the literature, studies have yet to explicitly address the role of leadership beyond the president and despite research on faculty culture and decision-making (Tierney, 2008) connections have not been make to DDDM yet. Although the use of reporting tools to provide more user-friendly access to data are addressed (Allen & Kazis, 2007; Datnow, Park, & Wohlstetter, 2007; Petrides, McClelland, & Nodine, 2004) the idea of distributed and collaborative access to creatively compensate for limited resources has not been explored. In sum, the findings suggest that colleges and researchers should attend to human capital and broader cultural issues such as collaboration and faculty/college relationships in DDDM. These findings that highlight collaboration, trust, and distributed knowledge and support imply that another form of capital—social capital—should be examined in an analysis of influences on the extent of DDDM at community colleges.

The limitations of the initial framework also have methodological implications. The study illustrates the applicability of purposive sampling in a multiple case design to permit the exploration and testing of a new framework through a mixed methods study. In addition, I propose that returning to the data after the merged analysis is important for a research design that included quantitizing qualitative data. The deeper inductive analysis illuminated the complexities that were not evident in the quantitized data.

The fact that the number of FTE did not reflect the creativity and distributed access that some colleges displayed in grappling with small IR offices or the ways in which data are difficult highlight the limits of numerical scales. The uniformity displayed in the IT scale (i.e., the fact that all the colleges scored a 2 on the 3-point scale) suggests that the scale itself was too blunt and captured neither the nuances among the colleges nor the challenges of working with ERP systems not designed to provide accessible data.

This study also highlights the strengths, weaknesses, and challenges of quantitizing qualitative data. Quantitizing enabled a pattern to be clearly seen between the qualitative and quantitative data, thus illustrating Sandelowski et al.'s (2009) suggestion that quantitizing can simplify data to enable interactions with the data, but in order to fully understand that pattern I engaged in in-depth analysis of the interview data. Such exploration may have been unlikely without the rich qualitative data or without the clarity gained in the quantitative analysis; the power of mixed methods research is demonstrated in the flexible design and the leveraging of the strengths of qualitative and quantitative data. Nonetheless, my experiences suggest that researchers considering quantitizing qualitative data might be better served beginning with an exploratory sequential design (Creswell & Plano Clark, 2011) that enables a better understanding of the phenomenon under study before reducing that phenomenon to numbers. Alternatively, researchers might use the process employed here: a parallel design with a directed sequential component that allows for greater exploration of emergent findings. In the end, this research benefitted from a creative approach that allowed the research questions and the results to drive the overall research design resulting in an adaptation of the existing parallel mixed methods design (Christ, 2009, 2010; Creswell & Plano Clark, 2011).

Conclusion

More than a decade after No Child Left Behind prioritized the use of data and evidence in K–12 schools, educational researchers are starting to challenge our understanding of how educational organizations use data and what impacts their use. By identifying the influences on DDDM as forms of capital and providing a new framework, this study extends our knowledge of DDDM in community colleges. In addition, the strengths and weaknesses of quantitizing are depicted and approaches to addressing the limitations of quantitizing are shared. Finally, this research reinforces the creativity that mixed methods research enables by illustrating how replication logic for case study research may be applied to a mixed methods research design to explore, test, and generate new theory.

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