**Data-Driven Decision Making**

As I discussed the features of Quality Rating Improvement System (QRIS) in the earlier chapters, data-driven decision making (DDDM) is considered one of the key features in continuous quality improvement by systematically gather, analyze, and disseminate various types of data to inform decision making for improvement (Los Angeles County Department of Children and Family Services [LA DCFS], 2013; Ikemoto & Marsh, 2007; Mandinach et al., 2006; Marsh et al., 2006). In this chapter, I will discuss what is DDDM, what are common practices and features of DDDM, why is it important to address DDDM in building high quality early childhood systems, and how a state agency foster DDDM at a system level.

**Overview of Data-Driven Decision Making (DDDM)**

Ongoing data collection and analysis is fundamental to build a system to understand what is working and what is not working (LA DCFS, 2013). As the field is claiming “we are completely data driven” (Marsh et al., 2006; p.1), DDDM plays a critical role in federal and state educational accountability policies (Guss et al. 2013; Marsh et al., 2006). Despite the increased interest in DDDM, the field is struggling to encompass how to utilize the information from its overwhelming abundance status (Celio & Harvey, 2005; Ingram et al., 2004) to inquire iterative processes and its impact in the field (Guss et al. 2013; Marsh et al., 2006).

DDDM was modeled from the ideas and features of Continuous Quality Improvement ([CQI], Byrk et al., 2016; Deming, 1986; Lemire et al., 2012; Perla et al., 2010). Marsh and her team (2006) described DDDM as an organizational improvement to enhance and response to various types of data including “input data such as material costs, process data such as production rates, outcome data such as defect rates, and satisfaction data including employee and customer opinion” (p.2). Marsh et al. (2006) further noted the concept of DDDM arose in the 1980s from early discussions of measurement-driven instructions (Popham, 1987; Popham et al., 1985) to initiatives of a state’s use of site-based planning and decision-making processes in the 80s (Massell, 2001), and efforts to engage in strategic planning in the late 80s and 90s (Schmoker, 2004). DDDM has gained more attention due to the introduction of No Child Left Behind ([NCLB], U.S. Department of Education, 2001). NCLB emphasized four initiatives including *accountability* to ensure disadvantaged students achieve academic proficiency, *flexibility* to allow school districts to use federal educational funds for improving student achievement, *research-based education* to emphasize implemented educational programs and practices have warrants as evidence-based practices, and *parent options* to increase the choices for allowing students to attend Title I schools (Ikemoto & Marsh, 2007; Marsh et al., 2006; Washington Office of Superintendent of Public Instruction, n.d.; U.S Department of Education, 2001).

As I further reflect the origin of DDDM in the education system, it seemed clear that the current version of CQI and DDDM addressed in the early learning initiative such as Race to the Top (RTT; U.S. Department of Education, 2009) and majority of the available studies focused on data use in K-12 school settings (Anderson et al., 2010; Horn et al., 2015; Means et al., 2009; Murnane et al., 2005; Sharkey & Murnane, 2003; Sutherland, 2004; Wohlstetter et al, 2008). It was also not surprising to see limited information was available from literature on why increased use of data is considered fundamental component for system change in the early learning system (Little et al., 2019). There were some examples from Ikemoto & Marsh (2007) that DDDM processes in NCLB failed to acknowledge how use of data for decision making among practitioners varies, yet studies have shown actors in all levels of an education program (classroom, school, and district) believed DDDM is an important process and deemed useful for change (Kerr et al., 2006; Marsh et al., 2005). What was still unclear to me was how professionals in the educational settings blend previous experiences by sensemaking what is presented from data. It seems valuable to understand the process and features of DDDM and how different models of DDDM plays a critical role and I hope to illustrate the use of DDDM in K-12 settings and how it differs in the early learning field in the upcoming sessions.

**DDDM in K-12 Settings and School Improvement**

Mandinach and her team’s work in 2006 is considered one of the cornerstones for conceptualizing the DDDM framework for school improvement in K-12 settings (Mandinach et al., 2006). As a synthesized work stemmed from Ackoff (1989), Brieter (2003), Drucker (1989), and Light’s team (2004), Mandinach et al. (2006) illustrated three key components of DDDM by referencing the work of Light et al. (2004): *data, information,* and *knowledge.*

“*Data* exist in a raw state. They do not have meaning in and of itself, and therefore, can exist in any form, usable or not. Whether or not data become information depends on the understanding of the person looking at the data.

*Information* is data that is given meaning when connected to a context. It is data used to comprehend and organize our environment, unveiling an understanding of relations between data and context. Alone, however, it does not carry any implications for future action.

*Knowledge* is the collection of information deemed useful, and eventually used to guide action. Knowledge is created through a sequential process. In relation to test information, the teacher’s ability to see connections between students’ scores on different item-skills analysis and classroom instruction, and then act on them, represents knowledge” (p.3).

The above components can be achieved by following four steps. Mandinach et al. (2006) added a progression for DDDM including *collecting and organizing data, understanding the situation by combining, sensemaking process by individuals to process information to knowledge,* and *collection of new data* for other knowledge for further improvement yields school level outcomes. Among all steps described above, the concept struck to me was the notion of sensemaking process. Mandinach et al. (2006) further described the implementation and practical application of DDDM in a school system. Despite there are multiple barriers to execute such process for DDDM including training, technical training, or access to data issues (Choppin, 2002; Cromey, 200; Mason, 2002; Wayman, 2005), findings from studies (Confrey & Makar, 2005; Hammerman & Rubin, 2003) suggest support for teachers to use data for effective strategic planning is necessary. Teachers often do not make use of data nor examine data in a systematic way for planning long-term goals (Confrey & Makar, 2005). Mandinach et al. (2006) added teachers either fail or neglect to understand statistical concept represented by data that present descriptive results such as distribution, sampling, and variance. It deemed reasonable to see educators focus only on simpler type of data analysis (Confrey & Makar, 2005; Streifer, 2002); however, other researchers (Celio & Harvey, 2005; Herman & Gribbons, 2002) claimed it is sufficient for educators to focus on simple data analysis for answer questions for instructional improvement. As Celio and Harvey (2005) suggested “less may be more” (p. 71), some educators felt it may be too much to understand the complexity and volume of data that may make them feel overwhelmed.

If Mandinach and her team’s (2006) framework conceptualized the baseline framework and progression of DDDM, Ikemoto and Marsh (2007) further improved the idea by specifying four quadrants of DDDM based on its complexity. The four models of DDDM including *basic, analysis-focused, data-focused,* and *inquiry-focused* fell into one of the four quadrants along two continua (Ikemoto & Marsh, 2007). *Basic* DDDM – quadrant I – describes using data for simple analysis and procedure whereas *inquiry-focused* DDDM – quadrant IV – uses complex data and analysis techniques (Ikemoto & Marsh, 2007). Ikemoto & Marsh (2007) described the term inquiry-focused was chosen as it’s influenced by other researchers in the previous studies (Copland, 2003; Halverson et al., 2005) which utilizes DDDM as a way for organizational learning and continuous quality improvement (Feldman & Tung, 2001).

In the *basic* DDDM model, educators mostly rely on single type of data (i.e. outcome data) from one time point in a school year from a prepopulated information (Ikemoto & Marsh, 2007). Often times, it involves an administrator or a principal of a school system makes her/his own decision based on one source of data which results in reallocation of training resources such as training for math instructional improvement (Ikemoto & Marsh, 2007).

In the *analysis-focused* DDDM model, Ikemoto & Marsh (2007) stated the model involves groups of individuals at a school system (i.e. leadership team, grade-level teachers) with data available from “iterative examination” (p. 114). Despite the model is considered complex and collective, Ikemoto & Marsh (2007) warned that this quadrant of model does not involve expertise from subject matter experts and researchers with limited access to sophisticated analysis technique such as modeling and forecasting.

In the third quadrant, *data-focused* ­model*,* educators make use of multiple sets of data yet these were often collected one time period of a year and does not draw empirical evidence nor expert knowledge (Ikemoto & Marsh, 2007). For instance, Ikemoto & Marsh (2007) provided another example from a school district where administrators were determined to gather and analyze survey information collected from multiple stakeholders including families, teachers, and administrators to address budget deficit and minimize direct impact to students. Despite the case illustrated multiple levels of satisfaction data were collected from multiple players in the system, the action based on the data did not fully utilize what the data actually mean, which could use a support from experts like educational researchers (Ikemoto & Marsh, 2007).

The last quadrant, *inquiry-focused* models, presented only on five out of 36 cases Ikemoto & Marsh (2007) displayed from their study. Examples included significant effort and time were dedicated to probe and solve a specific problem that targets improvement of instructional practices (Ikemoto & Marsh, 2007). Ikemoto & Marsh (2007) added the model also was emphasized by leadership members of a district and presented as an agenda item at a district principal meeting, teacher meeting, or even as a part of professional development. Despite the number of cases were relatively smaller than other models, it seemed clear that in this model, educators were drawing multiple sources of data and collectively use the information for examine its evidence and use it as a part of ongoing quality improvement process (Ikemoto & Marsh, 2007).

One highlighted example includes a district led initiative to improve infrastructural and instructional capacity for English Language Learners. In the Institute for Learning (IFL) study (Ikemoto & Marsh, 2007), a district noticed that it is not meeting a required activities based on the NCLB guidelines as it was evidence that low scores of English Language Learners (ELL) soared the total score for the district. The district developed a protocol to examine the situation by collecting evidence via series of observations in non-ELL and ELL classrooms across the district (Ikemoto & Marsh, 2007). Members in the district also gathered qualitative information by asking questions to students and examining their schoolwork including observations of teacher instructional sessions and classroom materials. Drawing conclusion based on the quantitative and qualitative data; the district acknowledged that the current teacher workforce in the district only has sufficient competency that is considered elementary level Spanish (Ikemoto & Marsh, 2007). This resulted in ELL teachers not providing same rigor of instructions to students. The district then offered training and professional development opportunities to instructional staff, as well as convening study groups involving master ELL teachers who provided and promoted rigorous instructional practices across the district (Ikemoto & Marsh, 2007).

Across all models described above, despite there are limited number of cases or instances of use of DDDM (Ikemoto & Marsh, 2007), it was clear that K-12 educators were adhering different processes for DDDM which aligns with the incidence in a school level. I am also still unclear how these examples or models are displayed in the early learning settings. Also, I am wondering what are considered the catalysts and barriers for DDDM in an education system.

**DDDM in Early Learning System**

DDDM featured in an early learning system presented both similar and different features from the model in K-12 settings. As early childhood programs are pressured to gather data about children and teachers for DDDM (Stein et al., 2013; Yazejian & Bryant 2013; Zweig et al., 2015), the study from Little et al. (2019) posited what could be addressed in the early learning setting by utilizing Cohen-Vogel and Harrison’s (2013) DDDM work. Little et al. (2019) described three distinctive features including *data access and availability, capacity for data use and action,* and *culture of data use.*

To inquire *data access and availability,* Little et al. (2019) highlighted recent studies that confirmed abundance of data in early childhood educational settings is inevitable (Firestone & González, 2007; Guskey, 2003; Halverson et al., 2007; Ingram et al., 2004; Louis et al., 2010; Yazejian & Bryant, 2013). Despite there are multiple types of data across the system, Little et al. (2019) organized different types of data referencing the work of Firestone and González (2007) by specifying data into *externally derived* versus *internally derived* data. *Externally derived* data are collected by actors that are not classroom teachers (i.e. coaches or administrators) and often include summative assessment or administrative data on student attendance (Little et al., 2019). These are considered and perceived as objective, valid, and reliable source of data especially from those from the educational measurement and evaluation field (Anderson et al., 2010). On the other hand, *internally derived* data are data that are collected by instructional staff inside of a classroom that are also considered as process oriented (Little et al., 2019). Researchers (Black & William, 1998; Firestone & González, 2007) view this type of data as a primary ingredient to improve instructional practices for teachers. Examples of *internally derived* data include observational notes, coaching notes, or activity logs (Little et al., 2019). Researchers (Petrides & Guiney, 2002) also emphasized the importance of understanding how data is available for teachers for access and DDDM. Data systems have become more and more complex and there’s a progression from the past where the central district office maintained independent source of data (Petrides & Guiney, 2002). Instead, early learning systems such as Early Achievers in the current era uses Online Analytical Processing platform (Subotić et al., 2013) that enables anyone with access to cubical form of data to query business-level data. This encompasses all types of activities for DDDM including using multiple sources of data via relational databases, report writing using available data, and data mining (Subotić et al., 2013).

As effort for centralization and access to data are evidence in the early learning system (Little et al., 2019), I too felt this may be too technical and complex for educators to access data as often times, analyzing information from OLAP tools require not only the understanding of what has been collected, it requires training of super users to query data, understanding of SQL – domain specific language for a relational database management system, and proper tools and resources for executing such query such as MySQL or VizQL from Microsoft Power BI or Tableau.

Another feature illustrated by Little et al. (2019) includes *capacity for data use and action*. Researchers (Datnow & Hubbard, 2016; Halverson et al., 2007; Murnane et al., 2005) have agreed that schools utilizing high level data use often emphasize capacity for teachers and administrators to collectively engage in DDDM processes whereas low level of data use in schools often rely on expertise of external partners. School administrators and instructional leaders also use data to guide learning environment or instructional practices for process improvement (Cohen-Vogel & Harrison, 2013; Firestone & González, 2007) yet it was unclear to me whether these described different levels of DDDM similar to the classification of four quadrants by Ikemoto & Marsh (2007).

The last pillar of the features of Little et al. (2019) describes *culture of data use among teachers.* Researchers have demonstrated having a culture of data use Having a culture of data use among teachers by setting norms and expectations enhance mutual accountability and positive environment in a school setting (Firestone & González, 2007; Wohlstetter et al., 2008). By having such atmosphere of “organizational learning” (Firestone & González, 2007, p. 152), the focus of data use becomes intentional that actors involved in such processes focus on improving instructions, solving problems, and incorporate long term investment by identifying support or professional development opportunities for future use. This seemed a cherry on a cake to me that rather than having an accountability system where monitoring and evaluating performances become the purpose of data meeting or check-ins, the promotion for healthier collaborations enhances the learning opportunities for teachers and administrators.

Examples above shown by Little et al. (2019) were mostly from pre-kindergarten programs or school-based programs. To inquire unique challenges addressed in the early learning system especially from other types of programs (i.e. inclusive classrooms, programs in QRIS), it is also important to acknowledge the work of Sandall and her team (2004). Sandall et al. (2004) shared insights on why collecting and using data in early learning settings is challenging. Sandall et al. (2004) stated the three primary tenets of data collection in the early childhood settings. As also referred by Wolery (2004), data collection and use of data in early childhood system has the following primary purposes: “a) to validate initial assessment information; (b) to develop a record of progress over time; and (c) to evaluate instructional effectiveness and make instructional decisions” (p. 161).

As the features and measures of quality assessments in early childhood programs have evolved, Sandall et al. (2004) also pointed out changes that are pivotal for monitoring progress of children. First, play-based or activity-based approaches are considered popular practices in early childhood settings in the 1990s and early 2000s (Bricker et al., 1998; Linder, 1993). As the approaches incorporate interests of children and their, instructions, documentations, goals, and action plans for monitoring children’s progress are all aligned with their play and routine activities choices (Sandall et al., 2004). As the nature of instructions becomes play-based and project oriented, Sandall et al. (2004) noted this makes it harder for teachers or other instructional staff to collect and monitor data as opposed to the traditional single-case behavior monitoring approach in a special education program.

The other change influenced the data use and collection in early childhood system includes approaches for building a portfolio for assessment (Grace & Shores, 1991; Lynch & Struewing, 2002). As a means to measure progress for children by collecting multiple sources of information that are considered developmentally appropriate (Bredekamp & Rosegrant, 1992), it is still unclear how assessment via portfolio strategies influence or impact use of data among teachers and administrators for improving instructional practices (Sandall et al, 2004). However, the approach is still viewed as purposeful and tells the “story of the child’s effort, progress, or achievement over time” (Sandall et al., 2004, p. 163) that may be slightly different than those assessment tools and approaches from K-12 settings.

Other approaches and findings were I llustrated in the recent years in the early childhood education (ECE) systems from the inquiry of implementation fidelity and program adherence using professional development tools or practices such as coaching. Downer (2013) referenced the studies conducted by Powell and Diamond (2013). Powell and Diamond (2013) found combination of intervention fidelity and child level outcomes assessed by coaches and using those data to inform decision making among the implementation team members yielded focused instructional strategies for child development (i.e. language skills) rather than having a broad inclusive goals and plans. As coaches were able to progress from a meta-dimensional improvement practices from improving language skills among children to narrow their scope to increased use of language-promoting practices such as labeling statements or scaffolding techniques, the progression provided a glimpse of blueprint in the ECE field that perhaps DDDM is more effective when reference category has been established and the strategy targets inquiry-based model (Ikemoto & Marsh, 2007; Downer, 2013). Downer (2013) added what we still don’t know in the field requires careful navigation of factors that are associated during the implementation stage of DDDM such as “if data are being collected at a population level, would it be useful to build a system that shows an individual’s fidelity data in comparison to the average fidelity data across the entire intervention?” or “Are there any unanticipated negative effects of data sharing, either in comparative fashion or otherwise?” (p. 163). Downer’s perspective (2013) could be investigated ideally by mixed-methods approach yet this may take more time and coordination among stakeholders to inquire and initiative such a large scale study.

Several themes came to my mind after reading the above collection of studies. It seemed clear that early childhood system has its own unique way of collecting and using data to monitor and understand developmental measures that are considerably unique compared to those programs in K-12 programs. What are still unclear to me is, especially reflecting what is available from the Washington Early Achievers system, that the emphasis of data use and building the culture of DDDM has concentrated information on one actor of the system – children. What I am still unclear is that the needs shown by Early Achievers implementation actors around building a system-wide database to capture coaching-relevant information – the actors outside of the core spectrum of QRIS support staff for quality improvement – and how the information can be utilized which is different than child development profiles. As noted by Downer (2013) that as accountability increases whereas funding decreases in early childhood systems, collecting of evidence for not only for documentation purposes for child progress but for understanding and informing strategies for continuous quality improvement across years of implementation of QRIS became inevitable.

**Factors for DDDM: Enabling versus Prohibiting Factors**

Regardless of program types or environment in K-12 or early childhood settings, Ikemoto & Marsh (2006) have identified factors enabling DDDM and factors prohibiting DDDM. Before displaying all factors for the current section, these factors can be classified into a broader classification of ***technical*** and ***adaptive*** change factors from system theorists (Heifetz & Linsky, 2002; Kauerz, 2020).

***Technical factors*.** Technical factors are considered known situations and finite challenges such as resources, funding, procedures, or documentations to address an issue (Heifetz & Linsky, 2002; Kauerz, 2020). Four areas of technical factors for addressing DDDM were identified by Ikemoto and Marsh (2006) including 1) *accessibility and* *timeliness of data,* 2) *capacity and* *support for staff,* 3) *time*, and 4) tools for DDDM.

***Accessibility and timeliness of data.*** Accessibility and timeliness of data “greatly influences individual use [of data]” (Ikemoto & Marsh, 2006, p.120). Ikemoto and Marsh (2006) pointed out most cases in their study, administrators in schools were able to see various types of data including student data. They had ability to disaggregate data from the source, run item-level analysis, and presented results in multiple modes (Ikemoto & Marsh, 2006). On the other hand, data captured from state-level (i.e. state assessment data) were not available to teachers in a timely manner for triangulating of data available from the school level, and the system received criticisms from teachers and principals (Ikemoto & Marsh, 2006). Despite the state’s inability, Ikemoto & Marsh (2006) pointed out teachers and administrators who were regularly reviewing and analyzing data were the ones who were in states or districts where data collection and available information for triangulation is beyond the scope of typical data collection including demographics, attendance, or achievement scores (i.e. parent survey data, student satisfactory data).

***Capacity and support for staff.*** Capacity and support for staff for DDDM were reported lacking in majority of the known studies (Choppin, 2002; Dembosky et al., 2005; Feldman & Tung, 2001; Ikemoto & Marsh, 2006; Mason, 2002). In one study (Ikemoto & Marsh, 2006), about 23% of teachers reported they felt prepared to interpret and reflect student test scores for decision making processes. In addition, lack of capacity for principals’ willingness to support teachers with professional development or training was also evident when Ikemoto & Marsh (2006) interviewed teachers for follow up questions after a survey was distributed.

***Time.*** Time is another factor that enables or prohibits DDDM in education systems. Lack of time for analyzing, synthesizing, reflecting, and interpreting data limited DDDM among teachers and school systems in several studies (Feldman & Tang, 2001; Ingram et al., 2004). If DDDM was considered one of the priority items for meetings or collaborations, it is more likely that educators will have understanding and competencies to implicate what data tells which would lead to quality improvement actions (Lacht, 2001).

***Tools.*** Tools and resources are one of the classic exemplar factors that are considered as a technical factor. As tools and resources often comes from external partners, Ikemoto & Mrash (2006) emphasized the importance of having those tools for guiding “the overall inquiry process” (p. 123). Even if educators had access to data dashboards or simple summarized records that displayed raw data to graphs, this allowed teachers and administrators a means to manipulate and interpret the meanings of data (Ikemoto & Marsh, 2006). This may be also particularly true in the early childhood settings as Guss et al. (2013) noted, having resources such as master teachers’ or coaches’ expertise will enhance teachers’ ability to better reflect observational data.

***Adaptive factors.***In comparison to technical factors, adaptive factors and challenges are considered ambiguous, unclear, and requires attention to behaviors, attitudes, and values to change a system (Heifetz & Linsky, 2002; Kauerz, 2020). These motivational inputs allow stakeholders in a system to engage and support to change the status quo exists at a system level, yet one of the primary challenges involves stakeholder’s inability to project aligned results will be considered better status than its current situation (Kauerz, 2020). People are inherently unwilling to change and change is considered hard for people (Fullan, 2001). This becomes especially evidence when new expectations or agendas appear to be different or inconsistent with pre-existing agendas (Spillane et al., 2002). In the context of DDDM models, Ikemoto and Marsh (2006) narrated 1) *perceived validity of data, 2) partnerships with internal and external organizations, 3) organizational culture and leadership,* and 4) *context from federal, state, and local government* should be considered for factors enhancing or prohibiting DDDM.

***Perceived validity of data.*** Marsh et al. (2017) pointed out educators in their study questioned the validity of data. For instance, teachers were wondering whether the assessment tests were aligned with curriculum, whether satisfaction data with low response rates accurately measure intended outcomes, or whether the test scores of students reflect students’ knowledge (Marsh et al., 2017). These perceived doubts about data affect buy-in of educators, acceptance, or support for the data that researchers agreed that factors affecting DDDM (Feldman & Tung, 2001; Herman & Gibbons, 2001; Ingram et al., 2004).

***Partnerships with external organizations.*** Partnering with external organizations for DDDM also yielded positive culture of data use (Marsh et al., 2017). Having solid partnerships with partner agencies often create a linkage between partners to share information and means of reflecting the information that is aligned with local needs (Coburn et al., 2005; Spillane & Thompson, 1997). This was also displayed in one of the studies that emphasized local-public-private partnerships for not only a program-level change, but also broader policy and system level changes (Guss et al., 2013; Yazejian & Bryant, 2013).

***Organizational culture and leadership.*** Ikemoto & Marsh (2007) have noted organization that have administrators and leadership staff with visions of DDDM who promotes collaboration for data use across the entity promoted DDDM whereas administrators with visions that instruction is considered private constrained the inquiry process for DDDM. It seemed obvious that leaders who are exposed to such DDDM practices as a regular routine were more likely to promote DDDM for effective data use, which leads to decision making that are committed for changes in schools (Choppin 2002; Copland, 2003; Feldman & Tung, 2001; Herman & Gribbons, 2001; Ikemoto & Marsh, 2007; Lachat & Smith, 2005; Symonds, 2003).

***Federal, state, and local policy context.*** Finally, context from federal, state, or, local policy context would influence implementing DDDM in a system. For instance, the NCLB act created a culture of incentivizing program that are examining student achievement data and as a result, schools would have more students meeting the standards (Ikemoto & Marsh, 2007). Despite the policy has contributed to improve accessibility and motivation for analyzing data, Ikemoto & Marsh (2007) pointed out it does not encourage use of multiple types and sources of data for inquiry processes. This was similar to the claim from Boller & Maxwell (2015) that states who implemented QRIS generally do not have capacities to inquire implementation practices or collect multiple evidence for system changes.

To summarize the information above, multiple factors influence DDDM by enabling or prohibiting such practice. Although these factors are mostly influencing complex forms of DDDM (Ikemoto & Marsh, 2007), as DDDM is not a straightforward nor monolithic activity, multiple considerations are required to examine whether DDDM works or not at a system level for policy implications.

**System Initiatives and Policy Implications of DDDM**

Let’s talk about how a state system can evaluate its own initiatives by utilizing data-driven decision-making processes. For a system to evaluate its own design, it is desirable to have a theory of change (Coffman, 2007). Coffman (2007, p.1) described the notion of “theory of change” gained its attention in the early childhood field especially in the 1990s. Connell and the team (1995) introduced the approach for evaluating complex initiatives such as Community Initiatives for Children and Families. Despite its popularity as a system level initiative, Coffman (2007) noted theories of change is not a “panacea for all evaluation dilemmas” (p.1). The approach was merely describing the system elements and its complexities rather than testing assumptions and validity of assessments (Coffman, 2007).

Coffman (2007) further described and introduced the theory of change that can be implemented for a Quality Rating Improvement System (QRIS). The five elements of a system initiative consist of *context, components, connections, infrastructure,* and *scale* (Coffman, 2007, p.2)*.* *Context* describes the political environment around the system that sketches policy and funding changes for sustaining the system. *Components* establishes high-performance systems that drives results for system initiatives. *Connections* creates linkages between system components for further improvement. *Infrastructure* develops and supports the system. And finally, *scale* ensures access to system to a broader community and beneficiaries so that it produces inclusive results for all. Not all system has all five element (Coffman, 2007) and it may be worth dissecting activities, outcomes, and impacts of the Coffman’s model that describes the elements of DDDM. All five elements of Coffman (2007)’s model describes a methodology for collecting and analyzing data for system improvements, yet I believe it’s worth further investigating the *connections* and *infrastructure* stages of the change.

During the *connections* phase*,* Coffman (2007) utilized questions to inquire whether the initiative connected implementation components as intended and whether those connections produced intended outcomes. Several approaches were introduced including Social Network Analysis (Durland & Fredericks, 2005) to understand the relationships among actors, groups, and entities in a system. By identifying nodes and networks among those ingredients, one can establish and determine whether the network connections look similar or different over time (Coffman, 2007). An experimental or quasi-experimental design can be constructed for understanding how connections produced intended outcomes (Coffman, 2007). For instance, Coffman (2007) introduced a case study from SPARK initiative evaluation as Berkley (2005) equipped a cluster evaluation where an overall evaluator assesses the initiative level assessment across the SPARK sites and project-level evaluators at a site level. Despite the methodology was not clearly articulated, findings suggest partnerships within the SPARK sites and the intentional leadership effort from key partners became catalysts for local, state, and national level change (Coffman, 2007). These outcomes were queried based on kindergarten readiness assessments, focus groups and key informant interviews at a site level, and surveys and quarterly calls among grantees which also lead to content analysis of key documentation (Berkley, 2005).

It seemed clear to me that the evaluation team utilized multiple approaches including quantitative and qualitative data collection, the effort resulted in a great example for creating a process for shared data systems for monitoring individual and organizational level outcomes for system linkages, alignment, and coordination (Coffman, 2007), so that the data can further describe elements for data-driven decision-making processes.

In the *infrastructure* phase, Coffman (2007) focused on asking whether the infrastructure for the initiative support the original objectives and inquiring whether the initiative achieved the objectives for “effectiveness, sustainability, and quality” (p.17). Case study or performance audit were introduced for understanding the effectiveness of such infrastructure (Coffman, 2007). As a type of post-hoc analysis for understanding success or failure of a system, Coffman (2007) described the success case method of Brinkerhoff (2003) combined storytelling features and deliverables such as reports that all actors in a system can “understand and believe” (p.23) the initiatives. Performance audit was also introduced which determines how well an entity is functioning for its intended initiative (Coffman, 2007). Performing customer satisfaction surveys or program evaluations can help stakeholders to understand whether a particular service is considered accessible and user-intuitive, or it has an impact to the intended recipient of the service (Coffman, 2007).

This was another great example where DDDM was employed by creating a cross-system governance protocol or system-wide use of data to describe how infrastructural outcomes connect to beneficiary impacts (Coffman, 2007). It seemed well organized to ensure the ecosystem of a complex system level initiatives which produces better impacts for beneficiaries across “a broad spectrum of domains and on a system-wide population level” (Coffman, 2007, p.8).

Finally, it is also worth noting the implications of DDDM at a practical and policy level. As noted earlier, DDDM is complex and it is not a linear process (Ikemoto & Marsh, 2007).

* Also consider recommendations from Marsh et al. (2017):
  + Practical Implications (which can be also addressed in the results/discussion section).
    - DDDM is complex (it's not a linear process)
    - DDDM in a classroom setting mostly focuses on "basic" model of DDDM as educators may not have quant background nor support from experts (i.e. Guss et al., 2013 implied perhaps that's one of the reason why when professionals review results of ERS/CLASS, expert coaching may help to reflect practices
    - Or counter claim that the basic model of DDDM is sufficient (Celio & Harvey, 2005; Herman & Gibbons, 2001) for answering questions addressed in a classroom level (i.e. less is more).
  + Policy implications
    - DDDM is not a straightforward process rather iterative processes requiring collection and reflection of multiple types of data sources (input, process, outcome, satisfaction data)
    - Improving the availability, timelines, and comprehensiveness of data is fundamental for DDDM
    - Providing resources and support such as professional development and resources for local and expert reviews will further enhance the processes.

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