THE CAPACITY-OPPORTUNITY-MOTIVATION (COM) MODEL OF DATA-INFORMED DECISION-MAKING IN EDUCATION

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Abstract

Data-informed decision-making is widely perceived as a powerful driver of school improvement but schools and districts continue to struggle with implementing effective data use routines. In recent years, a range of data use interventions have been implemented in many U.S. schools and districts, but studies that rigorously evaluate their impact are scant and the evidence regarding their efficacy is mixed. Conducting more rigorous evaluations of data use interventions requires clear explication of mechanisms and processes that connect inputs with patterns of data use by educators that can be empirically tracked. To this end, a scoping review of the literature on this topic was conducted to develop the capacity-opportunity-motivation (COM) model of data use. This paper describes the model and demonstrates its utility in guiding evaluations that track and evaluate data use by educators.

Keywords: Data-informed decisonmaking, professional learning, knowledge transfer.

1 INTRODUCTION

Data-informed decision-making (DIDM) is widely recognized as a powerful driver of school improvement and student achievement [1-2] and is a centerpiece of many U.S. federal and state education policies, including the recently enacted Every Student Succeeds Act [3]. However, research shows that schools and districts continue to struggle with implementing effective data use systems and routines [1, 4-5]. In response, significant investments have been made in implementing a range of data use interventions that aim to build schools' and educators' capacity to use data [4]. Some involve comprehensive, system-level reforms such as building data systems, increasing teacher access to data, and providing structured time for data-based collaboration [4, 6], but also establishing research-practice partnerships that enable researchers and practitioners to jointly study problems of practice [7]. Micro or educator-targeted approaches to building data use capacity include data coaching [8-9], data teams, and professional learning communities (PLCs) of educators [10-12], as means for assessing building educators' capacity to acquire, interpret, and use data to inform decisions about every aspect of school.

At present, research that evaluates the impact of these strategies is sparse, and the available evidence regarding their efficacy is mixed at best [4, 13]. While this may be in part due to the lack of standard measurement of data use, there is a growing recognition that tracking and evaluating data use by educators requires a clear sense of the mechanisms and processes that determine data use [1, 14]. The primary goal of this study was to conduct integrative review of the extant literature on data use in education, as well as consult the broader literature on knowledge transfer and exchange, to develop a theory-grounded framework of DIDM that explicates the key variables, mechanisms, and processes that facilitate or impede data use in education and other professional settings.

2 METHODOLOGY

2.1 Organizing Framework of Integrative Literature Review

Common methods for producing a synthesis of the literature on a particular topic such as meta-analyses or systematic reviews are typically inclusive of studies that meet stringent eligibility criteria given that they aim to produce generalized conclusions regarding the effects of some variables on others. An integrative review, in contrast, is more concerned with identifying cross-cutting themes across a broad and diverse range of studies with the goal of generating new insights or ideas that may productively inform theory development and research. At the same time, it is useful to employ an overarching organizing framework that provides logical connections among themes. Data use is a complex, non-linear, and iterative process that requires educators to access, collect, and analyze data, and then turn the data into meaningful and useful information, and an organizing framework is a useful means for handling this complexity without also losing sights of important insights.

Accordingly, and based on the notion that data use is essentially a form of human behavior, this study adopted the capacity-opportunity-motivation (COM) model of behavior as an organizing framework for the purpose of conducting the integrative review. Briefly, the COM model [15] is predicated on the recognition that human behavior follows predictable patterns, and that therefore all behaviors can be predicted from the combination of three elements: capacity, motivation, and opportunity to act. *Capacity* is generally defined as the individual's psychological and physical capacity to engage in the activity concerned. It is a function of having the necessary knowledge and skills, but also the tools needed to perform the behavior. *Motivation* is defined as the cognitive and affective processes that energize and guide a person's behavior. It is a function of held attitudes, perceptions, and emotions regarding the enactment of a specific behavior. *Opportunity* is defined as factors in a person's environment (physical, legal, economic, social, and cultural) that enable or impede the enactment of the behavior. The likelihood of enacting a particular behavior is high when a person is highly capable and motivated to act and objective barriers to action are absent. In that sense, the COM model can be used both to organize information about key variables and findings reported in the literature of the topic as well as be applied for diagnosing, designing, and evaluating data use interventions.

2.2 Literature Review Methodology

The primary scholarly work targeted for the purpose of conducting the integrative review were peer-reviewed conceptual and empirical studies on the topic of data use in education published in English as journal articles or conference proceedings from the year 2000 to date. The secondary body of work targeted for the review was review articles or book chapters on the topic of DIDM published in other professional fields (principally medicine, public health, criminal justice, and team science). The online databases searched included ERIC, Academic Search Premier, PsycINFO, CINAHL, Medline, PubMed, Web of Science, and Google Scholar. The basic search string used to search for and retrieve relevant work was developed with the help of an information specialist and included a combination of common data-related keywords (e.g., "data", "research", and "evidence") and use keywords (e.g. "test*", "assess*", "analysis", and "interpret*") to which keywords used to capture educational settings (e.g., "school*", "district*", "teach*", and "educat*"). The final version of the search string was developed through an iterative process of testing different combinations of keywords until no further improvement in recall (the fraction of relevant items retrieved from the possible universe of relevant items) and precision (the fraction of retrieved items that are relevant) were achieved. Both authors independently screened the same random sample of 50 titles and abstracts, blinded to authors and journal titles, and their degree of agreement was assessed using Cohen's kappa test and was found to be satisfactory (Kappa = .87), before the remaining titles and abstracts retrieved were divided and screened by the authors.

Following this procedure, an initial pool of 396 potentially relevant articles was retrieved of which 216 items were duplicates that were subsequently removed from further consideration. The pool of remaining articles was scanned manually by the authors to assess their relevance. Articles that included nothing more than prescriptions regrading optimal DIDM were excluded from further considerations as were research reports in which data use was not included as a major variable of interest. On the other hand, work that was centrally focused on conceptualizing data use without also testing this conceptualization empirically was included. In all, a total of 67 original and review articles met the study inclusion criteria.

In the next step, each article was analyzed by the authors to first extract key variables (e.g., data literacy), factors (e.g., data infrastructure), and mechanisms (e.g., learning) that were shown or otherwise hypothesized to facilitate or impede DIDM. In the next step, each author independently classified each of these based on their fit with the COM components (i.e., determining whether a particular variable or factor can be classified as either relevant to capacity, motivation, or opportunity), and any disagreements they had were reconciled through discussion. This classification was used in turn to construct two complementary COM-based models of data use, one at the level of the individual decision-maker and another at the level of the group.

3 RESULTS

Figure 1 represents the COM-based model of data use by educators that we developed based on the results of the integrative review of the literature. As shown in Figure 1, data use is actually composed of several different behaviors (e.g., acquiring data, cleaning and filtering data, analyzing data, interpreting data, etc.), and all of these ought to be measured and modeled separately. Moreover, it is crucial that each behavior be precisely defined in relation to the target of action (e.g., type and source of data, the person or group data is shared with), timing of action (e.g., before or after classroom assessment), and the context of enacting the behavior (e.g., individually or in collaboration with others), to improve the precision predicting the behavior from the other elements in the model [15-16]. Measuring behavioral intentions (or likelihood of performing the behavior) is appropriate if the goal is predicting future behavior, providing that the measure used is similarly defined by target, time, and context. It was apparent from the review that data use means different things to different actors, and this explication procedure will greatly facilitate the creation of standard measures of the construct.

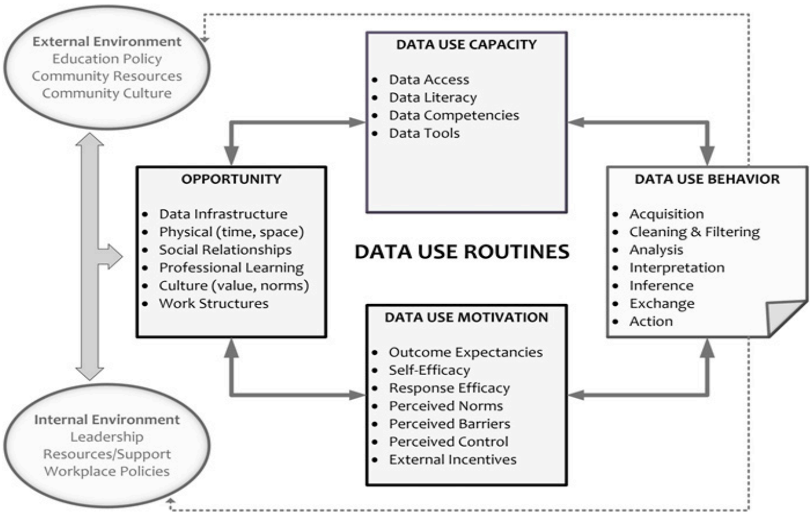

Figure 1. The Capacity-Opportunity-Motivation (COM) Model of Data Use in Education.

Importantly, data use in this model is decoupled from the potential outcomes of data use, such as individual decisions and actions, organizational structures, policies, and culture, and student outcomes. A potentially important finding of our review is that studying direct and indirect relationship between data use and outcomes of data use are generally guided by attention to three general causal mechanisms: cognitive (e.g., learning), social or relational (e.g., exchange, negotiation, and diffusion), and structural (e.g., networks, norms, and roles). For example, a change a teacher makes in his/her approach to teaching in the classroom may be an outcome of what this teacher learned from analyzing student assessment data, an outcome of collective deliberations among content-area teachers based on collaborative analysis of student data, and/or an outcome of a top-down imperative formulated by district leadership, or a combination of these. A rigorous theorizing and/or evaluation of DIDM would therefore consider all possible pathways that link data use, directly or indirectly, to outcomes of data use.

3.1 Individual-Level Model of DIDM

According to our model, any data use behavior can be predicted from the combination of capacity and motivation to enact this behavior, providing that an opportunity to enact the behavior is present. Capacity in this context is conceptualized as a function of an actor's ability to access data, be data literate, possess basic data competencies or "know-how", and use the tools needed to perform the task [17]. Motivation is conceptualized as a function of key cognitions that underlie the decision to enact a certain behavior – i.e., outcome expectancies, self-efficacy, response efficacy, perceived norms, perceived barriers, perceived control – but also as a function of external incentives (rewards or sanctions), although the studies we reviewed show that intrinsic motivations are a more powerful driver of data use [18]. The specific definition and implications of each capacity and motivation element is provided in Table 1. Clearly, this list is not exhaustive and there are likely other elements that define capacity and motivation to use data. The point we are making is that the assessment of both capacity and motivation should be integral to every data use evaluation and this is true for prospective and retrospective studies alike. In all cases, an important question the evaluation must answer is how exactly did the program or intervention impact (or is expected to impact) the capacity and motivation of educators to acquire, filter, classify, analyze, interpret, deliberate, and act on data?

Table 1. *Definitions and Implications of COM Model Components to Evaluations of Data Use.*

Component	Definition	Evaluation Implications
Data Use Capacity		
Data Access	The ability to search and retrieve data from a database or other repository.	Capacity is both objective (actual) and subjective (perceived) and it is useful to capture both. Subjective capacity is based on personal experience and is associated with motivation to use data; objective capacity is associated with performance, but requires a benchmarking standard and use of valid and reliable tests of the type developed in the field of information sciences.
Data Literacy	The ability to consume, comprehend and communicate data as information.	
Data Competencies	Planning and executing data collection and analysis, evaluating, interpreting and drawing inference from data, and communicating and sharing findings.	
Data Tools	Tools for the collection, storage, and analysis of data.	
Data Use Motivation		
Outcome Expectancies	Anticipated outcomes (personal, organizational, and student) of data use and the value placed on these outcomes.	Behavior change evaluations typically include measures of all of these constructs, both pre and post program implementation. Motivation is more fluid than capacity, and therefore requires shorter time intervals between successive measurements. Valid and reliable measurement instruments are readily available from the behavior change literature. If there is interest in predicting a future behavior, it is important to also measure intention to act.
Self-Efficacy	Confidence in one's ability to use data to achieve a specific goal or meet a certain standard.	
Response Efficacy	Confidence that data use can produce the desired outcomes.	
Perceived Norms	Belief that other group members expect one to use data in a particular way and for a particular purpose.	
Perceived Barriers	Perceived cost of or personal challenges posed by data use.	
Perceived Control	Perceived ease or difficulty of data use.	
External Incentives	Use of rewards or sanctions to regulate behavior.	
Data Use Opportunity		
Data Infrastructure	A digital infrastructure or system that promotes data sharing and consumption, including dedicated technical assistance resources.	Opportunities are factors that enable or impede the likelihood of behavior. As such they may act as moderators of the relationship between capacity and ability and data use, or their effect on data use may be mediated by their effect on capacity and motivation. In general, it is important to consider both moderation and mediation hypotheses, regardless if the study utilizes observational or experimental design. Important to consider unintended effects.
Physical Opportunities	Absence of objective constraints on data use such as time, space, and facility to access data (e.g., Internet connection).	
Social Opportunities	Structured opportunities to connect with and engage with other educators around data use (e.g., common planning time).	
Professional Learning	Activities that are intended to provide educators with the knowledge and skills necessary to improve practice.	
School Culture	Set of norms, values and beliefs regarding data use shared by members of the school community.	
Work Structures	The organization of roles, tasks, and responsibilities that can support and facilitate data use.	

Because capacity and motivation to use data alone are often insufficient to stimulate and sustain data use by educators unless favorable conditions, or opportunities, to use data are present [4], it is imperative that the evaluation also considers opportunities as an integral component of the investigation. Our model distinguishes among three classes of factors that can support (or suppress) the opportunities of educators to engage with data: physical, social, and organizational (see Table 1 for specific definition and implications of each element). Physical factors involve the logistics of data use such as having the time and technology needed to engage with data [9]. Social factors involve structured or regular opportunities for educators to interact with others in the context of data use, whether formal or informal [1, 19]. Organizational factors include elements such as data infrastructure (both data systems and technical assistance), formal policies and support structures such as PLCs or data coaches, and school culture that supports data use. In general, based on the findings of our review, opportunities to use data in schools are determined by the interplay between the external environment (e.g., federal and state education policies, community resources, etc.) and the characteristics of the internal environment such as leadership, available resources, and workplace policies. However, depending on the objectives of the evaluation, there may not be a need to factor these into the analysis. Still, if the goal is to assess the impact of such environmental factors, the primary question of interest would be how, if any, these factors increase opportunities for educators to use data, and how, if any, changing the opportunity structure influenced (favorably or unfavorably) educators' capacity and opportunity to use data. Importantly, opportunities are also assumed to be dynamically shaped by educators' capacity and motivation to use data, such as when informal networks of teachers that exchange data-based information emerge in schools [10], so it is important that the evaluation further explores this type of dynamics.

3.2 Team-Level Model of DIDM

The scholarly work included in our review point to the fact that DIDM frequently takes place in collaborative group structures such as data teams or PLCs and that such structures are key to the institutionalization of data use routines in schools [20-22]. At the same time, the process and mechanisms that govern collaborative DIDM are not adequately conceptualized or studied in the context of education research. Whereas cognitive mechanisms can reasonably account for DIDM at the individual level, team processes have to do with the scope, nature, and dynamics of social interactions among team members and the emergent perceptual states that result from these interactions (e.g., cohesion, trust, shared accountability, and collective efficacy), all of which have the potential to facilitate or impede DIDM-based collaborations. Fortunately, there is a sizable literature on the science of team collaboration that can inform this aspect of DIDM [23] and systematic reviews of this body of work where included in our integrative review. Our initial attempt to synthesize insights from this literature and adapt them to the context of DIDM in educational practice is featured in Figure 2. Thus, team capacity to collaborate on DIDM was consistently found to be a function of team composition (with diverse expertise of team members noted as strength), leadership (in terms of organizing and coordinating team activities), role knowledge (i.e., knowing exactly what others do), and conflict management style (or an agreed-upon procedure for resolving disagreements). Opportunities for team collaborations were generally found to be a function of organizational arrangements and resources (i.e., functional meeting space, regular meeting time, access to data and to technical assistance) as well as of the degree to which data use is integrated with workflow and professional routines (for example, whether teachers are expected to use data). Lastly, team motivation was primarily found to be a function of the relationships among team members, in particular the degree of mutual trust and social identification that exist among members).

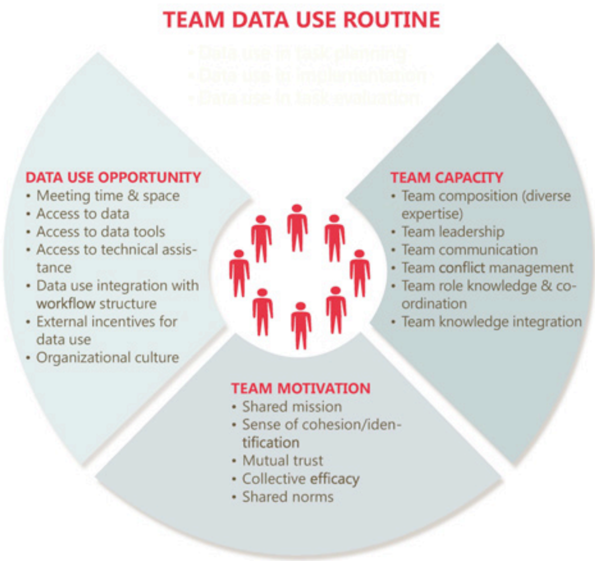

Figure 2. The Capacity-Opportunity-Motivation (COM) Model of Data Use in Teams.

4 CONCLUSIONS

The COM model is a useful framework for evaluating DIDM in education for a number of reasons: it places “data use” on a behavioral continuum that can inform the design and implementation of more tailored individual interventions and more optimal collaborative structures that aim to institutionalize DIDM in districts and schools; it unpacks the “black box” that connects program inputs to outcomes, thus allowing to track, monitor, and evaluate progress on goals; it can be used to diagnose the element (capacity, motivation, or opportunity) that can benefit the most from targeted investments; and it paves the way for the use of rigorous methodologies and measures to evaluate data use. One additional important feature of the COM framework to DIDM is that valid, reliable, and precise measures of many COM variables already exist, albeit in other fields, that could be readily adapted to the educational context. Our next task therefore is to compile an inventory of such instruments and measures and test them in educational setting.

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