Development and Initial Validation of a Measure for Early Childhood Program Readiness for Data Driven Decision Making

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Abstract

Harnessing the use of data to demonstrate program effectiveness, establish lines of accountability, and implement evidence-based programs is a present demand of social welfare and human service organizations. Early childhood service organizations, in particular, face requirements to use data to support decision-making, while having little research that offers best practices for data use in early childhood and limited programmatic capacity to collect and process data in ways that enhance decision-making. While literature promotes utilizing the *Active Implementation Drivers Framework (AIF Drivers)* as a theoretically-based strategy for data-driven decision-making (DDDM), there has yet to be an application of this idea in early childhood practice. To this end, this study sought to increase understanding of how early childhood programs use data and what factors drive program readiness for DDDM. The study involved the development and initial validation of the *Early Childhood Data-Driven Decision-Making (EC-DDDM)* survey based on the nine core *AIF Drivers*.

Three key questions were posed: 1) How do early childhood program administrators rate their organizations' readiness for DDDM? 2) Is the *AIF Drivers* an effective guide for understanding organizational readiness for DDDM? 3) How are demographic characteristics of program administrators and characteristics of early child programs related to factors of readiness for data-driven decision-making?

To answer these questions, 173 early childhood program administrators responded to the *EC-DDDM*. Findings from this study inform understanding of early childhood programs' data use and readiness for DDDM in three ways. First, the study provided a deeper and theoretically-grounded description of program administrators' perspectives on data use. Second, through confirmatory factor analysis and an evaluation of *EC-DDDM* based on Goodwin's (2002) measurement validity recommendations, it established initial evidence supporting the validity of

the *EC-DDDM* and confirming the *AIF Drivers* as a fitting underlying factor structure for understanding readiness for DDDM. And third, the study found no evidence of relationships between administrator demographics and program characteristics and readiness for DDDM.

These findings may inform future research attempts to develop theoretically-based measurement tools, especially as they pertain to developments that apply the *AIF Drivers.* Moreover, findings may advance early childhood practice as the *EC-DDDM* could serve as a platform for early childhood programs to understand their own readiness for DDDM and identify areas of strength or opportunities for improvement within their own practice. Future research is needed to accumulate validity evidence for the *EC-DDDM* and to understand the patterns and relationships between the nine *AIF Drivers* as well as what other external variables influence DDDM.

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Table of Contents

List of Figures

List of Tables

Chapter I
The Problem

Introduction

Early childhood is a critical period in the lives of infants, young children, and their families. While children's brains in their earliest years are capable of making one million neural connections each second (Center on the Developing Child, 2009), positive brain development and architecture is not solely the responsibility of genetic and biological factors. Development occurs in a more complex socio-ecological context where intersections of children's emotional, behavioral, and educational experiences through external forces like caregiver relationships and early education also play a significant role in brain development (Black & Hoeft, 2015; Children's Defense Fund-Minnesota, 2017; Center on the Developing Child, 2009).

Biopsychosocial factors interact constantly in the earliest years of a child's life leading to profound impacts on the rest of the life course (Black & Hoeft, 2015). Because young children's brains have high degrees of plasticity and flexibility, a window of opportunity opens during early childhood where early experiences play an important role in the ultimate well-being of children as they age (Shonkoff & Phillips, 2000). When early experiences are stressful, children are at greater vulnerability for disruption in brain development and risks and health disparities later in life (Shonkoff & Gardner, 2012). On the other hand, when early experiences are properly supported, children's brains are primed to establish the building blocks for future strength and resilience (Shonkoff, 2011).

These experiences may have compounding effects among society's most vulnerable. Young children living in poverty, children of color, and children with adverse childhood experiences (ACEs) experience systemic disparities correlated with lower achievement, poor health, and increased behavior problems (Braveman et al., 2018; Duncan, Magnuson, Kalil, &

Ziol-Guest, 2012). When provided with high quality early childhood programming, vulnerable children and families tend to experience higher net gains on outcomes related to school readiness, educational achievement, and improved health (Children's Defense Fund-Minnesota, 2017). Unfortunately, these children and families remain underserved in early childhood and encounter structural barriers to accessing early childhood programming (Children's Defense Fund-Minnesota, 2017).

The purpose of Chapter I of this dissertation is to establish the foundation for the current study intersecting the importance of using data and evidence in the implementation of high quality early childhood programs and interventions. The chapter will cover significant content and contextual ground providing an orientation to early childhood programming and its benefits to all children and families as well as society as a whole. Additionally, the chapter will elucidate problems experienced by early childhood service programs in their attempts to achieve their missions while maintaining performance and accountability in an era of limited resources. Chapter I concludes with a review of key terms and concepts and a review of the historical and policy contexts leading up to this dissertation research.

Early Childhood Programming and Intervention

Karoly and colleagues (1998) broadly distinguished early childhood programming from other human and social service interventions wherein early childhood programs and service providers external to the family offer formal and purposeful interventions aimed at improving the well-being of children prior to entering school. Children are not necessarily the exclusive focus and target of these programs and interventions. Understanding that the family and friends of a child provide the majority of support during these years, many early interventions, such as home

visitation programs, parenting classes, and home-based Head Start and Early Head Start promote early childhood development targeting parents and caregivers (Karoly et al., 1998).

The benefits of participation in early childhood programming and interventions are numerous. Among their measures of success are improved emotional and cognitive development, educational outcomes and school readiness, improvement in family self-sufficiency, reductions in crime, and the promotion of general health of children and pregnant women (Barton, 2016; Boller, Strong, & Daro, 2010; Karoly et al., 2001). Additionally, early childhood programs span a diverse array of health, education, and social service categories, including (Karoly, 1998):

- Public health programs seeking to improve prenatal care, childhood immunizations, and nutrition;
- Child care quality regulations and subsidies to support families in need of affordable child care;
- Income support, general welfare, and social safety nets like Supplemental Feeding Program for Women, Infants, and Children (WIC); and
- Home and center-based programs intended to promote early childhood development, parental support, and parent-child relationships and interactions

Given the far reach of early childhood programs and interventions, the current study narrowed its scope to the final category with special attention given to early childhood home visitation programs and programs geared at providing support to pregnant women, mothers, and other caregivers of young children. These programs were chosen for this study because they directly target both children and caregivers for the explicit purposes of promoting child development, parental support, and parent-child interactions (Karoly et al., 1998). While the

other program categories are valuable in their support to families, they focus on providing services for different purposes. For example, WIC and child care subsidy programs work to provide concrete assistance such as food supplements and money for child care to families and focus less on the aforementioned child development and parenting outcomes (Karoly et al., 1998). In their study, Karoly and colleagues (1998) also narrowed the focus to this final category using this same rationale.

Early childhood home visiting. Home visiting programs send trained providers into the homes of pregnant women and families of young children to aid families in strengthening parent-child relationships, support establishing safe and engaging home environments to stimulate early learning, and reduce child maltreatment and injuries (Barton, 2016; Boller et al., 2010). Multiple models and approaches to home visiting exist. Currently, the US Department of Health and Human Services (DHHS) recognizes 18 different models as "evidence-based" for meeting evidentiary requirements of established rigor and effectiveness (Health Resources and Services Administration, n.d.). Well known models include Nurse-Family Partnership (NFP), Healthy Families America (HFA), Parents as Teachers (PAT), and Early Head Start (EHS). Most models focus on targeting vulnerable populations such as families in poverty, pregnant teens, and households at-risk of child maltreatment (Boller et al., 2010).

Research in the last 20 years has established strong evidence with a wave of rigorous studies, systematic reviews, and meta-analyses supporting the effectiveness of early childhood home visiting (Barton, 2016). Sweet and Appelbaum's (2004) meta-analysis examined 10 child and parent outcomes areas and found families participating in home visiting had outcomes that are more positive in six of the 10 areas when compared to families not receiving home visiting. Systematic reviews found positive associations between home visiting and a number of relevant

outcomes, including: improving home environments and parent-child interactions (Kendrick et al., 2000; Goyal, Teeters, & Ammerman, 2013); reducing childhood poverty and child maltreatment (Bilukha et al., 2005; Geeraert, Van Den Noortgate, Grietens, & Onghena, 2004); supporting maternal depression (Ammerman, Putnam, Bosse, Teeters, & Van Ginkel, 2010); promoting child health and development (Avellar & Supplee, 2013); and reducing low birth weights and child health problems (Peacock, Konrad, Watson, Nickel, & Muhajarine, 2013).

Return on investment. In addition to these biopsychosocial gains for children, there is increasing evidence of economic returns to society when it invests in high quality early childhood programming. Rolnick (2015) synthesized studies looking at the return on investment of early child programs encompassing home visiting, home and center-based childcare, and preschool and found that for every $1 of public investment, these programs return anywhere from $4 to $16 to society. Similarly, the Center on the Developing Child (2009) reviewed three long-term, rigorous economic evaluations of early childhood programming and found a $4 to $9 return on investment. Societal benefits come in the form of higher workforce productivity and readiness, lower educational costs, lower crime, less use of public assistance, and the generation of higher tax revenues (Center on the Developing Child, 2009; Rolnick, 2015). Of special importance, the highest returns to society are gained when supporting children in poverty and children of color (Center on the Developing Child, 2009; Rolnick, 2015).

The Problem Statement

Taken together, it should come as no surprise that abundant research supports and recommends investing in the implementation of high quality, evidence-based programs in early childhood (Center for the Developing Child, 2007; Heckman, 2012). Despite all this, public investments for quality early childhood programs are not large enough to serve all children and

families in need. A quarter of 4-year olds and half of all 3-year olds do not attend preschool, and for those that do attend, quality is often called into question (Barnett & Hustedt, 2011). Access to evidence-based home visiting (EBHV) is also limited. The National Home Visiting Resource Center (NHVRC) (2017) estimates that less than half of the highest need families with children not yet in kindergarten benefit from receiving EBHV. That leaves the potential for over 9.5 million families experiencing poverty and families experiencing hardship because of teen pregnancy, single parenthood, or low educational attainment to benefit from high quality early childhood support (NHVRC, 2017). Adding to this problem, because poverty affects people of color disproportionately, limited resources and investments in early childhood maintain and perpetuate health disparities, economic disadvantages, and child development inequalities experienced in ethnic and racial minority communities (Braveman et al., 2018).

Because of these limited resources, organizations providing early childhood programs meet increased demands for maintaining their accountability to all public and internal stakeholders, proving their efficacy through implementation of evidence-based practices, and continuously using data to improve practices and decisions (Yazejian & Bryant, 2013; Zweig, Irwin, Kook, & Cox, 2015). In the broader human service context, social work scholars concerned with supporting human service organizations have commented definitively on the need for organizations to use and apply evidence as a critical strategy for supporting organizational credibility, competiveness, and survival (Lewis, Armstrong, & Karpf, 2005; Plath, 2013). Recent literature supports the mobilization and management of knowledge and evidence as a mechanism for successful change in human service organizations (Dill & Shera, 2015; Austin, Claasen, Vu, & Mizrahi, 2008). Finally, Stoesz (2014) warned that an absence of empirical evidence to support chosen interventions may ultimately lead to funds for human

services and social workers being diverted to programs with stronger evidence of efficacy. Despite all this, social work scholars have acknowledged that the social and human services are not widely integrating continuous streams of data and evidence to inform practice and policy (Coultan, Goerge, Putnam-Hornstein, & de Haan, 2015).

Key questions remain regarding how social work practitioners and administrators harness knowledge to implement more effective and evidence-informed practices, advocate for better social welfare policies, and ultimately, promote social good (Coultan et al., 2015; Dill & Shera, 2015). Yazejian and Bryant (2013) acknowledged these same demands as critical in early childhood work. Early childhood practitioners must base their practices on research evidence and use data to drive and support decisions. Unfortunately, two significant obstacles exist inhibiting early childhood programs from using data and evidence to support decision-making: 1) a dearth of research on best practices for using data in early childhood; and 2) early childhood programs have limited capacity to collect data and process the results for decision-making (Yazejian & Bryant, 2013).

The Current Study

The current study aimed to reduce these obstacles by exploring how early childhood programs use data, as well as through increasing understanding about capacity issues within early childhood programs related to "readiness" to use data for decision-making. Zweig and colleagues (2015) argued "that effective data-driven decision-making (DDDM) depends on what data are collected, how data are collected, how data are stored, and how data are analyzed" (p.1). While that framework worked for approaching their study, the current study aspired to move the conversation from the "what" and "how" of data collection, storage, and analysis to a conversation around understanding what factors drive and determine the readiness of early

childhood programs to use their data in support of decision-making. The study leaned heavily on implementation science as a line of inquiry concerned with transferring research findings to practice, integrating data, and the uptake of evidence-based practices (EBP). Specifically, the study relied on the National Implementation Research Network's (NIRN) *Active Implementation Frameworks (AIF)* to develop and initially validate an instrument measuring readiness for data driven decision making (DDDM) (Fixsen, Naoom, Blasé, Friedman, & Wallace, 2005; Fixsen, Blasé, Naoom, & Wallace., 2009).

Early childhood program administrators and their role in implementation. The target population of the study included individuals responsible for administrative decision-making in early childhood programs. Within organizations, individuals with decision-making responsibilities come from different professional and educational backgrounds and have differing titles such as directors, managers, coordinators, and supervisors. The study included individuals with any of these titles and refers to participants from here forward as "program administrators." Early childhood program administrators work in a variety of organizational settings including nonprofit organizations, family childcare homes, child development and education centers, and schools (Bruens, 2012). The study may include program administrators working in any of these settings.

Administrator responsibilities involve the orchestration of tasks to plan, implement, and evaluate programs (Freeman, Decker, & Decker, 2017; National Association for the Education of Young Children [NAEYC], 2007). As such, program administrators assume a wide range of roles, some of which are managerial in nature while others are leadership-based. As managers, their responsibilities fall under the broad category of human resources such as hiring, training, and coaching staff. As leaders, administrators function as disseminators of program vision and

values as well as functioning as advocates to ensure action on behalf of children and families (Freeman et al., 2017; NAEYC, 2007). In both managerial and leadership capacities, program administrators establish and maintain organizational systems to facilitate program goals and activities and develop and foster partnerships with key stakeholders including staff, families, policy-makers, and external community members, which support the well-being of the children and families (NAEYC, 2007).

Research has shown that early childhood leaders report difficulties engaging in reflective practices that support decision-making (Aubrey, Godfrey, and Harris, 2012). To support their efforts, the authors suggested future research into identifying pathways for program administrators to solve problems and make decisions (Aubrey et al., 2012). Combining this finding with the study's aim to understand decision-making in a theoretically-guided way, program administrators are an appropriate population for this study. Additionally, program administrators' roles and responsibilities map closely and logically to a number of components outlined in the *AIF* and will be further discussed in Chapter II.

Relevance for Social Work

The study is especially salient for social work given its professional mission "to enhance human well-being.... with particular attention to the needs and empowerment of people who are vulnerable, oppressed, and living in poverty" (National Association of Social Workers [NASW], 2017, Preamble). Achieving this mission requires a broader view of social problems within the context of numerous complex social systems affecting these populations. The direct practitioner and clients are not solely responsible as individuals for implementing evidence-based practice, utilizing the best possible evidence, and achieving positive outcomes. It requires political and organizational supports working toward this ideal as well. As such, this dissertation research

may support the development and responsibilities of macro practices needed to enhance human well-being.

Furthermore, the extent to which this issue is relevant and timely for social work is evident in two recent calls to action from significant research entities of the profession. First, the American Academy of Social Work and Social Welfare have placed the importance of harnessing the power of data among the profession's Grand Challenges (Coulton et al., 2015). The uptake of evidence and usefulness of data can support social work's mission to enhance human well-being if social workers move beyond a mindset that data and evidence are useful only for general compliance and accountability toward a mindset of understanding their value for demonstrating impact, supporting practice decisions, and addressing complex social problems. Second, at the most recent Annual Conference of the Society for Social Work Research (SSWR), a keynote speaker highlighted a need for social work scholars to create new measures in an effort to address limited progress being made in the evidence base of social work (LeCroy, 2019). To this end, pursuing this dissertation research may promote this vision by contributing to the development of effective measurement tools across the field.

Key Terms, Concepts, and Processes

Concepts and terms surrounding knowledge, evidence, data, and their related processes are ever evolving and often used interchangeably (Austin et al., 2008; Dill & Shera, 2015). For clarity, it is germane to clarify how these terms were defined, used, and conceptualized for the purposes of this study. The following discussion identifies key terms, concepts, and processes used in this study and provides definitions for each.

Data, information, & knowledge. Davenport and Prusak (1998) provided relatively straightforward definitions to the concepts of *data*, *information*, and *knowledge*. *Data* are

unorganized facts and unconnected findings, which convey no organization, interpretation, or judgement (Davenport & Prusak, 1998). Coutlan and colleagues (2015) frame data as the "byproducts of human activity" (p. 4). *Information* adds context to data, providing arrangement, organization, or categorization (Austin et al., 2008; Davenport & Prusak, 1998). *Knowledge* adds judgement to information, providing "a richer and more meaningful perspective derived from experience and the analysis of data and information" (Austin et al., 2008, p. 362).

Evidence. The term *evidence* describes "a thing or things helpful in forming a conclusion or judgement" (*The American Heritage*, 2002, p. 484). Graybeal (2014) accepts this general definition but refines the idea by describing the forms of evidence commonly available to and used by social workers. Given these definitions, it seems reasonable to conclude that the concept of *evidence* effectively subsumes the concepts of *data* and *information*. For the purposes of this dissertation, the terms evidence and data will be used most often and interchangeably. The term *information* will only be used when it is critical to the context of specific theoretical or empirical literature.

Evidence-based practice. In addition to these key terms, there are a few key processes related to the uptake of evidence to present. *Evidence-based practice* (EBP) is the decision-making process social workers use to determine the best approach to practice *with* their clients by equally integrating the best research evidence available, their clients' preferences, and practitioners' practical expertise and knowledge (Graybeal, 2014; Drisko, 2014; Lewis et al., 2005; Thyer & Myers, 2011). Graybeal (2014) likens EBP to a three-legged stool as practitioners focus attention across staying current on research literature, drawing from and applying personal and professional experience, and satisfying the expressed preferences of clients. Each of these domains represents an equally critical leg to the stool. Since establishing

EBP as a process, social workers should not confuse EBP with *empirically supported treatments* (ESTs) or *evidence-based interventions* (EBIs). According to Drisko (2014), these terms signify that particular treatments, interventions, or program models have "some form of research supporting their effectiveness… meeting some minimal standards for effectiveness" (p. 124-125). In summary, EBP is a process for considering the best approach for work with clients, and ESTs or EBIs are researched supported program models or interventions to deliver to clients.

Data-driven decision-making. *Data-driven decision-making* (DDDM) is the concerted effort to utilize data in a manner that supports and informs the practice and policy decisions (Lewis et al., 2005; Mandinach, 2012). DDDM is pervasive across fields (e.g., education, business, healthcare), is not bound exclusively to practice or policy contexts, and is not restricted to particular levels of organizational hierarchies (Jones, Lee, & Bayhi, 2016; Lewis et al., 2005; Mandinach, 2012). While these two processes—EBP and DDDM— have certain distinctions, both are decision-making processes valuing evidence. EBP and DDDM may have another interesting connection as some have suggested that DDDM offers a conduit for creating practice evidence (Schaaf, 2015; Trowbridge & Mische Lawson, 2017).

Implementation. *Implementation* refers to a detailed set of activities needed to establish programs or service interventions and activities (NIRN, n.d.). Implementation activities are intentionally installed and executed to the extent that an outside observer can recognize these activities and assess their strength and presence. Effective implementation is a necessary component to ensure that EBPs produce the same intended effects in real world conditions that they do in controlled conditions. NIRN (n.d.) provides a *Formula for Success* to visualize the linkage between EBP and implementation. Three components must combine in order to achieve socially significant outcomes: effective innovations (e.g., EBPs), effective implementation, and

enabling contexts. Figure 1 shows this formula as a multiplication problem to signify that intended outcomes are not possible if any of these components is absent or too weak (NIRN, n.d.).

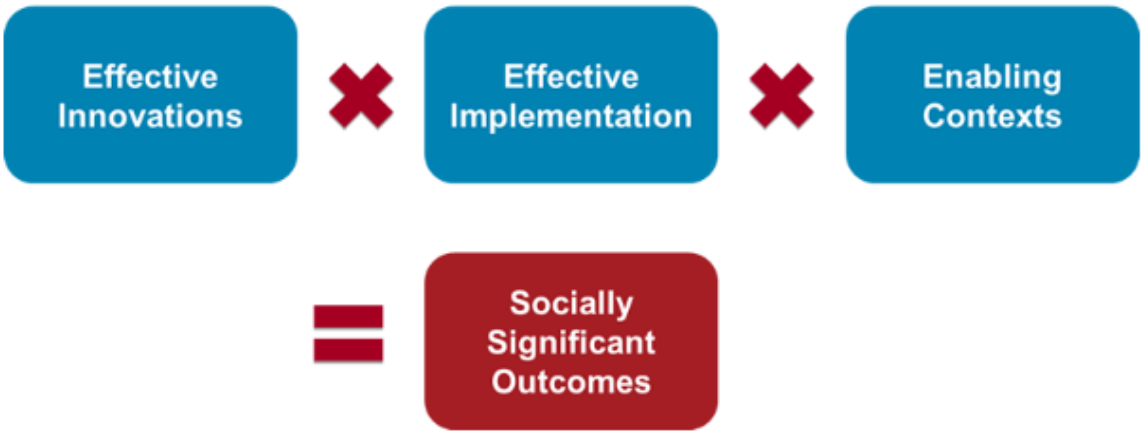

Figure 1. NIRN's formula for implementation success

Context and Historical Background

The idea of using evidence is part of a larger EBP-movement. Social work in the 21st century places high value and prestige on EBP. Indeed, the literatures describes EBP's impact in no feeble terms. Gambrill (2006) referred to EBP as social work's new practice paradigm. Maynard (2010) noted the growing acceptance and momentum of EBP calling attention to the growing body of evidence supporting programs and interventions. A decade after Gambrill, Okpych and Yu (2014) used some of the strongest language yet, "the evidence-based practice movement entered the profession of social work with all the force and fury of a major revolution" (p. 3). However, the profession has not always operated under this paradigm. Understanding the historical contexts behind these shifts and how EBP has evolved may help the profession react appropriately to the different contextual factors of the current state of EBP (Okpych & Yu, 2014).

Moral and authority based practice paradigms. Okpych and Yu (2014) identified three successive practice paradigms. They first classified early social work in the 1800s and early 1900s under a moral-based paradigm. Famous practice movements at this time included the settlement house movement and the charity organization movement. While different in their approaches and philosophies, a moral obligation to respond to urban poverty drove these early social workers to organize (Okpych & Yu, 2014).

The transition from a moral-based paradigm to an authority-based paradigm occurred in 1915. At that time, early social workers were attempting to define the clear function of social work and establish a knowledge base and methods of its own (Okpych & Yu, 2014). In a keynote speech delivered to the National Conference of Social Welfare in 1915, Abraham Flexner labeled social work a non-profession based on an assessment that it did not meet certain professionalization criteria including notably, a lack of its own specialized knowledge and methods. Because of this, the authority-based paradigm evolved and regarded valid practice as anything derived from experts, which ruled social work until the 1960s. Around that time, accountability demands and service competition increased, leading to a challenge to the authority-based paradigm to prove the methods of experts were effective for service recipients and opening the way for the third and current practice paradigm, the empirically-based paradigm (Gambrill, 2006; Okpych & Yu, 2014).

Empirically based practice paradigm. For the past few decades, social work has evolved under an empirically-based practice paradigm. Okpych and Yu (2014) highlighted two installments of an empirically-based practice paradigm. The first of these two installments, empirical clinical practice (ECP), was the predecessor to the present EBP movement between the 1970s and 1990s. Energized by a generation of scholars and doctoral students learning and

promoting empirical approaches to practice and the technological and methodological innovations of the time, ECP ascended around three core principles. First, the effectiveness of services and interventions should standardize practice over authority and expertise. Second, practitioners should actively use research tactics in their daily practice—i.e., searching the empirical literature for research-supported interventions and systematically evaluating the effectiveness of practices decisions. Third, the torrent of research generated by practitioners should be added to the work of researchers conducting large-scale evaluations to build a knowledge base for the profession (Okpych & Yu, 2014).

A number of key factors advanced ECP. In the late 1970s through the 1980s, social work scholars and researchers developed practice models to introduce and translate empirical findings into practice interventions, and practice textbooks began to incorporate findings from empirical studies (Okpych & Yu, 2014). Schools of social welfare also propelled ECP by integrating learning objectives into curricula, which developed students' skills in evaluating their own practices and linking coursework to practice by means of the field practicums. Finally, research programs expanded during the ECP movement with the establishment of the National Institute of Health's Social Work Research Development Centers, the Institute for the Advancement of Social Work and Research, and the Society for Social Work Research (Okpych & Yu, 2014).

The rise of EBP. Despite the promise of the ECP movement, practitioners' limited access to and uptake of empirical evidence and infrequent applications of evaluating their practice in the field led to its decline (Okpych & Yu, 2014). Witkin (1996) lamented, "the hoped for army of social work practitioner-researchers and their empirical knowledge base never materialized" (p. 70). Even with these problems, social work remained determined to establish an empirically-based practice paradigm giving rise to its second installment, the EBP movement.

Similar struggles to entrench EBP from other fields, especially evidenced-base medicine (EBM), influenced social work's attention to EBP (Drisko, 2014; Gambrill, 2006, Graybeal, 2014; Okpych & Yu, 2014). David Sackett is widely credited with the seminal writing and definition of EBM. He and his colleagues defined EBM as "the integration of best research evidence with clinical expertise and patient values" (Sackett, Straus, Richardson, Rosenberg, & Haynes, 2000, p. 1). Supporting EBM's momentum included the development of a five-step practice model aimed at guiding physicians' uptake and integration of research and evaluation in their practice and the establishment of clearinghouses such as the Cochrane Collaboration, which promoted the dissemination of evidence (Okpych & Yu, 2014).

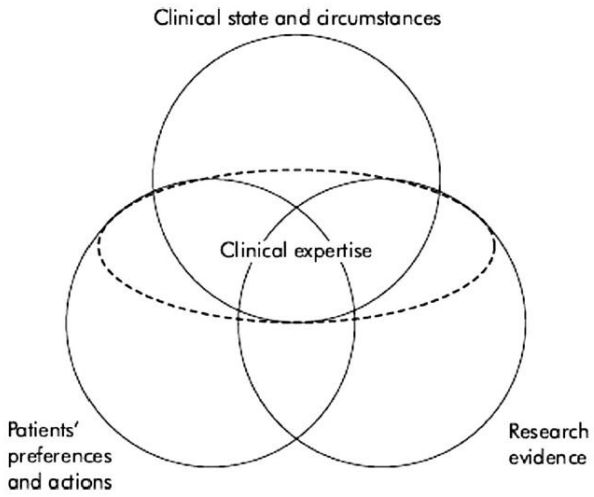

Figure 2. Evidence-based practice model from Haynes et al. (2002)

Haynes and colleagues (2002) built upon Sackett's original conceptualization of EBM/EBP by highlighting the evolving-process nature of EBP. Social work generally accepts and adopts this process approach to EBP (Drisko, 2014; Gambrill, 2006). Figure 2 contains these four parts, including: 1) the clinical state and circumstances of the client, 2) the best available evidence from the relevant research, 3) the client's personal preferences and values, and 4) the knowledge and expertise of the practitioner. Note from Figure 1 how the first three parts of the process are equally weighted and the fourth part's integration is implicit and necessary throughout. While social work scholars have adopted this view of EBP and its process, there is evidence to suggest this view is not pervasive amongst all educators and

practitioners regarding the exact distinctions between EBP, ESTs, and EBIs and understandings of levels of evidence and rigor (Okpych & Yu, 2014).

The EBP movement has gained traction similar to the rise of ECP and learning lessons from EBM. Like ECP and EBM, several initiatives have increased the research capacity and infrastructure to enhance the professional knowledge base. Organizations and institutions like the Campbell Collaboration, the Social Work Policy Institute, the Coalition for Evidence Based Policy, and the Evidence-Based Behavioral Practice emerged in the 2000s and 2010s to increase the reach and accessibility of EBP to social work (Drisko, 2014; Gambrill, 2006; Okpych & Yu, 2014). Schools of social welfare have advanced this paradigm by reforming curriculums to include EBP in practice courses, policy courses, and practicum fieldwork (Okpych & Yu, 2014).

There have been additional refinements during the EBP installment of the empirical paradigm, which offer benefits beyond the pitfalls of the first installment. For starters, the involvement and engagement of social work scholars with direct practitioners and the organizations providing services may provide one opportunity for partnerships that bridge the gap between evidence, knowledge, and practice (Bellamy, Bledsoe, Mullen, Fang, & Manuel, 2008; Okypych & Yu, 2014). Another significant boost to the EBP movement includes the advancement of implementation research and diffusion research in the past couple decades. While there is a diverse range of disciplines and models related to dissemination and implementation research, these lines of inquiry are generally concerned with the translation, uptake, and adoption of research and knowledge in practice (Bhattacharyya, Reeves, & Zwarenstein, 2009; Powell et al., 2015; Tabak, Khoong, Chambers, & Brownson, 2015). Okpych and Yu (2014) reviewed research aimed at helping direct practitioners bridge this gap including studies involving improving data management systems and fostering cultures of EBP.

Hierarchy of evidence. To support practitioners in their efforts to evaluate the quality of existing evidence, proponents of EBP have developed "levels" or "hierarchies of evidence" to rank evidence based on the quality of study design, methodology, and applicability. Table 1 reflects the hierarchy of evidence. While there are many variations on the hierarchy, the top levels of these hierarchies often include evidence from systematic reviews and meta-analyses of randomized control trials (RCTs) and combinations of RCTs. Middle levels include evidence from less rigorous studies (e.g., quasi-experimental studies and well-designed case-controlled studies), and the lowest levels include evidence from single case studies, qualitative studies, and expert opinion (Ackley, Swan, Ladwig, & Tucker, 2007; Soydan & Palinkas, 2014).

Table 1

Levels of evidence adapted from Ackley et al., 2007 and Soydan & Palinkas, 2014

Level	**Description**
Level I	Evidence from a systematic review or meta-analysis of all relevant RCTor evidence-based clinical practice guidelines based on systematic reviews of RCTs or three or more RCTs of good quality that have similar results.
Level II	Evidence obtained from at least one well-designed RCT
Level III	Evidence obtained from well-designed controlled trials without randomization (i.e. quasi-experimental).
Level IV	Evidence from well-designed case-control or cohort studies.
Level V	Evidence from cross-section surveys or systematic reviews of descriptive and qualitative studies (meta-synthesis).
Level VI	Evidence from a single descriptive or qualitative study.
Level VII	Evidence from the opinion of authorities and/or reports of expert committees.
Level VIII	Evidence from anecdotes

Criticisms of the EBP Movement. Amidst the movement to install EBP have been a number of criticisms. Webb (2001) argued the planned and systematic decision-making processes and assumptions underlying an EBP practice model might not be realistic for social

workers who opt instead to use less deterministic and reflexive heuristics for practice decisions. Building upon this point is the concern from direct practitioners that EBP may undermine the value of the therapeutic relationship of client and worker and downplay the importance of practitioner wisdom (Borntrager, Chorpita, Higa-McMillan, & Weisz, 2009). Interestingly, other criticisms have surfaced calling out the EBP movement for claiming ethical and evidentiary high grounds without having enough rigorous research or a complete knowledge base to demonstrate superior outcomes and generalize their applicability (Okpych & Yu, 2014). The need for appropriate cultural adaptations of ESTs and EBIs is a common criticism as well, and social workers should consider this challenge prior to recommending particular treatments to particular clients (Marsiglia & Booth, 2015). Moreover, the use of evidence related terms in the literature might contribute to confusion around what constitutes evidence. Demonstrating this point, Petticrew and Roberts (2003) noted, "it is not uncommon for discussion papers to use the terms 'evidence,' 'evidence-based,' and 'hierarchies of evidence,' while avoiding any discussion what sort of evidence they are advocating (or rejecting)" (p. 528). Strict adherence to the top levels of the hierarchy of evidence for evaluating evidence is often times problematic for social work interventions (Petticrew & Roberts, 2003). In light of these criticisms, it seems reasonable to understand how and why few practitioners routinely practice EBP (Bellamy, Bledsoe, & Traube, 2006).

Policy Impacts on the Uptake of Evidence

Much has been said about social work and the installation of an empirically-based paradigm, but at this point, the discussion focused on professional and philosophical pressures to legitimize social work's knowledge base. There are also a number of policy and funding decisions starting in the 1980s and extending through recent initiatives under President Obama's

administration that contributed to the shift toward EBP. As one example, the Family Support Act of 1988 (section 487(a)(2) of the Social Security Act) changed Aid to Families with Dependent Children (AFDC) to a welfare-to-work program model. It set clear requirements for federal agencies to recommend and set performance standards to Congress on the basis of effectiveness and impact rather than outputs and processes (Gueron & Rolston, 2013):

> Recommendations shall be made with respect to specific measurements of outcomes and be based on the degree of success which might reasonably be expected of States in helping individuals to increase earnings, achieve self-sufficiency, and reduce welfare dependency, and shall not be measured solely by levels of activity or participation. (Section 487(a)(2) of Social Security Act as cited in Gueron & Rolston, 2013, p. 346)

Around the same time as the transition between ECP and EBP movements, the federal government enacted the Government Performance and Results Act of 1993 requiring federal grantees to measure and report precise values on performance targets (Hatry, 1997; Okpych & Yu 2014). This particular legislation had a large influence on how federally funded anti-poverty organizations (i.e., community action agencies) developed their approach to outcomes management and results (Pope, Prassas, & Cunningham, 2000). These legislations demonstrate the federal government's desires for more accountability and outcomes-focused social welfare policies. As a result, grantees began engaging in efforts around planning for performance including goal setting, strategic planning, and data collection (Okpych & Yu, 2014).

Federal investments in evidence-based home visiting. The accumulation of evidence produced to advance social programs has led policymakers to uptake evidence as a means to improve and garner support for policies they develop (Haskins, 2018). President Obama's Administration invested heavily in promoting six major social initiatives based on rigorous

evidence and proven effectiveness (Haskins & Margolis, 2014). These initiatives incorporate a number of social welfare domains including early childhood home visiting, teen pregnancy prevention, employment, and education and training. For early childhood programming in particular, the federal initiative known as the Maternal Infant and Early Childhood Home Visiting Program (MIECHV) generated significant discourse around the uptake of rigorous evidence, the implementation of EBP, and the use of data in federally funded early childhood programming. As part of the Patient Protection and Affordable Care Act (ACA), the federal government invested heavily into EBHV across the country. Along with these investments came federal mandates to expand early childhood programming to communities and target populations experiencing significant risk, to demonstrate performance improvement and accountability through data collection efforts in six benchmark areas, and to spend at least 75% of federal investments directly on evidence-based models meeting DHHS' criteria mentioned earlier (Barton, 2016). This sparked debates around the levels of evidence and what constitutes a program or intervention as "evidence-based". It also inspired and encouraged the continued evaluation and understanding of social programs and provoked innovative collaboration and coalition-building among service providers, program model developers, and advocates (Barton, 2016; Haskins & Margolis, 2014).

Emerging funding trends. One final policy impact of note pertains to emerging funding trends of government agencies as well philanthropic foundations aimed at holding social programs, organizations, and providers accountable for their effectiveness. Performance-based contracts have become a popular mechanism for ensuring program accountability and anticipated to become norm for human services (Hannah, Ray, Wandersman, & Chien, 2010; Martin, 2007). Performance-based contracts stipulate that service contractors provide evidence of program

impact and service utilization in order to receive payment for their work. If this is to become the norm, it is critical that human service organizations have sufficient staff knowledge, accountability practices, and outcome measures to meet the demands of performance-based contracts (Hannah et al., 2010). Similarly, the emergence of social impact bonds (SIBs), also known as "pay for success," has picked up momentum as a funding trend in human services (Coulton et al., 2015). Pay for Success models also attract bipartisan attention from prominent policymakers supporting current evidence-based policy movements (Haskins, 2018). As with the performance-based contracting model, SIBs direct focus on outcomes and tying payments to outcome delivery; however, SIBs take even further steps. SIBs build in expectations that outcomes will produce a cost savings to the government or society as well as positive individual improvements (Stoesz, 2014). The assumed potential of SIBs is that they will open partnerships between the social sector and the philanthropic interests of the business sector all with the goal of improving social problems, providing a return on investment, and saving the government money (Coulton et al., 2015). Sadly, social work may be ill prepared for such a trend. Success within these trends requires large volumes of data and empirical evidence. Stoesz (2014) pointed out, "Absent empirical evidence to support its interventions, funding for social workers will be diverted away from traditional social services toward programs that have demonstrated efficacy through strategies such as SIBs" (p. 184).

Summary

Overall, the uptake of evidence is critical in current practice and policymaking contexts. Social programs that use their information to support decision-making may be better prepared to adapt to a multiplicity of demands including calls for accountability, demonstrating their impact, and ensuring they are preserving the core mission of our profession. Unfortunately, some

significant social programs including those that support vulnerable children and families during early childhood may not have the necessary capacities and understanding to use evidence, information, and data effectively. This study aims to promote an understanding of organizational readiness to use data to support decision-making.

Chapter II
Literature Review

Introduction

Certainly, the EBP movement brought the need for uptake of evidence and data in practice and policy making to the forefront of human service delivery. A growing body of theoretical and empirical literature emerged in the previous two decades in relation to implementation science, EBP, and translating research and evidence into practice. Among this literature are theoretical frameworks that attempt to explain how human service organizations mobilize knowledge and use evidence to inform, implement, and improve social work practice, policy, and decision-making and a number empirical studies applying these frameworks, exploring the uptake of evidence, and implementing EBPs.

Despite all this, human service organizations may not integrate continuous streams of data into practice to support decision-making (Coultan et al., 2015). As such, this study aims to understand the readiness of human services organizations delivering evidence-based early childhood programs. Chapter I articulated the problem, described the current study, and established the relevance of the study within professional and policy contexts. The aims of Chapter II are two-fold. First, the chapter will provide a discussion of *NIRN's Active Implementation Drivers Framework* as the guiding theoretical framework for this study and the framework's connection to the problem. Second, the chapter includes a review of key studies applying this framework to implementations of EBPs in child and families programs and studies focused on the use of data to support decision-making.

Implementation Science and Active Implementation Frameworks

Implementation science is a line of inquiry particularly interested in how innovations, research, and evidence are systematically translated and integrated into routine practice (Eccles

& Mittman, 2006). Social work scholars, increasingly concerned with limited field use of research-supported interventions and treatments, promote implementation science as a vehicle to transfer science-to-service and translate research-to-practice (Fixsen, Blase, Naoom, & Wallace, 2009; Metz & Bartley, 2012). Given the complexity of this line of inquiry, a remarkable number of theoretical models and conceptual frameworks emerged over time to support and enhance inquiry in this field of study (Moullin, Sabater-Hernandez, Fernandez-Llimos, & Benrimoj, 2015; Nilsen, 2015; Tabak et al., 2012). NIRN developed the *Active Implementation Frameworks* (*AIFs*) to guide the study of factors influencing practice uptake of innovations (NIRN, n.d.). Individual factors may be present in multiple frameworks and can act independently or in conjunction with other factors in their influence. As such, all factors are subject to empirical and practical study (NIRN, n.d.). Metz and Albers (2014) acknowledged the professional and political aspirations demanding the implementation of EBPs and improved outcomes and the struggles organizations experience in their endeavors to meet this demand. They suggested federal funders should support the implementation of EBPs, and two AIFs (i.e., the *AIF Stages* and *AIF Drivers*) are at the heart of their recommendations (Metz & Albers, 2014).

The current study relies heavily on the *AIF Drivers*. The next section provides a rationale for selecting the *AIF Drivers* to guide this study. Following this rationale is an in depth description of the *AIF Drivers* and a discussion of data use within the context of the framework.

Rationale for Using the Active Implementation Drivers Framework

Over the past two decades, a multitude of frameworks, conceptual models, and theories have emerged to guide the implementation of innovations and the study of implementation. Recent studies from Moullin and colleagues (2015) and Nilsen (2015) aimed at helping

researchers make sense of the various implementation frameworks reviewed 49 and 39 different frameworks respectively. Acknowledging the breadth of existing frameworks for implementation science, it is germane to justify why the *AIF Drivers* guides the study.

When deciding between implementation frameworks, Nilsen (2015) recommends narrowing them down and choosing one based on the overarching aim of the framework. Conceptually, determinant frameworks aim to understand what factors influence implementation outcome. Nilsen (2015) specifically cited *AIFs* as examples of determinant frameworks. The general assumption of the *AIF Drivers* that core factors lead to successful implementation outcomes is a logical framework to guide the study, which aims to understand how the implementation drivers influence organizational readiness for DDDM. Furthermore, because this study involves the development of a new scale, the nine implementation drivers will serve as the core themes and concepts guiding item and scale development.

While the *AIF Drivers* makes theoretical sense, it also has a direct practical link to the content area of this study. Metz and Albers (2012) pointed out that, despite improvements to development of evidence-based early childhood programs for children and families, little evidence related to successful implementation of these programs has emerged resulting in a gap between research and practice. To this end, the authors recommended using science-based implementation frameworks to guide implementation and change efforts in organizations delivering evidence-based treatments, interventions, and program models (Metz & Albers, 2012). They specifically address the *AIF Drivers* as a promising framework for determining how drivers present in early childhood programs improve infrastructure, drive the selection of program strategies, and ultimately, lead to improve outcomes for children (Metz & Albers, 2012).

Active Implementation Drivers Framework

The ultimate purpose of implementation is an increased understanding of what influences and drives the effective use of innovations in practice (NIRN, n.d.). For results, programs must intentionally install certain components that facilitate implementation and enable success. These components, referred to here as *implementation drivers*, hone in on core structures and activities that successful implementation and innovation efforts have in common (Fixsen et al., 2005; Fixsen et al., 2009). Implementation drivers interact, and when integrated purposefully, support uptake, fidelity, and sustainability of practices and active as the engine of change (Metz & Bartley, 2012; NIRN, n.d.). Furthermore, drivers compensate for one another as the strengths of a program in one driver can overcome the weaknesses of a program in another driver (Fixsen et al., 2005; Fixsen et al., 2009).

Developers identified nine distinct implementation drivers classified under construct-level categories: *Competency Drivers*, *Organizational Drivers*, and *Leadership Drivers* (Fixsen et al., 2009; Metz & Bartley, 2012; NIRN, n.d.). The importance of effective data use to drive decisions is widespread across implementation drivers. In support of this claim, several of the best practices for assessing implementation drivers in practice identified by Fixsen, Blasé, Naoom, and Duda (2015) involve the collection, assessment, and use of data to inform decision-making, support practice and implementation processes, and

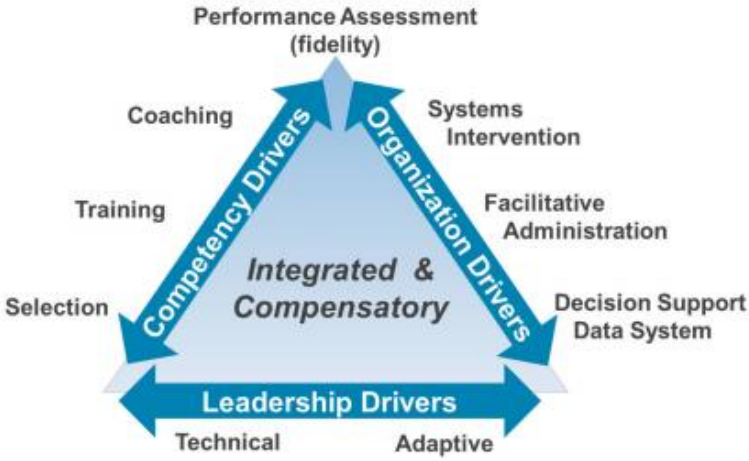

Figure 3. Active Implementation Drivers from Fixsen, et al., 2015.

focus staff and teams around desired outcomes. Figure 3 provides a visual representation of the nine implementation drivers within these three construct-level categories. The remaining discussion surrounding these drivers is organized by the three classification categories. It includes an overview of each driver and the importance of data for each driver.

Competency drivers. *Competency Drivers* include four processes that identify and build the capacity of program staff. First, the process of *staff selection* involves specifying the staff competencies needed to implement the program model or innovation's requirements (Fixsen et al., 2009; Metz & Bartley, 2012; NIRN, n.d.). Methods for recruiting, interviewing, and selecting candidates are key to the *staff selection* driver as well (Metz & Bartley, 2012). The second process involves the *training* of selected staff. Effective training occurs preservice and imparts staff with an understanding of "when, where, how, and with whom to use new approaches and skills" (Fixsen et al., 2009, p. 534). *Training* should include information on theory and underlying values and provide rationales for chosen approaches and practices. *Training* should also offer staff a safe space to practice new approaches and receive feedback (Fixsen et al., 2009; Metz & Bartley, 2012). The third *Competency Driver* process, *coaching and supervision*, acknowledges that most skills introduced in training are developed and mastered on the job with a coach. Coaches identify opportunities for improvement, provide guidance, and encourage quality practice (Fixsen et al., 2009). Coaching plans should spell out critical details regarding why, how, and what and incorporate multiple sources of data both empirical and observation to ensure continuous quality improvement and fidelity (Metz & Bartley, 2012). *Performance assessment* is the final *Competency Driver* in which transparent evaluations determine how well *staff selection*, *training*, and *coaching* performed and how well staff follow program requirements, demonstrate use of necessary skills, and achieve desired

outcomes (Fixsen et al., 2009; Metz & Bartley, 2012). Like coaching, performance evaluations should rely on multiple sources of data to identify opportunities for improvement (Metz and Bartley, 2012).

Competency drivers and data use. Organizations should make use of data across all *Competency Drivers* to ensure continuous improvements in *staff selection, training, coaching*, and *performance assessment* processes (Fixsen et al, 2015). For example, during training processes where new and existing staff are learning how to implement evidence-based interventions or innovations, the authors recommend collecting pre and posttest results of knowledge and skill. Training pre/post results provide more immediate feedback and decision support throughout other *Competency Driver* processes. As a feedback mechanism, organizations can use these data to inform how well they assess the potential of new staff during recruitment and selection processes. As a "feed-forward" mechanism, coaches should utilize training data as a guide to focus on areas of strengths and needs for developing staff (Fixsen et al., 2015). Longer term, performance assessment data are needed to understand the progress staff and organizations make toward outcomes and provide feedback on the distal effects of their *staff selection, training*, and *coaching* processes (Fixsen et al., 2015).

Organizational drivers. The organization, through *Organizational Drivers*, plays a key role in creating a welcoming environment for implementation and innovation (Metz & Bartley, 2012; NIRN, n.d.). When established intentionally, *Organizational Drivers* provide the backbone support for the *Competency Drivers*. Developers have identified three *Organizational Drivers: decision-support data systems, facilitative administration,* and *systems intervention* (Fixsen et al., 2005; Fixsen et al., 2009; Metz & Bartley, 2012; NIRN, n.d.).

Decision-support data systems contain key information that practitioners, supervisors, and administrators leverage to inform decisions (NIRN, n.d.). These systems should include multiple types of data to measure quality assurance, fidelity, and outcomes. To maximize its impact, program staff need to build data built into practice routinely and translate data into user-friendly reports that inspire action (Fixsen et al., 2009; Metz & Bartley, 2012). *Facilitative administration* drives implementation and innovation efforts at the administrative level. While it is practitioners' responsibility to provide interventions directly with clients, it takes committed administrators modeling the use of data to support decision-making and preserving staff focus on desired outcomes to ensure successful implementation. To support uptake of a new program model or innovation, effective administrators also reduce barriers, realign policies, and recognize opportunities to improve staff skills (Fixsen et al., 2009; Metz & Bartley, 2012). Because implementation occurs within a larger social-political context, the last of the *Organizational Drivers*, *systems intervention*, focuses on strategies to cope with or leverage external systems and ensure the availability of sufficient financial, human and organizational resources to sustain implementation (Fixsen et al., 2009; Metz & Bartley, 2012; NIRN, n.d.).

Organizational drivers and data use. Making use of data is a matter of central importance for *Organizational Drivers* because these drivers provide the structural requirements needed for leaders, administrators, and practitioners to use data and make informed decisions (Fixsen et al., 2015). Effective data use depends on the extent to which the *decision support data systems* include data and measures related to intermediate and long-term outcomes and performance assessment and fidelity data on practitioners as well as how accessible these data are to the people who need to use them (e.g., practitioners, coaches, supervisors, administrators) (Fixsen et al., 2015). A number of other factors including the reliability, frequency, and

distribution of data also influence the effective use of data for decision-making. Because of this, Fixsen and colleagues (2015) acknowledge the importance of the *facilitative administration* driver as a key driver to successful implementation. As such, facilitative administrators model and, in some cases, champion the use of data within organizations when through identifying opportunities to improve implementation processes and support practitioners (Fixsen et al., 2015).

In addition to using data to improve the organization internally, the *systems intervention* driver demonstrates the importance of organizations making use of data to work with systems outside the organization. Organizational leaders and staff must find ways to ensure sustainability of their services when external financial or political forces pose potential barriers or threats (Fixsen et al., 2015). As discussed in Chapter I, organizations that can demonstrate their impact through effective data use and evidence may be better prepared to face these challenges (Coultan et la., 2015; Stoesz, 2014).

Leadership drivers. *Leadership Drivers* represent the final core components needed to drive implementation of evidence-based program models, new interventions, and innovation. Competent leaders must drive implementation in both technical and adaptive realms (Fixsen, Blasé, Metz, & Van Dyke, 2013; NIRN, n.d.). NIRN (n.d.) likens *technical leadership* to good management wherein leaders engage quickly to issues and identify solutions because consensus exists around the solution's ability to achieve the desired result. When issues are more complex and solutions are less certain, *adaptive leadership* is needed. Adaptive leaders mobilize teams to uncover underlying problems, build consensus around how to approach solutions, and monitor progress (NIRN, n.d.). Given the multitude of complex drivers, stages, and external forces associated with implementation and innovation, leaders often find themselves in the realm of

adaptive problems and should take care not to jump to a *technical leadership* approach with issues that require *adaptive leadership*.

Leadership drivers and data use. Similar to the critical role leaders play in organizational efforts to implement innovations, programs, and change (Fixsen et al., 2015), leaders may have a strong influence on the use of data to support decision-making in organizations. While most of the best practices described in the *Competency Drivers* and *Organizational Drivers* focused on what processes and structures are needed for successful implementation, the best practices Fixsen and colleagues (2015) distinguished for *Leadership Drivers* focus heavily on who is needed during these processes to lead change efforts, develop champions, and support decisions. Furthermore, because organizational leaders actively engage in hiring, training, and performance assessment, they have a large impact on processes related *Competency Driver*. From a technical perspective, leaders provide rationale for policy, procedure, and staffing decisions. From an adaptive perspective, leaders seek feedback from multiple sources to assess organization effectiveness and inform decision-making as well as open communication lines with practitioners to understand successes and concerns (Fixsen et al., 2015). Combining *Leadership Drivers* with best practices of *Competency* and *Organizational Drivers*, it is reasonable to conceive how leaders must make use of data throughout implementation.

Application of AIFs in Child and Family Services

The importance of using implementation frameworks to understand successful implementation of innovations and EBPs has become increasingly apparent in social services and particularly for services to children and families. A recent scoping review of literature from Albers, Mildon, Lyon, and Shlonsky (2017) found the application of implementation frameworks

across a variety of child, youth, and family service areas including family and parenting support, child welfare, foster care, juvenile justice, family violence, and community-based programs. Their study identified 33 studies applying eight different implementation science frameworks, and *AIFs* were the most commonly applied framework of the eight. Of the 33 studies identified in this review of the literature, nine studies examined the application and testing of *AIF Drivers* in child and family services and what evidence these studies produced informing the current state of the field (Albers et al., 2017). The following discussion of this literature organizes the studies into three categories: 1) case studies using *AIF Drivers* to guide implementation of EBP, 2) program evaluations informed by *AIF Drivers*, and 3) measurement validation studies informed by *AIF Drivers*.

AIF Drivers for organizational implementation of EBPs. Eight studies using single case study designs described the experiences and insights of organizational change efforts utilizing the *AIFs* as a model for implementing EBPs in child and family service initiatives. The service areas of these initiatives include domains of interest to social work including child and youth behavioral healthcare (Barwick, Kimber, & Fearing, 2011; Fearing, Barwick, & Kimber, 2014; Graff, Springer, Bitar, Gee, & Arredondo, 2010; Kimber, Barwick, & Fearing, 2012) and child welfare (McCrae, Scannapieco, Leake, Potter, & Menefee, 2014; Metz et al., 2015; Salverson et al., 2015).

Child behavioral healthcare applications. Over the course of four years, a large child and youth behavioral healthcare organization made intentional efforts to install ESTs and EBIs in its clinical practices with children. However, recognizing the complex contexts in which these practices take hold, the organization used *AIF* as a model for planning, structuring, and implementing this change effort (Barwick et al, 2011). Three studies resulted from this

implementation effort. All three revealed findings that *AIFs* provide a viable and effective guide for scaling EBPs in real-world contexts (Barwick et al., 2011; Fearing et al., 2014; Kimber et al., 2012).

The first study's methodological approach mixed a number of methods including observation and audio-recordings of group meetings around the change effort, interviews of staff at randomly selected settings within the organization, annual questionnaires of staff, and goal and milestone tracking (Barwick et al., 2011). The study sample consisted of 22 staff involved in implementation of the change effort. Decision-making authority across the staff participants varied as 14 staff were direct service providers and six staff held managerial roles. Barwick and colleagues (2011) identified several important themes relevant to the context of this study. First, during the selection period where staff were determining which ESTs and EBIs to consider, staff work groups took a holistic EBP approach to ensure that organizational data on its current clients' needs and characteristics were given consideration in addition to research evidence. Second, staff addressed competency drivers such as staff recruitment, selection, and training to ensure the proper alignment between human resources and the selected ESTs and EBIs. Third, staff acknowledged the transformation as complex and potentially overwhelming. To counter this, staff addressed another implementation driver—*Leadership*—as critically important. Staff suggested that a participatory leadership model where multiple voices provide input could help develop distribute understanding and open transparency in decision-making (Barwick et al., 2011). Relevant to this study, Barwick and colleagues (2011) provided commentary on the lack of guidance and parameters for decision-making processes within *AIFs*.

The second study examined staff perceptions of the implementation of these ESTs and EBIs in the child behavioral healthcare organization (Kimber et al., 2012). In addition to annual

questionnaires sent to all of the organization's staff across four years, 13 randomly selected staff including six front-line service providers, five managers, and two administrators participated for individual qualitative interviews. The findings of this study provided evidence for the utility of *AIF* to plan and implement more EBPs, as well as demonstrated improvements of staff perspectives and knowledge of EBP and their willingness to accept change efforts when implementation drivers are specified to the context of the organization (Kimber et al., 2012). While staff understanding of EBP grew from 57% in 2007 to 77% in 2009, the change effort realized far less gain in staff understanding of the organizational transformation underway. The authors suggested the tendency of staff to focus on the EBPs being installed versus the larger vision of should be a consideration of other organizations implementing similar changes. Essential to this is the driving role of leadership. Staff reported appreciation for opportunities to lead supporting the participatory leadership approach described in the first study (Barwick et al., 2011; Kimber et al., 2012).

The third study focused on manager insights of this change effort (Fearing et al., 2014). Similar to the first and second studies, the findings revealed support for using *AIFs* to implement ESTs and EBIs in real organizational settings. Fearing and colleagues (2014) highlighted the numerous implementation driver roles managers fulfill as hirers, trainers, coaches, and performance evaluators, as well their roles as technical leaders and facilitative administrators. Furthermore, managers assume unique positions balancing these roles with the aspirational transformation of the organization, existing workloads, and resource capacity issues that may hinder effective implementation (Fearing et al., 2014).

A separate study from Graff and colleagues (2010) provided lessons learned from a case study of using *AIF Drivers* to plan and implement a protocol to deliver evidence-based

adolescent behavioral health screenings, assessments, and interventions in five primary care sites. The study uniquely examined the perspective of purveyors who Fixsen and colleagues (2005) describe as a team actively dedicated to the work required to install and implement evidence-based programs, ESTs, or EBIs with fidelity to their intended effect. In Graff and colleagues' (2010) study, the purveyors used the *AIF Drivers* as a guiding framework for assessing the feasibility of installing EBPs at select sites. Ultimately, the researchers concluded that the framework was "invaluable in meeting the challenges of implementing evidence-based practices in a diversity of primary care settings" (Graff et al., 2010, p. 366). In a two-year follow up of the five sites, four sites reported continued provision of the evidence-based programming with each site citing the purveyors' implementation process as a major contributing factor to facilitate program uptake (Graff et al., 2010). In a nod to the importance of data use, the researchers credited the purveyors' regular use of training, coaching, and program evaluation data in formal meetings as an effective mechanism for consensus-building around decision-making (Graff et al., 2010).

Child welfare applications. A descriptive case study from Metz, Bartley, and colleagues (2015) illustrates how *AIF Drivers* facilitated implementation of ESTs and research-informed practices in a county child welfare department's effort to promote child wellbeing. Specifically, the study examined how technical assistance providers (i.e., NIRN) assembled and built capacity in an implementation team charged with driving best practices, installing implementation drivers, and assessing fidelity. The data from these assessments showed that strengthening capacity and competency in *AIF Drivers* is associated with improvements in fidelity to ESTs (Metz et al., 2015). In a similar nod to the importance of using data as described earlier, the authors of this

study commented on the implementation team's intentional and continually use of data to strengthen implementation drivers and drive decision making (Metz et al., 2015).

In a mixed methods study, McCrae and colleagues (2014) examined the extent of staff buy-in for the implementation of a statewide practice model in child welfare and the relationship between buy-in and staff characteristics as well the relationship between local agency readiness and implementation progress. The study mixed methods combining a quantitative survey of 568 child welfare staff across 13 local child welfare agencies with qualitative focus groups and interviews of 52 staff from four randomly selected agencies. Quantitative results at the staff level revealed buy-in was higher among males and staff with 16 years or more of experience (McCrae et al., 2014). At the organizational level, implementation progress was higher for agencies experiencing lower job stress and smaller agencies (McCrae et al., 2014). Qualitative themes for buy-in converged around including staff in intervention design, decisions, and transparent communication. To address these job stress and inclusivity themes and bolster implementation, the authors reflected on the importance of *staff selection*, *coaching*, and *facilitative administration* drivers (McCrae et al., 2014).

These two studies provide insights to the utility of *AIF Drivers* for county and state levels. Salverson, Bromfield and colleagues' (2015) retrospective study of implementing an evidenced-supported casework model for child protection in Western Australia provides an international perspective for applying *AIF Drivers*. Researchers conducted semi-structured interviews of 27 staff and practitioners in the child welfare department to understand the key themes and experiences of participants related to systematic implementation of the *Signs of Safety* framework approach to child protection casework. Rather than using the *AIF Drivers* as a guiding framework for installing the casework model, the researchers in this study used the

implementation drivers as a heuristic to structure the themes emerging from their interviews (Albers et al., 2017). Salverson, Bromfiled and colleagues (2017) address themes emerging from the interviews in terms of the implementation drivers that both facilitated and hindered program uptake. Facilitators included *Organizational* and *Leadership Drivers*. Barriers involved the general lack of knowledge around how to navigate complicated *decision support data systems* (Salverson et al., 2017). While not calling into question the appropriateness of implementation efforts in some areas, participants also warned about the challenges presented in rural districts and aboriginal communities to implementing ESTs including the need for culturally appropriate adaptations and understanding that implementation uptake takes longer in because of a general lack of human, organizational, and leadership resources (Salverson et al., 2017).

AIF Drivers for program evaluation. There is also evidence to indicate *AIF Drivers* are useful for program evaluation and revision (Albers et al., 2017; Bertram et al., 2014). A participatory program evaluation involving families, mental health professionals, and an evaluation team of Houston's *System of Hope* (a wraparound initiative of Substance Abuse and Mental Health Services Administration [SAMHSA] Children's Mental Health Systems of Care) revealed confusion among partners regarding the wraparound model's definition, theory of change, and implementation (Bertram et al., 2014). As such, partners committed to improving wraparound provision using the *AIF Drivers* as a theory-guided approach and focusing lens to revise and repurpose infrastructures to support hiring practices, fidelity to the wraparound model, and data usage in practice and supervision. Within 18 months, a number of compelling positive impacts surfaced. Staff skill and knowledge development improved; staff delivered services in more efficient manners; adherence to model fidelity scores raised above national averages; and population level outcomes improved (Bertram et al., 2014). This repurposing resulted in culture

change over time despite initial skepticism of staff implementing the revisions (Bertram et al., 2014).

AIF Drivers for measurement validation. The literature review revealed one study where *AIF Drivers* were used to inform measurement and instrument development. Ogden and colleagues (2012) pilot tested and sought to validate the psychometric qualities of *Implementation Components Questionnaire* (*ICQ*), a questionnaire with scales and items developed specifically to each of the implementation drivers. Study participants totaled 218 individuals consisting of 149 therapists trained in one of two ESTs, 45 supervisors, and 24 agency leaders. The survey was administered as a cross-sectional study ten years after the initial implementation of one of two ESTs to ensure their sustainability. The two ESTs included the Parent Management Training Oregon Model (PMTO) and Multisystemic Therapy (MST). The researchers analyzed the underlying factor structure, tested the reliability of scale scores, and measured their associations with implementation outcome variables. All their analyses on measures of internal consistency, factor analyses, and group comparisons resulted in evidence supporting the questionnaire's psychometric qualities, including moderate and consistent associations between implementation component scores and expected implementation outcomes (Ogden et al., 2012).

Another noteworthy group of findings from this study is the cross group differences it found. When comparing groups based on their role, therapists scored statistically lower on *decision support data system* and *leadership* scores than their supervisors and agency leaders. Therapists also differed from their supervisors when it came to subscales related to recruitment and *staff selection, training, coaching and supervision*, *facilitative administration*, and *systems interventions* (Ogden et al., 2012). When comparing groups based on which EST they

implemented, the total ICQ scores were statistically different between PMTO and MST participants with MST scoring higher in general (Ogden et al., 2012).

Data Use to Enhance Other Drivers, Performance Assessment, and Outcome Promotion

Kaye, DePanfilis, Bright, and Fisher (2012) sought to understand the challenges and opportunities of changing child welfare systems through applying the *AIF Drivers*. They searched electronic databases using implementation drivers as key words and provided examples of how child welfare agencies utilized the drivers for system change. Studies they identified were mostly retrospective looking at the challenges and successes to implementation rather than systematically testing implementation drivers (Kaye et al., 2012). Despite a lack of studies testing drivers systematically, the literature the authors identified provided support for the core *Leadership, Organizational,* and *Competency Drivers* identified in the *AIF Drivers*.

Of particular interest to this paper is how Kaye and colleagues used the *decision support data system* driver as an example to identify challenges and strategies. Because this driver integrates with *leadership, performance assessment,* and *facilitative administration*, the main challenge is how to develop effective *decision support data systems*, which facilitate the work of all these areas. The system must enhance *staff selection, training*, and *coaching* of direct practitioners while also informing practice and policy decisions of leaders (Kaye et al., 2012). Common strategies Kaye and colleagues (2012) identified included preparing and developing staff to become better consumers and users of data, integrating informatics specialties into social work education, and using computer and mobile technologies to aid practice in real-time. These strategies are similar to suggestions from Webster and colleagues (2011) recommendations of changing workers' mindsets to make them "data fans" (p. 6) and preparing the next generation of child welfare workers with more skills in data use.

There are at least two cross-sectional studies, which empirically tested the *Competency* and *Organizational Drivers* in terms of using data for performance assessment and outcomes promotion in child welfare agencies (Collins-Camargo et al., 2011; Collins-Camargo & Garstka, 2014). Part of a larger survey to assess barriers and strategies of recruiting and retaining foster families, the first study explored frontline child welfare worker views of evidence-informed practice, the extent that work activities focus on evidence, and the extent to which organizational and data supports make evidence uptake possible (Collins-Camargo et al., 2011). In terms of team and work unit use of data, the vast majority of participants claimed their teams understood the outcomes used to evaluate their performance (77.8%) and believed their teams had common understandings on how they were performing (77.9%). Conversely, only 17.8% agreed that their agencies collected the adequate data to understand the impact of their work on permanency outcomes, and only a quarter of (27.5%) agreed they had access to such data (Collins-Camargo et al., 2011). Almost a third of respondents said they did not routinely use information to examine outcome achievement and only a quarter reported coming together to evaluate work as a team. When asked to rate their own skills regarding data use, workers rate their skills relatively low as slightly more than a third (37%) rated themselves as having a high level of skill. Encouragingly, the data suggests the integration of more evidence to inform their work as 40 percent believed evidenced-informed practices were not practiced enough (Collins-Camargo et al., 2011). Furthermore, the study provides empirical insight into the compensatory qualities of the implementation drivers as the influence of agency supports on the promotion of worker skills and using data in practice activities tended to be stronger than the influence of their perception of their own skill (Collins-Camargo et al., 2011). The study, however, lacked the data needed to

describe precisely which agency supports, data processes, and infrastructures influenced respondents' work.

The study also examined differences between public and private child welfare agencies. The results found statistically significant differences between public child welfare staff and private agency staff with private staff reporting higher levels of data understanding, access, and team and organizational activities infusing data to inform practice (Collins-Camargo et al., 2011). Collins-Camargo et al (2011) suggested factors such as higher percentages of private staff having graduate degrees, bureaucratic forces in public agencies limiting innovation, and competition for performance-based contracts amongst private agencies. Private agency staff also tended to rate all types of evidence-informed activities (e.g., peer record and supervisory reviews, outcomes management, and program evaluation) as effective means for improving practices as compared to public agency staff who had more ineffectual views of these activities.

In the second study, Collins-Camargo and Garstka (2014) hypothesized the uptake of evidence-informed practices is a function of data-driven supervision practices and team goals related to using data and outcomes to inform their performance. Similar to the Collins-Camargo et al. (2011), this study was a part of a larger study focused on evaluating three states' implementation of performance-based contracts (PBC) between public child welfare agencies and private contractors. In total, 597 frontline case managers and supervisors across the three states completed a 30-item survey designed to determine the extent to which they form goal-oriented approaches to outcome achievement, incorporate data and evidence in supervision, and use data and evidence to improve practice (Collins-Camargo & Garstka, 2014). Using hierarchal linear modeling (HLM), they were able to test first whether fixed factors including site location and staff position accounted for any variance in the uptake of evidence-informed practices. They

found the fixed factors to be non-significant; however, when team goals and supervisory practices were included as predictors in the second block of the HLM model, Collins-Camargo and Garstka (2014) found statistically significant results for each. As such, *Organizational Drivers* related to team and supervisory functions appears to influence the uptake of evidence-informed practice. The researchers included a mediation analysis with these significant results hypothesizing that before individual staff learn to use data and evidence, the organization must have a goal-based team approach already in place and is coached into routine practice through individual supervision that highlights outcomes and performance data. Collins-Camargo and Garstka's (2014) mediation analysis showed a partial mediation of supervisory practices meaning the relationship between team goals and evidence-informed practice uptake reduced yet it remained significant. In other words, goal-oriented teams that focus on outcome achievement are more likely to use data and evidence to guide practice with children and families, and this relationship was more robust when supervisors reinforced evidence individually during direct supervision (Collins-Camargo & Garstka, 2014). The authors recommended further research to understand how goal-oriented teamwork and supervision promote evidence-informed practices and encouraged adding the achievement of desired client outcomes as well.

Data Use and Early Childhood Programming

Much of the research reviewed in this chapter commented on the limited uptake of EBPs and research evidence in child and family services and the difficulties with studying implementation despite widespread calls to do so (Albers et al., 2017; Barwick et al., 2011; Bertram et al., 2014; Fearing et al., 2014; Graff et al., 2010; McCrae et al., 2014). Similarly, the research on applying implementation frameworks to uptake of EBP and data usage in the peer-reviewed literature is largely contained within the fields of child welfare and behavioral health.

If data are essential components of effective implementation (Bertram et al., 2011), early childhood programs attempting to deliver ESTs and EBIs would need to use data effectively as well. Unfortunately, studies on the use of data to inform decisions in early childhood practice and programming are rare. The final series of literature reviewed for this chapter include research studies that focus specifically on this topic.

Preschools' use of data for decision-making in early learning. There is some evidence that preschools' use of data is useful for decision-making and quality improvement and desired by preschool staff. Zweig and colleagues (2015) interviewed administrators and teachers at seven preschools to explore how early educations programs and service providers collect and use data to make decisions. In particular, they focused their study around three types of data: dosage (i.e., the amount of time children spend in early education), quality of classrooms (i.e., teacher child interactions), and early learning outcomes such as early literary and social-emotional development. Common across the reports from the seven preschools were their description of collecting, storing, and reporting of assessments of early learning outcomes. These practices, however, were largely in place for compliance purposes. Even so, a few of the administrators interviewed expressed a desire to use their data for understanding impact (i.e., link attendance data to outcomes) and to inform practice decisions including targeted outreach to parents and classroom quality measure to improve teaching (Zweig et al., 2015). The study revealed three distinct challenges to using data for decision-making, including: 1) time and capacity issues related to combining multiple data sources (e.g., combing attendance records in a dataset with classroom quality ratings), 2) the impact that missing data have on programs' abilities to analyze and interpret findings, 3) and the understanding of the multiple explanations or external factors possibly contributing to outcomes (Zweig et al., 2015).

Utilizing integrated data to inform decision-making access in early childhood programming. Recent examples of early childhood integrated data systems (ECIDS) provide some evidence of the importance of using integrated data systems in early childhood to inform policy and practice decisions (Coultan et al., 2015; Fischer, Anthony, & Dorman, 2014). Two recent examples show the impacts of ECIDS at state and county levels. At the state level, the Children's Defense Fund in Minnesota (2017) analyzed secondary data from the state's ECIDS large datasets to determine access to and participation in quality early childhood programming for vulnerable children (e.g., children in poverty, children of color, and American Indian children). The analysis compared a stratified dataset from the ECIDS of children who access the Minnesota Family Investment Program (MFIP) and food programs to an entire cohort of children in kindergarten. The analysis revealed a number of trends related to the types of early childhood services accessed. For example, children who received MFIP and/or food programs were less likely to have received early childhood family education (ECFE) support than the comparison group (Children's Defense Fund—Minnesota, 2017). Similarly, trends emerged related to the characteristics of children accessing early childhood services. Nearly eight of ten children participating in ECFE programs were white children (Children's Defense Fund—Minnesota, 2017).

The existence of these data from the ECIDS led the Children's Defense Fund of Minnesota (2017) to make several practice and policy recommendations, a number of which have implications for the influence of data use to drive decisions in organizations delivering early childhood programs. First, they recommended expanding access and use of the ECIDS across the state to ensure a broader understanding of early childhood experiences leadings to program access and inform targeted outreach of certain populations. Second, they advocated for

increased investments in data capacities for early childhood programs and staff (e.g., updated data systems, resources for data management, staff training) to make effective use of data for immediate and long-term outcomes. Third, they encouraged continued support of innovative practices to make data more accessible and useful such as state-sponsored technical assistance and data system centralization (Children's Defense Fund—Minnesota, 2017).

At the county level, Fischer and colleagues (2014) provide a case example of how Cuyahoga County in Ohio made concerted efforts to implement an ECIDS. Over the course of three decades, the county made progress to link early childhood data into schooling and young adult systems longitudinally across a number of service domains (e.g., schools, health and mental health, postsecondary education). Because of these efforts, the county has data to inform a more realistic understanding of the organizations, programs, and services children and families interact with and receive, and ultimately, data-driven policy and practice decisions (Fischer et al., 2014). Examples include the installation of engagement programs in health clinics to increase well-child visit attendance, the promotion of new born home visits and high quality early education to ensure school readiness, and the launching of a "Pay for Success" initiative to reduce foster care stays and costs in families experiencing homelessness (Fischer et al., 2014).

While common challenges such as funding and data sharing exist, Fischer and colleagues (2014) emphasized the readiness of organizations to develop data-driven cultures in organizations. They stressed the need to build data skills in practitioners and administrators with backgrounds in early childhood and social work rather than rely exclusively on computer programmers and quantitative statisticians to leverage and make decision with data (Fischer et al., 2014). Universities and schools of social welfare may play a critical role in overcoming these pitfalls by providing technical assistance, developing integrated data systems, and

integrating data and implementation science concentrations into educational curricula (Bellamy et al., 2008; Bertram et al., 2015; Fischer et al., 2014).

Summary and Critique of the Literature

This chapter highlighted the available research and literature on the *AIF Drivers* and reviewed empirical literature related to applying this framework in programs targeted at children and families with particular attention paid to data practices. Additionally, this review included relevant literature regarding DDDM in early childhood initiatives. Overall, these studies revealed noteworthy findings relevant to the current study. First, the studies largely supported core implementation drivers (i.e., *Competency, Organizational, and Leadership Drivers*) as a common strategy influencing implementation, the uptake of research-supported practices, and the use of data to inform decision-making (Albers et al, 2017; Barwick et al., 2011; Fearing et al., 2014; Graff et al., 2010; Kimber et al., 2012; McCrae et al., 2014; Metz et al., 2015; Salverson et al., 2015). Second, studies demonstrate the applicability of *AIF Drivers* across several topical service areas of interest to social work (e.g., child welfare, children's mental health, and family-centered or community-based programs). Finally, the studies demonstrate the wide-ranging practical utility of *AIF Drivers* to inform a variety of research activities including measurement validation studies (Ogden et al, 2012), program evaluations (Bertram et al., 2014) and studies with qualitative or mix method designs (Barwick et al., 2011; McCrae et al., 2014).

A few notable gaps and limitations emerged from this review. To begin with, few of these studies tested implementation science in large samples, contained quantitative designs, or were rigorous in nature. Nine of the studies were retrospective case studies of single organizations or initiatives, and in most cases, the theoretical basis for the studies was applied retrospectively and under developed (Albers et al, 2017). In other words, these studies used *AIFs*

as a general ‘lens’ and may be missing specific and critical elements of the *AIF Drivers* needed for successful implementation. Because of this, implementation frameworks tend to be seen as packages where all implementation processes and components appear equally important. Albers and colleagues (2017) suggested that further research on modular approaches to implementation may offer insight on implementation in practice contexts. Finally, while two studies empirically tested *AIF Drivers* on the use of data to improve child welfare performance and outcomes (Collins-Camargo et al., 2011; Collins-Camargo & Garstka, 2014), a gap emerged from this review as it revealed no studies testing implementation drivers in early childhood programs such as home visiting or early childhood education. Data use to inform decision-making in early childhood program policy and practice came from grey literature and lacked theoretical foundations (Children’s Defense Fund—Minnesota, 2017; Fischer et al., 2014; Zweig et al., 2015).

The current study attempted to account for these limitations in two ways. First, it used the *AIF Drivers* intentionally to ground and inform instrument and item development specifically around each driver. Second, it takes a ‘modular’ approach as suggested by Albers et al. (2014) in that the study examines a specific construct needed for implementation—the readiness for DDDM. Following in Chapter III is a description of the methods used for this study.

Chapter III
Methods

Introduction

Chapter III outlines the methods of this study and includes discussions of research questions and design, the participant sample, data collection procedures, instrumentation, and data analysis. The purpose of the study was to explore early childhood program administrators' perceptions of data use and understand factors related to organizational "readiness" to use data to support decision-making. The overall design of the study was cross-sectional and involved the development and initial validation of a new instrument on organizational readiness for DDDM. Items and scales reflect the *AIF Drivers*. Furthermore, the study assessed the initial validation of the instrument based on Goodwin's (2002) recommendation to consider the accumulation of evidence across five validity categories: 1) evidence based on test content, 2) evidence based on response processes, 3) evidence based on internal structure, 4) evidence based on other variables, and 5) evidence based on consequences of testing using a quantitative analysis of its underlying factor structure and internal consistency. Recognizing the establishment of measurement validity and reliability as a lengthy process unfolding over the course of multiple studies (Carpenter, 2018; Hinkin, Tracey, & Enz, 1997; Streiner & Kottner, 2014), this study may serve as the first of a series of validation studies.

Research Questions and Design

Given this purpose and the opportunities for further research identified from an empirical literature review in Chapter II, the study posed three research questions:

1. How do early childhood program administrators rate their organization's readiness for data-driven decision-making?

2. Is the *Active Implementation Drivers Framework* (AIF Drivers) an effective guide for understanding organizational readiness for data-driven decision-making?
3. How are demographic characteristics or program characteristics of early childhood program administrators related to factors of readiness for data-driven decision-making?

Participants

Participant recruitment. The target population for the study included 545 early childhood program administrators working in state or federally funded programs in six Midwestern states including Colorado, Illinois, Iowa, Kansas, Nebraska, and Wisconsin. To identify the population in these states, the researcher engaged leaders of statewide early childhood initiatives to request permission from officials at state agencies overseeing public funding and programs to recruit participants and to obtain lists of program administrator contacts throughout their respective states. In four states, Colorado, Illinois, Nebraska, and Wisconsin, state leaders supported recruitment by distributing the survey invitation to participants and allowing the researcher to email an invitation to their contacts. For two states, Iowa and Kansas, state leaders allowed the researcher to use available program contact information from a shared outcomes system called *Data Application and Integration Solution for the Early Years* (DAISEY). Programs using DAISEY in these states include a variety of early childhood programs targeted at pregnant women and families with young children including evidence-based home visiting programs, family and parent support programs, and maternal and child health programs. The researcher attempted to engage programs in two additional unnamed states but was unable to recruit participants in these states due to limited responses from state leads.

Initial lists contained 579 potential contacts. The researcher verified the current work status and active status of each email account to pare the list down to active accounts only. After removing 34 inactive accounts, a final list of 545 active recruits were sent an email invitation introducing the study and inviting program administrators to complete an online questionnaire beginning in March 2019 (see email invitation in Appendix A). Weekly follow-up emails were sent to program administrators reminding them about the study for two weeks following the initial invitation. The first responses to the online survey began March 14, 2019, and the last responses occurred on April 8, 2019. Of the 545 eligible program administrators, a final sample of 173 responded representing a 32% response rate.

Protection of research participants. The researcher obtained data for this study through self-reported responses from early childhood program administrators. As described in the proceeding second, prior to study recruitment, the researcher sought permission from state leads and funders of early childhood programs to recruit potential respondents. Furthermore, the Human Research Protection Program (HRPP) at the University of Kansas reviewed and approved the study prior to its launch to ensure the study met legal and ethical requirements. Participation was voluntary and anonymous, and each participate received a statement of informed consent prior to the portions of the questionnaire containing survey questions. All data collected for this study was stored, maintained, and analyzed on a secure server at the University of Kansas. No respondents reported experiencing risk or harm while completing the online questionnaire.

Sample characteristics.

Program administrator demographics. Of the 173 program administrator respondents, the vast majority (95.3%) were female (164 females, 6 males, 0 gender non-conforming/non-

binary, 2 prefer not to answer). In terms of race, 2.9% identified as American Indian or Alaska Native (n = 5), 5.8% as Black or African American (n = 10), 89% as White (n = 154), and 1% or less identified as either Asian (n =1), Native Hawaiian or Other Pacific Islander (n = 1), or other (n = 2). Additionally, 8.8% of respondents identified ethnically as Hispanic or Latino (n = 15). The majority of program administrators' highest level of education included a college degree as 49.1% (n = 84) had obtained a Bachelor's Degree and 40.9% (n = 70) had obtained a Master's Degree or higher. Fifteen respondents' highest level of education was some college (8.8%), and two respondents' highest level of education was equivalent to finishing high school (1.2%). No respondents reported less than a high school equivalent education. The mean age of respondents was 46.6 years old (*S.D.* = 11.2). The mean years of experience they have in early childhood programs is 15.2 years (*S.D.* = 8.9). Table 2 contains the descriptive statistics for program administrator demographic characteristics.

Program characteristics of respondents. Two-thirds of the administrators (n = 116) identified their program as a home visiting or other home-based early childhood program. Of the remaining programs, 16.3% (n = 28) were preschool or other center-based programs, 3.5% (n = 6) were reported as parenting groups, 3.5% (n = 6) were maternal-child health programs, and 9.3% (n = 16) were reported as some other type of early childhood program. Large majorities of program administrators reported their programs targeting families with a variety of social, health, and risk disparities. Ninety-six percent (n = 166) reported targeting low-income families. Over three-quarters of respondents' programs targeted families with young parents under 21 years of age (82.7%, n = 143), households with histories of substance abuse (75.7%, n = 131), and histories of child abuse or neglect (75.7%, n = 131). Nearly two in three programs targeted families speaking languages other than English (64.7%, n = 112). Thirty-one administrators

Table 2

Demographic Characteristics of Respondents (N = 173)

Categorical Participant Demographics	N (%)
Gender Identity	
Male	6 (3.5)
Female	164 (95.3)
Non-conforming/non-binary	0 (0.0)
Prefer not to answer	2 (1.2)
Race	
American Indian or Alaska Native	5 (2.9)
Asian	1 (0.6)
Black or African American	10 (5.8)
Native Hawaiian or Other Pacific Islander	1 (0.6)
White	154 (89.0)
Other	2 (1.2)
Ethnicity	
Hispanic or Latino	15 (8.8)
Highest Education Level Completed	
Less than high school education	0 (0.0)
High school graduate or GED	2 (1.2)
Some college	15 (8.8)
Bachelor's degree	84 (49.1)
Master's degree or higher	70 (40.9)
Continuous Participant Demographics	**M (S.D.)**
Age	46.6 (11.2)
Years work experience in EC programs	15.2 (8.9)

Note. Number of missing not included in the calculation of number, percent, or mean.

Table 3

Characteristics of Respondents' Programs (N=173)

Categorical Program Characteristics	N (%)
Program Type	
Preschool or other center-based program	28 (16.3)
Home visiting or other home-based program	116 (67.4)
Parenting groups	6 (3.5)
Maternal-child health program	6 (3.5)
Other	16 (9.3)
Target Population Served by Program	
Low income families	166 (96.0)
Parents under 21 years old	143 (82.7)
Households with a history of substance abuse	131 (75.7)
Households with a history of child abuse or neglect	131 (75.7)
Non-English speaking families	112 (64.7)
Other	31 (17.9)
Target Outcomes of Program	
Prevention of child abuse and neglect	145 (83.8)
Child development	155 (89.6)
School readiness and kindergarten readiness	141 (81.5)
Maternal health	116 (67.1)
Infant and child health	135 (78.0)
Family economic self-sufficiency	108 (62.4)
Continuous Program Characteristics	**M (S.D.)**
Number of Families Served	276.6 (696.6)
Number of Program Staff	24.1 (40.8)

Note. Number of missing not included in the calculation of number, percent, or mean.

(17.9%) reported targeting families in some other population. Similarly, majorities of program administrators report similar targeted outcomes of their programs. More than three in four programs target outcomes included child abuse and neglect prevention (83.8%, n = 145), child development (89.6, n = 155), school and kindergarten readiness (81.5%, n = 141), and infant and child health (78%, n = 135). Nearly two in three program administrators reported their programs

targeting outcomes involving maternal health (67.1%, n = 116) and family economic self-sufficiency (62.4%, n = 108). The mean number of families served was 276.6 and varied widely with a standard deviation of 696.6 families. The mean number of program staff was 24.1 with a standard deviation of 40.8. Table 3 contains the descriptive statistics of the characteristics of the programs in which program administrators work.

Instrumentation

Instrument development. The researcher developed the *Early Childhood Data Driven Decision Making* (EC-DDDM) survey over the course of four months (November 2018 to February 2019) using steps recommended by Carpenter (2018) and Hinkin, Tracey, and Enz (1997). First, the researcher generated several items related to each of the constructs and factors of interest. As such, the researcher wrote each item in the EC-DDDM intentionally to correspond with one of the nine *AIF Drivers*. Items were written in the form of a statement, which participants would respond to on a five-point, Likert-style scale where 1=Strongly disagree, 2=Disagree, 3=Neither agree nor disagree, 4=Agee, and 5=Strongly agree. Second, upon compiling an initial instrument, the researcher performed content adequacy analysis to ensure the face validity and conceptual consistency of the items (Carpenter 2018; Hinkin et al., 1997). To accomplish this, the researcher engaged a panel of seven experts to review the instrument and provide feedback. Panelists included two social work academics familiar with the study, two applied researchers with backgrounds in instrument development and early childhood program research and evaluation, two state-level leads and funders of statewide early childhood programs, and one early childhood program administrator in charge of overseeing the data and performance operations at her organization.

Panelist reviews and instrument refinement occurred through a series of three iterations (Goodwin, 2002; Holmbeck & Devine, 2009). During the first iteration, the two social work academic panelists reviewed the initial version of the instrument and provided feedback leading to the editing of item wording, the provision of more detailed instructions for respondents, and the addition of some demographic questions and a definition for the terms "coach" and "coaching." For the second iteration of instrument reviews, the researcher built an electronic web-based version of the questionnaire using a secure, web-based data collection platform known as Research Electronic Data Capture (REDCap) (Harris et al., 2009). During this second iteration, the remaining five panelists accessed the revised instrument through REDCap's development and provided feedback via email to the researcher. Their feedback included discussions of their understanding of specific items, the amount of time it took to complete the instrument, suggestions for removing and adding items, and whether or not they believed the EC-DDDM survey would be clear to program administrator respondents. As a result, seven items were removed from the instrument because they were determined to be either redundant or unrelated to the corresponding implementation driver. Two additional items corresponding to *AIF Drivers* and four additional demographics or program characteristics items were added at panelists' suggestions. The third and final iterative review of the instrument involved the researcher compiling final instrument, updating the electronic REDCap survey, and vetting it through the two social work academics. Appendix B provides a print-out of the electronic version of the EC-DDDM.

Final EC-DDDM instrument. The final EC-DDDM questionnaire contained 69 total items divided across two primary sections (see Appendix B). The first primary section contained 54 items corresponding to the constructs and factors of interest to the study (i.e., the nine *AIF*

Drivers). This first section contained nine sub-sections for each of the nine sub-component implementation drivers. In each of these sub-sections, items corresponding to the factor were grouped together. All items were combined with the five-point agreement scale described in the previous section. The second primary section contained 15 participant demographics and program characteristics items intended to support the description of the sample as well as understand possible relationships with ratings to items in the first section. Consistent with Munford and colleagues (2005) recommendations for the desired sample size, the final items-to-factors ratio was 6.0 based on 54 items divided by the nine factors.

Final data collection procedures. The final version of the EC-DDDM was built in a web-based production deployment of REDCap. REDCap is an intuitive, web-based survey platform designed specifically for the secure provision of research data (Harris et al., 2009). Program administrators responding to EC-DDDM accessed the questionnaire via a URL link provided to them in the email invitation. Once respondents accessed the URL, they were brought immediately to the statement of informed consent and upon continuing were taken to the EC-DDDM instrument. No identifying information about participants were tracked in this system and responses are maintained on a secure server at the University of Kansas. REDCap's general infrastructure and user interface made this type of data collection possible and provided for intuitive exporting of the data into a format readable by the statistical software packages used in this study's analysis (Harris et al, 2009).

Data Analysis

Descriptive analysis of RQ1. The researcher utilized a descriptive analytic approach to answer the first research question regarding how early childhood program administrators rate their organizational readiness for DDDM. Frequencies, means, and standard deviations for each

of item were observed. Descriptive data analysis occurred in IBM's Statistical Package for the Social Sciences (SPSS) version 25 (IBM Corporation, 2017).

Confirmatory Factor analysis of RQ2. For question two, to determine if the *AIF Drivers* act as a guiding framework for assessing readiness for DDDM, a confirmatory factor analysis (CFA) of responses evaluated the goodness-of-fit of two different factor models. The first model evaluated a 3-factor model where each of the three construct-level implementation components (i.e., *Competency*, *Organizational*, and *Leadership*) was considered a factor. The second model evaluated a 9-factor model where each of the nine sub-component drivers within these constructs (e.g., *selection*, *facilitative administration*, and *technical leadership*) was considered a factor. Indexes of model fit suggested by Brown (2015) and Lewis (2017) were used to evaluate model goodness-of-fit. These indices include the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), the Room Mean Square Error of Approximation (RMSEA), and Chi Square fitness indices as well as statistical significance (*p*-values). Table 4 provides a snapshot of the two models and the specified factors in each model. Path-based depictions of both 3-factor and 9-factors models are shown in Figure 4 and Figure 5.

Table 4

Factors included in CFA Models

Construct level model (3 factors)	Sub-component driver level model (9 factors)
1. *Competency drivers*	*Competency drivers* 1. Selection 2. Training 3. Coaching 4. Performance assessment
2. *Organization drivers*	*Organization drivers* 5. Systems intervention 6. Facilitative administration 7. Decision support data systems

3. *Leadership drivers*	*Leadership drivers* 8. Technical 9. Adaptive

CFA analysis occurred in R version 3.5.3 (R Core Team, 2019) with the *lavaan* package to test model fitness of both the 9-factor and 3-factor models (Rosseel, 2012). The researcher chose to use a robust weighted least squares estimator (WLSMV) in this CFA due to the ordinal structure (i.e., Likert-style) of the survey's responses options (Brown, 2015). An analysis of the missing data found patterns missing completely at random (MCAR). Because of this, pairwise deletion was used to handle 26 patterns of MCAR data (Brown, 2015; Peugh & Enders, 2004). The researcher applied pairwise deletion function within R's *lavaan* package (Rosseel, 2012).

CFA was a suitable statistical method for the study given its purpose and a number of its advantages. First, many recommend CFA when examining the underlying factor structure of a survey, data collection tool, or questionnaire (Brown, 2015; Carpenter, 2018; Goodwin, 2002; Lewis, 2017; Holmbeck & Devine, 2009). Second, CFA helps researchers understand variable-factor relationships to determine how many factors can and should serve as subscales in the questionnaire (Brown, 2015). In terms of this study, the researcher analyzed two different factor models, one with three factor subscales and one with nine factor subscales, (see Figures 4 & 5) to determine if either model fit or if some other configuration is needed. Finally, CFA can stand alone, rather than follow an exploratory factor analysis, when a strong conceptual basis exists to pre-determine the factors being studied (Brown, 2015). Given this study's use of *AIF Drivers* as its hypothesized factor structure, CFA is defensible without prior exploratory factor analyses.

Sample size must be considered when conducting CFA. This study aimed for a final sample size of 200 respondents and ended up with 173 respondents. While general rules abound

for the needed sample size range from 50 to 500 based on participants per item ratios, authors have argued for the use of more statistically robust approaches to sample size estimation such as a variable-to-factor ratio where the number of items used to observe each factor is used to guide sample size decisions based on the levels of communality (Mundform, Shaw, & Ke, 2005). As variable-to-factor ratios rise or levels of communality increase, the number of respondents needed decreases. With a ratio of five variables per factor, Mundform and colleagues (2005) suggested a sample size of 130 participants for high communality to 200 participants for low communality. If that ratio grows to eight variables per factor, they suggest a minimum sample size of 80 when low communality exist. Similarly, Worthington and Whittaker (2006) provided recommendations on best practices for factor analysis and suggested a sample size of 150 to 200 when communalities are at least .50. EC-DDDM's final variable to factor ratio was 6.0, and an examination revealed wide community communality scores. Based on these recommendations from Mundform and colleagues (2005) and Worthington and Whittaker (2006), the sample size of this size should provide sufficient power to provide sound results.

Internal consistency. Cronbach's alphas (α) were determined for both 3-factor and 9-factor models as a measure of internal consistency (Nunnally, 1978; Taber, 2018). Calculations occurred in SPSS version 25 (IBM Corporation, 2017).

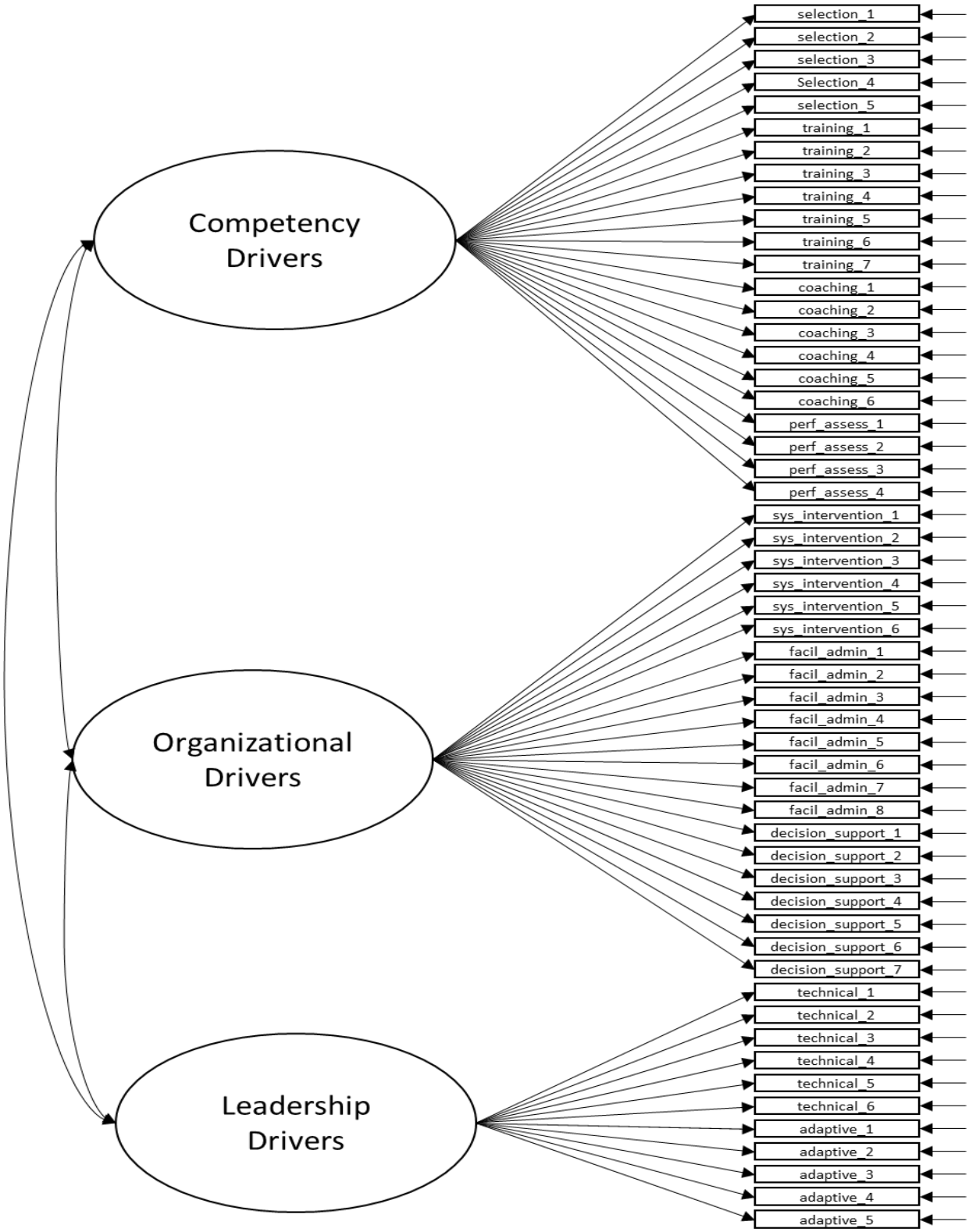

Figure 4. Construct level 3-factor path model.

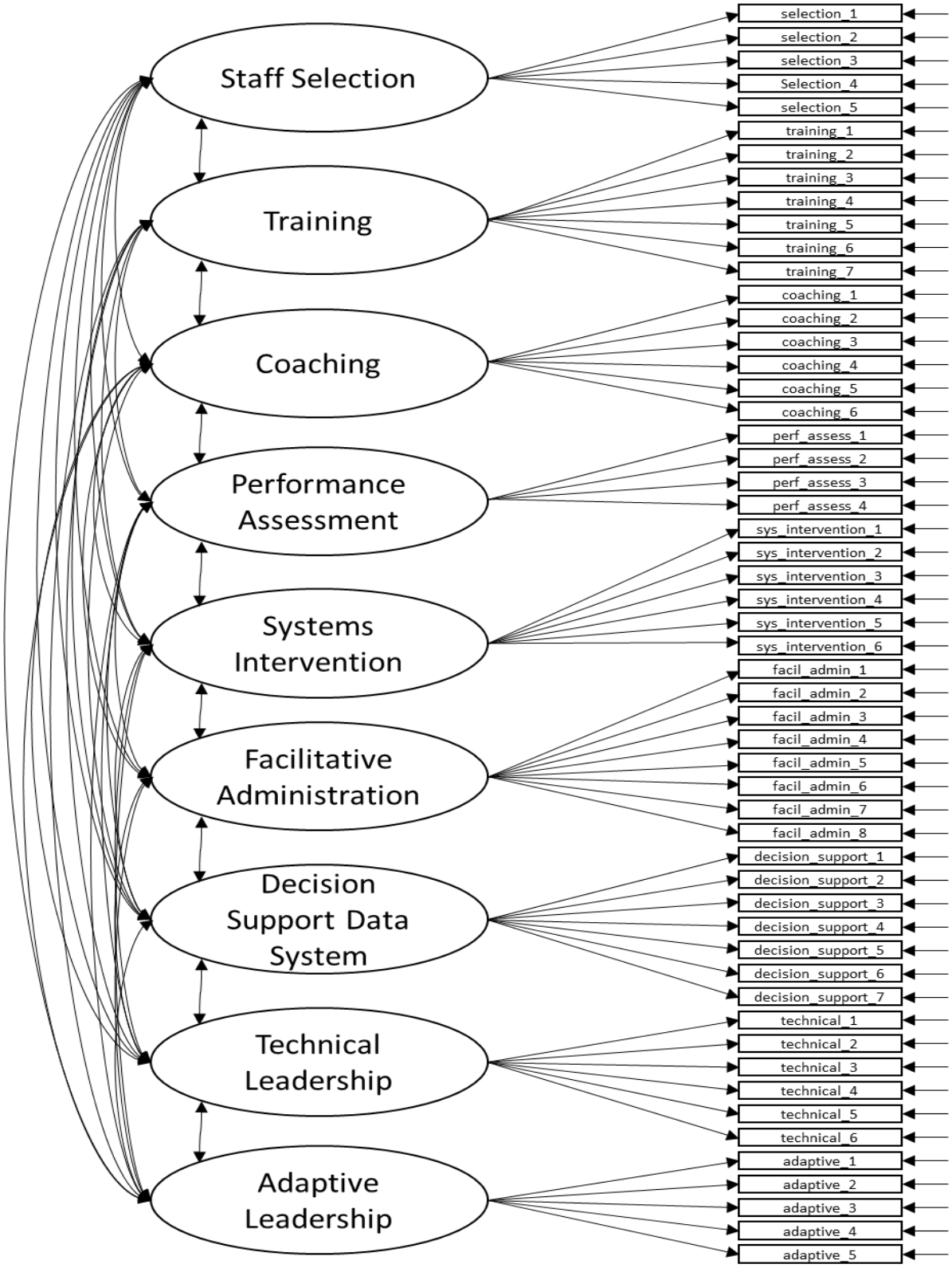

Figure 5. Driver level 9-factor path model.

Bivariate analysis of RQ3. The third research question sought to understand potential relationships between multiple demographic and program characteristic variables collected in the EC-DDDM and the scaled scores of each factor measured in EC-DDDM. In total, 72 relationships were analyzed between nine score variables and eight covariate demographic and program characteristic variables. The nine score variables were computed variables that summed items corresponding to the nine driver-level factors examined. The eight covariates included three categorical demographic variables, two continuous demographic variables, and three categorical program characteristic variables. The three categorical demographics included race (recoded as 0=white, 1=non-white), ethnicity (coded as 0=non-Hispanic/non-Latino, 1=Hispanic/Latino), and education (recoded as 0=Less than 4-year college degree, 1=Bachelor's degree, 2=Master's degree or higher). The two continuous demographics included age in years and early childhood work experience in years. The three categorical program characteristic variables included number of families served annually (recoded as 1= 60 or fewer families served, 2= 61 to 199 number of families served, 3=200 or more families served), number of staff in program (recoded as 1=5 or fewer staff, 2=6 to 14 staff, 3=15 or more staff), and program type (recoded as 0=Other program, 1=Home visiting program).

As with the descriptive analysis, the researcher conducted bivariate analyses within IBM SPPS version 25 (IBM Corporation, 2017). An analysis of the distribution of the score variables revealed normality, and as such, appropriate parametric tests were used based on the categorical or numerical status of the covariates (Norman, 2010; Rubin & Babbie, 1993). One-way analysis of variance (ANOVA) tests were performed for relationships between categorical covariates and the scale scores. One relationship tested—program type and the performance assessment score—required a robust non-parametric test because it violated the Levene's test for the

assumption of homogeneity of variances. Accordingly, a Welch-ANOVA test was used to test this relationship (Moder, 2010). For relationships between scores and continuous covariates, Pearson correlation coefficients (*r*) with two-tailed significance tests were computed. Given the MCAR assumption, missing data for bivariate analyses were handled on a case by case basis using pairwise deletion functions in SPSS (IBM Corporation, 2017; Peugh & Enders, 2004).

Given the quantity of covariate relationships tested with each score variable, statistical significance of each relationship were evaluated based on an adjusted alpha level using the Bonferroni correction method (McDonald, 2014). For these analyses, the general alpha level of 0.05 was divided by eight representing the eight comparisons of each score dependent variable resulting in a corrected alpha level of 0.006 (i.e., 0.05 / 8 = .006). Effect sizes for the Welch-ANOVA test were determined based on the omega-squared value (ω^2) (Skidmore & Thompson, 2013). Effect sizes for all other categorical variables were determined based on the eta-squared values (η^2) while effect sizes for continuous variables were determined based on the Pearson correlation coefficients (*r*) (Lakens, 2013).

Summary

Chapter III focused on methods used for this study. The researcher posed three research questions of focus: 1) how do program administrators rate organizational readiness for DDDM, 2) is the *AIF Drivers* framework an effective guide for understanding organizational readiness for DDDM, and 3) how are program administrator demographics or program characteristics related to factors of readiness for data-driven decision-making? The chapter provided details of the methods used to answer these questions including an account of the EC-DDDM development process, a description of the recruitment and characteristics of the program administrator respondents, the actions taken to project human subjects, and the analytic approaches for each

research question. The researcher followed a number of steps and best practices outlined in the literature to develop the EC-DDDM, administer it to a sample of program administrators, and initially validate the instrument (Brown, 2015; Carpenter, 2018; Goodwin, 2002; Lewis, 2017; Hinkin and colleagues, 1997; Holmbeck & Devine, 2009). The following chapter presents the results of these efforts.

Chapter IV

Results

Chapter IV details the results of the statistical analyses used to investigate three research questions. Statistical analyses used in this study included descriptive statistics, confirmatory factor analysis, an internal consistency analysis, and bivariate correlations. The following discussion presents each research question and its subsequent results.

Question 1 - Results

How do early childhood program administrators rate their organizations' readiness for data-driven decision-making?

Descriptive analysis. Responses to 54 items on the *Early Childhood Data Driven Decision Making Survey* (EC-DDDM) were measured on a five-point Likert scale ranging from "Strongly Disagree" coded as 1 to "Strongly Agree" coded as 5. Three items were reversed scored to ensure higher scores would reflect or imply higher use of data. These three items included selection_3, perf_assess_4, and decision_support_5. The researcher conducted descriptive analyses in IBM SPSS Statistics version 25 (IBM Corporation, 2017). Table 5 provides descriptive statistics for each item including number of respondents, means, standard deviations, and response frequencies. Means ranged from 2.68 to 4.49. The lowest mean scoring item was "program supervisors use their own discretion to evaluate the performance of individual service providers" (M = 2.68, SD = 0.97). The highest mean scoring item was "using data is critical to demonstrate worth to external stakeholders" (M = 4.49, SD = 0.58). Means generally indicated a slight, moderate, or strong agreement from respondents on items as 47 items' mean scores were 3.5 or higher. Five items' means were between 3.0 and 3.5 implying a

somewhat neutral response to the item (i.e., neither agree nor disagree), and two items were slightly below a mean of 3.0 implying a slight disagreement with the item.

Because each item on the EC-DDDM corresponded to one of the nine *AIF Drivers*, summative scores and mean item scores for nine distinct subscales were calculated, which allowed for analysis and comparison across different factors. Scoring involved the creation of two index scores for each of the nine subscales of the EC-DDDM: 1) a summative index score and 2) a mean per item index score. For the summative index score, the researcher summed each item within a given subscale. The summative index of *Staff Selection*, for example, was computed by summing up the five items corresponding to it. Because each subscale contained different numbers of items, the second index score was created to standardize comparison and analysis across subscales. The mean per item index score was calculated by dividing the summative index score by the number of items in the subscale. Using the same example, the *Staff Selection* summative index score was divided by the five items in the subscale. Doing this standardized the mean per item index score on a five-point scale with the lowest possible mean per item index score being 1.0, and the highest possible mean per item index score being 5.0. Descriptive statistics for these constructs are located in Table 6. For comparison and ranking purposes across all nine subscales, the mean index score per item is used throughout the following descriptive analysis of scores by *AIF Driver* and later on in the discussion chapter.

Descriptive analysis by implementation driver subscale.

Staff selection. The *staff selection* subscale contained five items. Of the nine subscales, it ranked eighth with mean per item index score of 3.55 (*S.D.* = 0.63). Mean scores for individual items ranged from 3.25 for selection_3 to 3.81 for selection_2. Two of the five items (selection_1 and selection_3) indicated a somewhat neutral response to the item (i.e., neither

agree nor disagree) while the remaining three items (selection_2, selection_4, and selection_5) indicated a slight agreement with the statement with mean scores at or exceeding 3.5. The majority of respondents agreed or strongly agreed with four of the items. For selection_3, the majority of respondents disagreed or strongly disagreed, which may be expected given the item's reverse coding.

Training. The *training* subscale contained seven items. The *training* subscale was the lowest ranking (ninth of nine subscales) with a mean per item index score of 3.34 (*S.D.* = 0.64). Mean scores for individual items ranged from 2.76 for training_4 to 3.80 for training_1. One item (training_4) regarding trainers giving staff pre-training knowledge and skill tests indicated a slight disagreement with the item (*M* =2.76, *S.D.* = 1.03). Two of the five items (training_5 and training_7) indicated a somewhat neutral response to the item while the remaining four items (training_1, training_2, training_3, and training_7) indicated a slight agreement with the statement. The majority of respondents agreed or strongly agreed with four of the items (training_1, training_2, training_3, and training_7). For the training_4 item, nearly half (47%) of respondents disagreed or strongly disagreed and a quarter (25.3%) responded neither agree nor disagree.

Coaching and supervision. The *coaching and supervision* subscale contained six items and ranked second highest with a mean per item index score of 4.08 (*S.D.* = 0.58). Mean scores for individual items ranged from 3.80 for coaching_6 to 4.35 for coaching_2. All six items indicated some agreement with the statement. At least three-quarters of respondents agreed or strongly agreed with all six items.

Performance assessment and evaluation. The *performance assessment and evaluation* subscale contained four items. It ranked seventh and was among the bottom third subscales in

terms of its mean per item index score (*M* = 3.57; *S.D.* = 0.66) was among the lowest. Mean scores for individual items ranged from 2.68 for perf_assess_4 to 3.90 for perf_assess_2. The majority of respondents agreed or strongly agreed with four of the items; however, the mean for perf_assess_4 item indicated a slight disagreement with the statement, which may be expected given the item's reverse coding.

Systems intervention. The *systems intervention* subscale contained six items and ranked first with the highest mean per item index score of all the subscales (*M* = 4.23; *S.D.* = 0.52). Mean scores for individual items in the *systems intervention* subscale ranged from 3.86 for sys_intervention_6 to 4.49 for sys_intervention_4, which represents the highest mean score for any item studied. Five of the items (sys_intervention_1 through sys_intervention_5) indicated a moderate to strong agreement with each item having at least 85% of responses agree or strongly agree. Approximately three-quarters of respondents (76.3%) for sys_intervention_6 agreed or strongly agreed with the statement.

Facilitative administration. The *facilitative administration* subscale contained eight items. Ranking third, it scored among the highest mean per item index scoring subscales (*M* = 4.07; *S.D.* = 0.58). Mean scores for individual items ranged from 3.83 for facil_admin_1 to 4.33 facil_admin_7. Six of the items (facil_admin_2 through sys_intervention_7) indicated a moderate to strong agreement with each item having at least 83% of responses agree or strongly agree. Approximately three-quarters of respondents for facil_admin_1 (76.6%) and facil_admin_8 (73.5%) agreed or strongly agreed with the statement.

Decision support data system. The *decision support data system* subscale contained seven items. Of the nine subscales, it ranked sixth with a mean per item index score of 3.62 (*S.D.* = 0.63). Mean scores for individual items ranged from 3.12 for decision_support_3 to 3.92 for

decision_support_2. One item (decision_support_1) indicated a somewhat neutral response to the item (i.e., neither agree nor disagree) while the remaining six items indicated a slight agreement with the statement with mean scores exceeding 3.5 but less than 4.0. The majority of respondents agreed or strongly agreed with every item except for decision_support_3. For that item, nearly half (46.8%) disagree or strongly disagree or neither agree or disagree (23.7%), which may be expected given the item's reverse coding.

Technical leadership. The *technical leadership* subscale contained six items. *Technical leadership* ranked in the middle of all nine subscales, fifth overall, with a mean per item index score of 3.86 (*S.D.* = 0.65). The analysis of the items found mean scoring ranging from 3.70 for technical_4 to 4.04 technical_5. As such, all six items indicated a slight to moderate agreement with the statement. Over 85% of respondents agreed or strongly agreed with technical_5, and at least three-quarters of respondents either agreed or strongly agreed with the remaining five items.

Adaptive leadership. The *adaptive leadership* subscale contained five items ranked fourth with a mean per item index score of 3.90 (*S.D.* = 0.69). Mean scores for individual items ranged from 3.80 for adaptive_5 to 3.95 adaptive_3. All five items indicated a slight agreement with the statement with mean scores exceeding 3.5 but less than 4.0. More than 70% of respondents agreed or strongly agreed with each item.

Summary of descriptive analysis patterns. The descriptive analysis of items and ranking of the nine subscales on the EC-DDDM based on their mean per item index scores. While program administrators tend to agree with the items overall, the three highest ranking subscales included the *systems intervention, coaching, and facilitative administration* where all mean per item index scores exceeded 4.0. Ranking in the middle with index scores of higher than 3.6 but less than 4.0 were *adaptive leadership, technical leadership,* and *decision support data system*

subscales. The lowest index scoring subscales—*performance assessment, staff selection,* and *training*—all had mean per item index scores of less than 3.6.

Considering these rankings, a couple notable patterns emerged with regards to the relationship between the rankings of the nine subscales of the EC-DDDM and their corresponding construct levels in the *AIF Drivers* framework. Overall, a pattern consistency emerged between the construct level of the *AIF Drivers* (i.e., *Competency, Organizational,* and *Leadership* constructs) and the ranking of their sub-component drivers. As evidence of this, the first consistency found two highest ranking subscales (i.e., *Systems Intervention* and *Facilitative Administration*) associated with the *Organizational* construct level of the *AIF Drivers* framework. Similarly, the second consistency found two subscales ranked in the middle scoring group (i.e., *technical* and *adaptive leadership)* corresponding to the same *Leadership* construct of the framework. And finally, the last pattern of consistency found correspondence between the three lowest scoring subscales (i.e., *performance assessment*, *staff selection,* and *training)* and the *Competency* construct of the framework. Two exceptions to these consistency statements emerged as well. The *coaching* subscale ranked second highest of all nine subscales, which is a stark contrast to the other *Competency* based subscales that clustered in their rankings at the bottom. Furthermore, even though two *Organizational* based subscales ranked in the top three, the *decision support data system* subscale ranked sixth out of nine.

Question 2 - Results

Is the Active Implementation Frameworks an effective guide for understanding organizational readiness for data-driven decision-making?

Confirmatory factor analysis. To understand if the *AIF Drivers* served as an effective factor structure for the EC-DDDM, the researcher conducted a CFA. Analysis for the CFA

occurred in R version 3.5.3 (R Core Team, 2019) with the *lavaan* package to test model fitness of both the 9-factor and 3-factor models (Rosseel, 2012). The researcher chose to use a robust weighted least squares estimator (WLSMV) in this CFA due to the ordinal structure (i.e., Likert-style) of the survey's responses options (Brown, 2015). Standardized and unstandardized parameter estimates are provided in Table 7 for the 9-factor model and Table 8 for the 3-factor model. Appendix C contains polychoric correlation coefficients between observed variables. The final sample size was 173 with a total 26 patterns of missing data. Pairwise deletion methods were deemed an acceptable approach to handle these missing data because the patterns were missing completely at random (MCAR) (Brown, 2015). As such, the researcher used the *lavaan* package's pairwise deletion function (Rosseel, 2012).

Goodness-of-fit. The researcher evaluated the 3-factor and 9-factor models based on four different goodness-of-fit indices (i.e., CFI, TLI, RMSEA, and Chi Square). Based on Schreiber and colleagues' (2006) suggested cutoff criteria for model fitness, both 3-factor and 9-factor models indicate a good fit; however, results from the 9-factor model indicate a better fit in comparison. Results from the 3-factor model included a CFI & TLI both equal to .94 with the RMSEA equal to .04 with a 90% Confidence Interval =.038 - .049. The Chi Square Test of Model Fit for the 3-factor model was also sufficient ($X^2(1374) = 1830.335$, $p < .001$). Results from the 9-factor model showed better fit across the goodness of fit indices (CFI=.98; TLI=.97; RMSEA=.03, 90% C.I. = .021 - .036) and the Chi Square Test ($X^2(1341) = 1534.65$, $p < .001$). A comparison of these goodness-of-fit measures is located in Table 9.

Internal consistency. To analyze the internal consistency of the instrument, the researcher calculated Cronbach's Alpha (α) for the 9-factor and 3-factor models. For the 9-factor model, eight of the nine factors exceeded Nunnally's (1978) recommended accepted level (see

Table 10). The remaining factor, *staff selection*, fell slightly below this threshold ($\alpha = 0.67$). However, considering the full context of the study, this Cronbach's Alpha may be sufficient based on Taber's (2018) recommendations given its proximity to the threshold combined with the results of the factor analysis presented earlier. Furthermore, the full questionnaire is provided in Appendix B for readers to judge the face validity of the Selection and Hiring factor for themselves (see recommendations in Taber, 2018). For the 3-factor model, all three factors demonstrated high internal consistency with Cronbach Alpha values ranging from .886 to .931 (see Table 10).

Question 3 - Results

How are demographic characteristics or program characteristics of early childhood program administrators related to factors of readiness for data-driven decision-making?

Bivariate analyses. To understand the extent to which demographics and program characteristics were related to summative scores of each factor, the researcher performed bivariate analyses for each combination of independent and dependent variables. Given the results of the CFA described earlier suggesting a better fit with the 9-factor model, the researcher chose to sum items for each of the 9-factors resulting in nine new score variables corresponding to each of the sub-component implementation drivers. The researcher chose eight demographic and program variables in bivariate analyses with the score variables. The five demographics variables included three categorical variables and two continuous variables. The three demographic categorical variables were race (recoded as 0=white, 1=non-white), ethnicity (0=non-Hispanic/non-Latino, 1=Hispanic/Latino), and education (recoded as 0=Less than 4-year college degree, 1=Bachelor's degree, 2=Master's degree or higher). The two demographic continuous variables were age in years, and work experience in years. Additionally, three

categorical program characteristic variables included number of families served annually (recoded as 1= 60 or fewer families served, 2= 61 to 199 number of families served, 3=200 or more families served), number of staff in program (recoded as 1=5 or fewer staff, 2=6 to 14 staff, 3=15 or more staff), and program type (recoded as 0=Other program, 1=Home visiting program).

After examining the normality of the distributions of the score variables, the researcher determined that parametric were appropriate for the bivariate analyses (Norman, 2010). To analyze the six categorical variables, one-way analysis of variance (ANOVA) tests were performed. For statistical analysis of the two continuous variables, the researcher computed Pearson correlation coefficients with two-tailed significance tests. All bivariate analyses were computed using IBM SPPS version 25 (IBM Corporation, 2017). The researcher analyzed a total of 72 variable combinations as each of the nine factor score variables were observed with each of the eight demographic and program characteristics variables. One variable combination, the program type variable and performance assessment factor score, violated the Levene's test for homogeneity of variances and contained unequal sample sizes between groups; therefore, the researcher chose a robust non-parametric, Welch-ANOVA test to examine the relationship between program type and performance assessment (Moder, 2010). Because of the multiple comparisons for each dependent variable, the researcher assessed statistical significance with an adjusted alpha level ($p < .006$) based on the Bonferroni correction method (McDonald, 2014). For this study, the general alpha level of 0.05 was divided by eight representing the eight comparisons of each dependent variable resulting in a corrected alpha level of 0.006 (i.e., 0.05 / 8 = .006). Effect sizes for the Welch-ANOVA test were determined based on the omega-squared value (ω^2) (Skidmore & Thompson, 2013). All other categorical variables were determined based on the eta-squared values (η^2) while effect sizes for continuous variables were determined

based on the Pearson correlation coefficients (*r*) (Lakens, 2013). Table 11 shows the effect sizes and statistical significance results of these bivariate analyses.

No statistically significant relationships were found in any of the variable combinations tested. However, the relationship between groups on ethnicity and the facilitative administration factor score approached statistical significance based on the one-way ANOVA test ($F(1,159) = 7.027$, $p = .009$). The mean facilitative administration score was higher for non-Hispanic/Latino respondents ($M = 32.79$, $S.D. = 4.07$) than for Hispanic/Latino respondents ($M = 29.54$, $S.D. = 5.94$). Appendix D contains descriptive statistics including the mean scores, standard deviations, and confidence intervals between groups analyzed in the one-way ANOVA tests. Appendix E contains statistical tests including statistical significance and eta-squared values of the one-way ANOVAs and Welch-ANOVA tests.

Summary of Results

Taken together, these analyses offered a number of conclusions for the three research questions. The descriptive analysis showed general agreement in the importance of data use according to program administrators in early childhood programs. Further descriptive analyses revealed patterns of data use across the various implementation drivers such that there is general consistency between the subscale rankings and the constructs of the *AIF Drivers*. The CFA suggested a goodness-of-fit for the factor structure of both 3-factor and 9-factor models with the 9-factor model serving as a better fitting model overall. Internal consistency was sufficient for factors in both models as well. Finally, bivariate analyses found small and non-statistically significant relationships between demographics, program characteristics, and factor scores.

Table 5

Descriptive Statistics of EC-DDDM Items

Variable Name	*Survey item*	*N*	*M (SD)*	*Strongly Agree* n (%)	*Agree* n (%)	*Neither Agree nor Disagree*	*Disagree* n (%)	*Strongly Disagree* n (%)
STAFF SELECTION & HIRING								
selection_1	Hiring of early childhood service providers for our program includes assessment of applicants' skills and experience related to using data.	173	3.43 (1.04)	22 (12.7)	72 (41.6)	45 (26.0)	26 (15.0)	8 (4.6)
selection_2	Data gathered during the hiring process about applicants' experience and skills are used to inform training needs of new hires.	173	3.81 (0.94)	34 (19.7)	96 (55.5)	23 (13.3)	16 (9.2)	4 (2.3)
selection_3	Our program relies primarily on the gut feelings and opinions of the hiring team to hire new staff.	172	3.25 (1.02)	5 (2.9)	44 (25.6)	39 (22.7)	71 (41.3)	13 (7.6)
selection_4	Our program uses data on past employee performance to inform our hiring practices (e.g., job descriptions, interview questions, recruitment materials).	173	3.69 (0.89)	21 (12.1)	101 (58.4)	33 (19.1)	13 (7.5)	5 (2.9)
selection_5	Hiring teams use data to make adjustments to recruitment materials (e.g., job descriptions, interview questions, job announcements) during the hiring process.	173	3.55 (0.92)	19 (11.0)	88 (50.9)	39 (22.5)	24 (13.9)	3 (1.7)
TRAINING								
training_1	Trainers make adjustments to training plans based on data gathered from assessments or evaluations of current staff performance.	172	3.80 (0.86)	27 (15.7)	105 (61.0)	20 (11.6)	19 (11.0)	1 (0.6)

Table 5 (continued).

Variable Name	*Survey item*	*N*	*M (SD)*	*Strongly Agree* n (%)	*Agree* n (%)	*Neither Agree nor Disagree*	*Disagree* n (%)	*Strongly Disagree* n (%)
training_2	Trainers make adjustments to training plans based on assessment data gathered on new staff during the hiring process.	172	3.56 (0.93)	18 (10.5)	92 (53.5)	32 (18.6)	28 (16.3)	2 (1.2)
training_3	Trainers customize training plans based on reviews of child and family level data collected by our program.	171	3.63 (0.93)	24 (14.0)	86 (50.3)	37 (21.6)	21 (12.3)	3 (1.8)
training_4	Trainers give staff PRE-training knowledge and skills tests to identify opportunities for targeted training.	170	2.76 (1.03)	7 (4.1)	40 (23.5)	43 (25.3)	66 (38.8)	14 (8.2)
training_5	After training, trainers give staff POST-test knowledge and skills tests to identify opportunities to improve future trainings.	173	3.05 (1.04)	8 (4.6)	62 (35.8)	45 (26.0)	46 (26.6)	12 (6.9)
training_6	After training, trainers provide coaches and/or supervisors with feedback and POST-test results to aid in future coaching and/or supervision efforts.	173	3.09 (1.06)	10 (5.8)	64 (37.0)	41 (23.7)	47 (27.2)	11 (6.4)
training_7	Training sessions include activities to help staff understand how to use data to support decision-making in practice.	173	3.53 (0.97)	16 (9.2)	97 (56.1)	29 (16.8)	25 (14.5)	6 (3.5)
COACHING & SUPERVISON								
coaching_1	Coaches and/or program supervisors access multiple data sources to inform decision-making (e.g., child and family records, observation data, and performance assessment data).	173	4.25 (0.67)	59 (34.1)	103 (59.5)	7 (4.0)	3 (1.7)	1 (0.6)

Table 5 (continued).

Variable Name	*Survey item*	*N*	*M (SD)*	*Strongly Agree* n (%)	*Agree* n (%)	*Neither Agree nor Disagree*	*Disagree* n (%)	*Strongly Disagree* n (%)
coaching_2	Coaches and/or program supervisors understand the data requirements of our program's desired outcomes.	172	4.35 (0.67)	76 (44.2)	83 (48.3)	10 (5.8)	3 (1.7)	0 (0.0)
coaching_3	Coaches and/or program supervisors use data to craft personalized coaching plans for individual service providers.	173	3.92 (0.85)	38 (22.0)	98 (56.6)	24 (13.9)	11 (6.4)	2 (1.2)
coaching_4	Coaches and/or program supervisors have access to data across multiple levels of our work (e.g., child, family, and provider-level records).	172	4.16 (0.73)	54 (31.4)	100 (58.1)	10 (5.8)	8 (4.7)	0 (0.0)
coaching_5	Coaches and/or program supervisors understand how to use our program's data system to support decision-making.	173	4.06 (0.78)	46 (26.6)	101 (58.4)	17 (9.8)	8 (4.6)	1 (0.6)
coaching_6	Supervision or coaching sessions include activities to help staff understand how to use data in their practice to support decision-making.	172	3.80 (0.91)	29 (16.9)	104 (60.5)	17 (9.9)	19 (11.0)	3 (1.7)
PERFORMANCE ASSESSMENT & PERFORMANCE EVALUATION								
perf_assess_1	Performance assessments and evaluations of program service providers include reviews of child and family data to verify provider performance.	173	3.86 (0.85)	32 (18.5)	103 (59.5)	20 (11.6)	17 (9.8)	1 (0.6)
perf_assess_2	Our program uses child and family level data to set realistic performance targets and goals.	173	3.90 (0.84)	34 (19.7)	104 (60.1)	20 (11.6)	13 (7.5)	2 (1.2)

Table 5 (continued).

Variable Name	*Survey item*	*N*	*M (SD)*	*Strongly Agree* n (%)	*Agree* n (%)	*Neither Agree nor Disagree*	*Disagree* n (%)	*Strongly Disagree* n (%)
perf_assess_3	Data collected for performance assessment are linked to intended outcomes of the program.	173	3.87 (0.86)	35 (20.2)	97 (56.1)	25 (14.5)	15 (8.7)	1 (0.6)
perf_assess_4	Program supervisors use their own discretion to evaluate the performance of individual service providers.	173	2.68 (0.97)	12 (6.9)	77 (44.5)	44 (25.4)	35 (20.2)	5 (2.9)
SYSTEMS INTERVENTION								
sys_intervention_1	Using data is necessary to generate support for our program from those outside our organization.	173	4.36 (0.65)	76 (43.9)	87 (50.3)	7 (4.0)	3 (1.7)	0 (0.0)
sys_intervention_2	Data helps us decide where we allocate our time and resources for advocacy.	172	3.97 (0.88)	50 (28.9)	81 (47.1)	27 (15.7)	14 (8.1)	0 (0.0)
sys_intervention_3	To strengthen our case for funding, we include data on program results and child and family level outcomes into grants and funding proposals.	173	4.46 (0.62)	91 (52.6)	72 (41.6)	9 (5.2)	1 (0.6)	0 (0.0)
sys_intervention_4	Using data is critical to demonstrate our worth to external stakeholders.	173	4.49 (0.58)	91 (52.6)	75 (43.4)	7 (4.0)	0 (0.0)	0 (0.0)
sys_intervention_5	Data helps our program reduce external threats (e.g., funding cuts or competing programs) to our program's sustainability.	171	4.25 (0.71)	68 (39.8)	80 (46.8)	21 (12.3)	2 (1.2)	0 (0.0)
sys_intervention_6	We have the data it takes to communicate our program's impact on children and families to stakeholders outside our organization.	173	3.86 (0.96)	41 (23.7)	91 (52.6)	21 (12.1)	16 (9.2)	4 (2.3)

Table 5 (continued).

Variable Name	*Survey item*	*N*	*M (SD)*	*Strongly Agree* n (%)	*Agree* n (%)	*Neither Agree nor Disagree*	*Disagree* n (%)	*Strongly Disagree* n (%)
FACILITATIVE ADMINISTRATION								
facil_admin_1	Our program's administrators model data-driven decision-making for staff to see examples of it in practice.	171	3.83 (0.79)	25 (14.6)	106 (62.0)	28 (16.4)	10 (5.8)	2 (1.2)
facil_admin_2	Program administrators speak about data in terms that program staff can understand.	172	4.00 (0.73)	37 (21.5)	107 (62.2)	19 (11.0)	9 (5.2)	0 (0.0)
facil_admin_3	Using data to support decision-making is a part of our program's culture.	172	4.04 (0.75)	45 (26.3)	95 (55.6)	24 (14.0)	7 (4.1)	0 (0.0)
facil_admin_4	Information on program results are shared with staff across our program.	171	4.13 (0.67)	46 (26.9)	107 (62.6)	13 (7.6)	5 (2.9)	0 (0.0)
facil_admin_5	Program administrators encourage staff to use data for continuous quality improvement (CQI).	171	4.15 (0.74)	56 (32.7)	91 (53.2)	18 (10.5)	6 (3.5)	0 (0.0)
facil_admin_6	The use of data has helped my program make better decisions.	173	4.16 (0.73)	55 (31.8)	96 (55.5)	17 (9.8)	4 (2.3)	1 (0.6)
facil_admin_7	Our program will improve if we continuously review program data.	172	4.33 (0.64)	72 (41.9)	86 (50.0)	13 (7.6)	1 (0.6)	0 (0.0)
facil_admin_8	Our organization invests resources (e.g., money, time) into improving the quality of data collection.	173	3.88 (0.92)	43 (24.9)	84 (48.6)	30 (17.3)	14 (8.1)	2 (1.2)

Table 5 (continued).

Variable Name	*Survey item*	*N*	*M (SD)*	*Strongly Agree* n (%)	*Agree* n (%)	*Neither Agree nor Disagree*	*Disagree* n (%)	*Strongly Disagree* n (%)
DECISION SUPPORT DATA SYSTEM								
decision_support_1	My program has an electronic data system that meets our program's needs.	173	3.69 (0.94)	28 (16.2)	91 (52.6)	30 (17.3)	31 (12.1)	3 (1.7)
decision_support_2	Data entered into our system are relevant to the goals of our program.	171	3.92 (0.82)	39 (22.8)	92 (53.8)	28 (16.4)	12 (7.0)	0 (0.0)
decision_support_3	Even though we put data into our system, we cannot get data out in meaningful reports.	173	3.12 (1.09)	14 (8.1)	41 (23.7)	37 (21.4)	72 (41.6)	9 (5.2)
decision_support_4	Staff are adequately trained to use the parts of the data system, which support their specific work.	172	3.78 (0.90)	28 (16.3)	101 (58.7)	23 (13.4)	17 (9.9)	3 (1.7)
decision_support_5	Our data system supports decision-making in a variety of program activities (e.g., training, coaching, supervision, reporting, practice, policy-making).	173	3.58 (0.92)	22 (12.7)	83 (48.0)	43 (24.9)	23 (13.3)	2 (1.2)
decision_support_6	When needed, our data system is updated to ensure its relevance to our program's work.	171	3.65 (0.88)	22 (12.9)	89 (52.0)	40 (23.4)	18 (10.5)	2 (1.2)
decision_support_7	My program analyzes data by relevant subgroups (e.g., outcomes by race, age group, etc.)	173	3.65 (0.97)	30 (17.3)	81 (46.8)	37 (21.4)	22 (12.7)	3 (1.7)
TECHNICAL LEADERSHIP								
technical_1	Leaders in my organization have the technical skills needed to use data for strategic planning.	172	3.95 (0.82)	43 (25.0)	88 (51.2)	31 (18.0)	10 (5.8)	0 (0.0)

Table 5 (continued).

Variable Name	*Survey item*	*N*	*M (SD)*	*Strongly Agree* n (%)	*Agree* n (%)	*Neither Agree nor Disagree*	*Disagree* n (%)	*Strongly Disagree* n (%)
technical_2	Leaders have emerged within my program in terms of promoting or 'championing' data use in our program.	172	3.74 (0.89)	32 (18.6)	80 (46.5)	45 (26.2)	13 (7.6)	2 (1.2)
technical_3	Leaders seek feedback from program staff regarding challenges using data.	171	3.86 (0.84)	33 (19.3)	96 (56.1)	29 (17.0)	11 (6.4)	2 (1.2)
technical_4	Leaders in my organization are directly involved in determining the data needed to demonstrate program impact.	171	3.70 (0.90)	24 (14.0)	95 (55.6)	31 (18.1)	18 (10.5)	3 (1.8)
technical_5	Leaders at my organization review program results and child and family data to stay informed of program performance.	173	4.04 (0.78)	43 (24.9)	105 (60.7)	16 (9.2)	7 (4.0)	2 (1.2)
technical_6	Leaders include data as a part of their rationale for implementing changes or policies in our organization.	173	3.94 (0.81)	37 (21.4)	102 (59.0)	23 (13.3)	9 (5.2)	2 (1.2)
ADAPTIVE LEADERSHIP								
adaptive_1	Leaders create an organizational culture, which values data and encourages its use for decision-making.	173	3.91 (0.81)	35 (20.2)	99 (57.2)	29 (16.8)	8 (4.6)	2 (1.2)
adaptive_2	Leaders in our organization have a clear vision of the long-term impact of our work supported with data.	172	3.90 (0.89)	43 (25.0)	84 (48.8)	32 (18.6)	11 (6.4)	2 (1.2)
adaptive_3	Leaders at our organization are willing to adapt messages and modify plans as data emerge.	173	3.95 (0.71)	34 (19.7)	101 (58.4)	35 (20.2)	2 (1.2)	1 (0.6)

Table 5 (continued).

Variable Name	*Survey item*	*N*	*M (SD)*	*Strongly Agree* n (%)	*Agree* n (%)	*Neither Agree nor Disagree*	*Disagree* n (%)	*Strongly Disagree* n (%)
adaptive_4	Leaders are competent in interpreting data to inform decisions that make sense for our program.	173	3.92 (0.80)	34 (19.7)	103 (59.5)	26 (15.0)	8 (4.6)	2 (1.2)
adaptive_5	When data doesn't tell us what we expect, leaders in my organization respond in ways that instill confidence in the program's future.	173	3.80 (0.86)	30 (17.3)	93 (53.8)	39 (22.5)	7 (4.0)	4 (2.3)

Table 6

Mean Summative and Mean Per Item Index Scores of Nine EC-DDDM Subscales

Subscale	*N*	*Mean Summative Index Score*	*Std. Dev.*	*Mean per Item Index Score*	*Std. Dev.*	*Rank**
Staff Selection	172	17.73	3.16	3.55	0.63	9th
Training	167	23.40	4.50	3.34	0.64	8th
Coaching and Supervision	170	24.50	3.51	4.08	0.58	2nd
Performance Assessment	173	14.29	2.63	3.57	0.66	7th
Systems Intervention	170	25.39	3.12	4.23	0.52	1st
Facilitative Administration	163	32.54	4.30	4.07	0.54	3rd
Decision Support Data Systems	168	25.35	4.39	3.62	0.63	6th
Technical Leadership	168	23.17	3.91	3.86	0.65	5th
Adaptive Leadership	172	19.48	3.46	3.90	0.69	4th

*Note: Rankings based on the highest to lowest mean per item index score.

Table 7

9-factor CFA Standardized and Unstandardized Parameter Estimates

Observed Variable	*β*	*B*	*SE*	*p-value*
Selection & Hiring				
selection_1	0.667	1	**	**
selection_2	0.594	0.89	0.142	<.001
selection_3	0.494	0.74	0.158	<.001
selection_4	0.651	0.976	0.161	<.001
selection_5	0.769	1.152	0.164	<.001
Training				
training_1	0.727	1	**	**
training_2	0.719	0.99	0.102	<.001
training_3	0.793	1.091	0.1	<.001
training_4	0.567	0.781	0.127	<.001
training_5	0.641	0.882	0.129	<.001
training_6	0.794	1.092	0.114	<.001
training_7	0.55	0.757	0.137	<.001
Coaching & Supervision				
coaching_1	0.787	1	**	**
coaching_2	0.853	1.084	0.116	<.001
coaching_3	0.86	1.093	0.103	<.001
coaching_4	0.653	0.829	0.091	<.001
coaching_5	0.904	1.148	0.103	<.001
coaching_6	0.79	1.004	0.103	<.001
Performance Assessment & Evaluation				
perf_assess_1	0.726	1	**	**
perf_assess_2	0.943	1.299	0.15	<.001
perf_assess_3	0.802	1.105	0.129	<.001
perf_assess_4	0.299	0.412	0.162	0.011
Systems Intervention				
sys_intervention_1	0.704	1	**	**
sys_intervention_2	0.71	1.009	0.099	<.001
sys_intervention_3	0.824	1.171	0.121	<.001
sys_intervention_4	0.897	1.274	0.127	<.001
sys_intervention_5	0.754	1.071	0.089	<.001
sys_intervention_6	0.749	1.064	0.134	<.001
Facilitative Administration				
facil_admin_1	0.792	1	**	**
facil_admin_2	0.745	0.94	0.057	<.001
facil_admin_3	0.906	1.145	0.05	<.001
facil_admin_4	0.762	0.962	0.071	<.001
facil_admin_5	0.738	0.932	0.06	<.001
facil_admin_6	0.783	0.989	0.057	<.001
facil_admin_7	0.689	0.87	0.066	<.001

Table 7 (continued).

Observed Variable	*β*	*B*	*SE*	*p-value*
facil_admin_8	0.683	0.863	0.067	<.001
Decision Support Data System				
decision_support_1	0.687	1	**	**
decision_support_2	0.84	1.223	0.168	<.001
decision_support_3	0.361	0.526	0.149	<.001
decision_support_4	0.715	1.041	0.151	<.001
decision_support_5	0.877	1.277	0.171	<.001
decision_support_6	0.675	0.983	0.15	<.001
decision_support_7	0.54	0.786	0.136	<.001
Technical Leadership				
technical_1	0.875	1	**	**
technical_2	0.775	0.886	0.049	<.001
technical_3	0.765	0.875	0.048	<.001
technical_4	0.656	0.75	0.082	<.001
technical_5	0.832	0.951	0.04	<.001
technical_6	0.852	0.974	0.047	<.001
Adaptive Leadership				
adaptive_1	0.87	1	**	**
adaptive_2	0.906	1.042	0.049	<.001
adaptive_3	0.829	0.953	0.058	<.001
adaptive_4	0.938	1.078	0.05	<.001
adaptive_5	0.801	0.921	0.043	<.001

Note: *β* = Standardized parameter estimate coefficient. *B* = Unstandardized parameter estimate coefficient. *SE* = Standard error of the unstandardized parameter estimate coefficient.
** Denotes that the model specification fixes each factor on the first observed variable for each factor.

Table 8

3-factor CFA Standardized and Unstandardized Parameter Estimates

Observed Variable	*β*	*B*	*SE*	*p-value*
Competency Drivers				
selection_1	0.491	1	**	**
selection_2	0.431	0.877	0.145	<.001
selection_3	0.354	0.72	0.161	<.001
selection_4	0.457	0.929	0.167	<.001
selection_5	0.548	1.114	0.171	<.001
training_1	0.567	1.154	0.188	<.001
training_2	0.553	1.125	0.168	<.001
training_3	0.617	1.256	0.176	<.001
training_4	0.397	0.809	0.163	<.001
training_5	0.488	0.992	0.165	<.001
training_6	0.628	1.279	0.174	<.001
training_7	0.439	0.894	0.157	<.001
coaching_1	0.753	1.532	0.233	<.001
coaching_2	0.808	1.644	0.245	<.001
coaching_3	0.816	1.659	0.188	<.001
coaching_4	0.618	1.258	0.173	<.001
coaching_5	0.862	1.754	0.214	<.001
coaching_6	0.73	1.484	0.181	<.001
perf_assess_1	0.66	1.343	0.187	<.001
perf_assess_2	0.823	1.674	0.213	<.001
perf_assess_3	0.705	1.434	0.207	<.001
perf_assess_4	0.249	0.506	0.219	0.021
Organizational Drivers				
sys_intervention_1	0.585	1	**	**
sys_intervention_2	0.566	0.967	0.098	<.001
sys_intervention_3	0.774	1.324	0.167	<.001
sys_intervention_4	0.787	1.346	0.153	<.001
sys_intervention_5	0.672	1.149	0.112	<.001
sys_intervention_6	0.583	0.997	0.129	<.001
facil_admin_1	0.795	1.359	0.14	<.001
facil_admin_2	0.743	1.271	0.135	<.001
facil_admin_3	0.914	1.563	0.153	<.001
facil_admin_4	0.757	1.295	0.138	<.001
facil_admin_5	0.741	1.267	0.128	<.001
facil_admin_6	0.804	1.375	0.147	<.001
facil_admin_7	0.686	1.172	0.129	<.001
facil_admin_8	0.688	1.177	0.139	<.001
decision_support_1	0.511	0.874	0.163	<.001
decision_support_2	0.612	1.047	0.115	<.001
decision_support_3	0.249	0.426	0.169	0.012
decision_support_4	0.574	0.982	0.134	<.001
decision_support_5	0.677	1.158	0.133	<.001
decision_support_6	0.514	0.878	0.143	<.001
decision_support_7	0.406	0.695	0.122	<.001

Table 8 (continued).

Observed Variable	*β*	*B*	*SE*	*p-value*
Leadership Drivers				
technical_1	0.864	1	**	**
technical_2	0.757	0.876	0.049	<.001
technical_3	0.748	0.865	0.047	<.001
technical_4	0.639	0.739	0.081	<.001
technical_5	0.811	0.938	0.04	<.001
technical_6	0.825	0.954	0.045	<.001
adaptive_1	0.853	0.987	0.036	<.001
adaptive_2	0.891	1.031	0.036	<.001
adaptive_3	0.816	0.944	0.044	<.001
adaptive_4	0.914	1.057	0.035	<.001
adaptive_5	0.787	0.911	0.035	<.001

Note: *β* = Standardized parameter estimate coefficient. *B* = Unstandardized parameter estimate coefficient. *SE* = Standard error of the unstandardized parameter estimate coefficient.
** Denotes that the model specification fixes each factor on the first observed variable for each factor.

Table 9

Goodness-of-Fit Statistics of the 9-Factor and 3-Factor Models

Model	*df*	X^2	X^2/df	*CFI*	*TLI*	*RMSEA (90% C.I.)*
9-factor	1341	1534.65***	1.14	.98	.97	.03 (.021 - .036)
3-factor	1374	1830.34***	1.33	.94	.94	.04 (.038 - .049)

Note: CFI = comparative fit index; TLI = Tucker Lewis index; RMSEA = root mean square error of approximation.
*** $p < .001$

Table 10

Cronbach's Alpha (α) for 9-factor and 3-factor models.

9-Factor Model	*# of Items*	*α*
Competency Drivers		
Selection	5	.670
Training	7	.779
Coaching & Supervision	6	.850
Performance Assessment	4	.732
Organization Drivers		
Systems Intervention	6	.787
Facilitative Administration	8	.863
Decision Support Data System	7	.795
Leadership Drivers		
Technical Leadership	6	.865
Adaptive Leadership	5	.904
3-Factor Model	*# of Items*	*Cronbach's Alpha*
Competency Drivers	22	.886
Organization Drivers	21	.888
Leadership Drivers	11	.931

Table 11

Correlations (r), eta-squared (η^2), or omega-squared ($\omega 2$) of demographics, program characteristics, and factor scores

	Effect Test	9-Factor Score Correlations (*r*), Eta-Squared Values (η^2), or Omega-Squared values (ω^2)								
		Selection & Hiring	Training	Coaching & Supervision	Performance Assessment	Systems Intervention	Facilitative Admin	Decision Support Data System	Technical Leadership	Adaptive Leadership
Categorical Variables										
Race	η^2	.000	.000	.017	.001	.009	.010	.008	.017	.002
Ethnicity	η^2	.003	.014	.022	.023	.016	.042	.006	.020	.016
Education	η^2	.001	.009	.012	.015	.001	.000	.013	.013	.008
# of Families Served	η^2	.008	.025	.004	.010	.013	.037	.008	.050	.013
# of Staff	η^2	.002	.015	.019	.022	.013	.009	.001	.027	.012
Program Type	η^2 *or* ω^2	.000	.012	.016	.039[ab]	.021	.000	.031	.001	.000
Continuous Variables										
Age in years	*r*	.150	.096	.080	.033	-.147	.179	.039	.117	.169
Experience in years	*r*	.076	.127	.182	.157	-.010	.196	.159	.168	.136

Notes: *Statistical significance based a Bonferroni corrected alpha, $p < .006$.

[a] Relationship tested using a Welch-ANOVA

[b] Effect size value based on Omega-Squared (ω^2)

Chapter V

Discussion

Existing literature supports the application of core implementation drivers as a theoretically-based strategy for influencing the uptake of research-supported practices and supporting DDDM (Albers et al, 2017; Barwick et al., 2011; Fearing et al., 2014; Graff et al., 2010; Kimber et al., 2012; McCrae et al., 2014; Metz et al., 2015; Salverson et al., 2015). Additionally, the literature contains specific calls to support early childhood programs' efforts to make data more accessible and build organizational capacity for DDDM (Children's Defense Fund—Minnesota, 2017; Fischer et al., 2014). Despite research on applying core implementation drivers to inform research supported practices and DDDM, and the push for integrating these strategies into early childhood programs, no literature emerged demonstrating how the application of implementation drivers may support DDDM in early childhood programs. Filling this gap is particularly timely because it has been suggested that proving program efficacy through implementation and continuous data use to improve decision-making is vital to meet accountability demands and secure limited funding resources (Coultan et al., 2015; Yazejian & Bryant, 2013; Zweig et al., 2015). To that end, this study sought to increase the understanding of how early childhood programs use data and what factors drive program readiness for DDDM.

Three key questions were posed: 1) How do early childhood program administrators rate their organizations' readiness for DDDM? 2) Is the *Active Implementation Drivers Framework (AIF Drivers)* an effective guide for understanding organizational readiness for DDDM? 3) How are demographic characteristics of program administrators and characteristics of early child programs related to factors of readiness for data-driven decision-making? Answering these questions required the development and initial validation of a theoretically-grounded instrument tailored specifically to early childhood program administrators' perspectives on data use based

on NIRN's *AIF Drivers*. Overall, this study's findings inform our understanding of early childhood programs' data use and drivers for program readiness for DDDM in at least three ways. First, the study provided a deeper and theoretically-grounded understanding of program administrators' perspectives on data use. Second, it established initial evidence supporting the *AIF Drivers* as a fitting underlying factor structure for measuring DDDM. Finally, the study found no evidence of relationships between administrator demographics and program characteristics and readiness for DDDM. The following discussion is organized by research question and discusses the findings in more depth.

RQ1: How do early childhood program administrators rate their organizations' readiness for DDDM?

The target population for the study included early childhood program administrators. The researcher engaged statewide early childhood initiatives and funding agencies across six Midwestern states to access and recruit participants. Of 545 program administrators invited, 173 responded, representing a 32% response rate. Respondents to the EC-DDDM questionnaire reported on organizational data practices related to nine distinct implementation drivers. Mean responses to 47 of the 54 items indicated agreement with the statement, implying that program administrators tended to agree with the importance of data use and DDDM for their program. Of the remaining seven items, responses to five items indicated a somewhat neutral response, and responses to two items implied a slight disagreement.

These findings suggest that program administrators largely agree with data use and DDDM across the C*ompetency*, O*rganizational*, and *Leadership* construct domains. And at the very least, these topics are not foreign to program administrators. As such, connecting these findings to theories of change may be key to understanding program readiness for DDDM.

Conceptual models of behavioral change have suggested that readiness for change occurs gradually overtime across a number stages (DiClemente, Schlundt, & Gemmell, 2004). In the first stage, known as *pre-contemplation*, individuals are uninterested, in denial, or completely unaware of a need for change. To this end, any progress beyond the initial *pre-contemplation* stage is viewed as a positive change (DiClemente et al., 2014). In relation to this study, program administrators' general agreement with items on the EC-DDDM provides evidence of readiness vis-à-vis their movement beyond the *pre-contemplative* stage of change and their awareness and openness to DDDM.

Ranking the EC-DDDM subscales. To understand potential patterns among responses, the mean per item index scores of each of the nine driver subscales were analyzed and ranked. The results of this analysis will now be explored in reference to the patterns that emerged.

Highest ranking EC-DDDM subscales. In terms of the highest ranking subscales, this study discovered two notable findings. First, a consistency emerged as two of the highest scoring subscales (i.e., *systems intervention* subscale and the *facilitative administration* subscale) corresponded to the *Organizational* construct of the *AIF Drivers* framework. These findings may reflect the pressure program administrators feel to demonstrate program worth to external entities and funders and may strongly suggest that program administrators are genuinely hearing the calls for accountability, continuous quality improvement, and demonstration of impact (Coultan et al., 2015; Lewis et al., 2005; Yazejian & Bryant, 2013; Zweig et al., 2015). The other important finding from the highest ranking group involves the biggest outlier in rankings. While all other *Competency* based subscales ranked at the bottom, the *coaching and supervision* subscale ranked second highest. Items in this scale involved coaches and supervisors understanding of data requirements for the program's desired outcomes, their access to multiple

sources of data across multiple levels (i.e., child, family, and provider levels), and their competency at using data to inform decision-making. Given the reality that many program administrator job titles reflect and identify as supervisors, coaches, or managers (Bruens, 2012; Freeman et al., 2017; NAEYC, 2007), their familiarity with coaching and supervision competencies is understandable and may have contributed to its high ranking. It is also of note that panelists emphasized clarifying this particular concept during the instrument development phase.

Lowest ranking EC-DDDM subscales. On the opposite end of these rankings, subscales that the fell to the bottom scoring group came exclusively from *Competency* based drivers and included *performance assessment, staff selection,* and *training drivers.* This finding may be congruent with previous research on data use in early childhood programs that suggested programs primarily use data for compliance (Zweig et al., 2015). In other words, competencies and practices related to hiring, training, and ongoing performance monitoring may be less linked to compliance in the minds of program administrators, and as such, are not at the forefront when it comes to DDDM to support hiring, training, and performance assessment processes. If so, opportunities for strategy development around integrating data into these processes are worth further consideration. Developing tools to boost data use in these areas could serve as a practical application for implementation scientists and social work researchers to build strategic relationships with organizations and practitioners with the aim of promoting the practical uptake of evidence and EBP (Bellamy et al., 2008; Bertram et al., 2015; Fischer et al., 2014; Okypch and Yu, 2014).

Middle ranking EC-DDDM subscales. Finally, the middle ranking subscales revealed two prominent findings. A consistency emerged as two subscales related to the *Leadership*

construct were present. The *adaptive leadership* and *technical leadership* subscales formed a small cluster ranking fourth and fifth respectively. While we have already learned that program administrators assume a wide range of managerial and leadership roles (Freeman et al., 2017; NAEYC, 2007), these findings may suggest a tension with these respective roles. Empirical evidence elucidated a multi-level view of leadership wherein the effects of transformational leaders in change and implementation efforts are mediated through the actions of middle managers (Guerrero, Frimpong, Kong, Fenwick, & Aarons, 2018). In light of this research and given that the respondents are administrators themselves, the results of this study seem to align with Guerrero and colleagues' (2018) conclusions and appear as though program administrator respondents identify more with the middle manager functions of DDDM rather than the functions of a transformational leader.

What remains unclear from this study is why they felt more strongly about DDDM in their administrative and coaching roles than they did in their leadership roles. Perhaps the high ratings on *systems intervention*, *administrative facilitation*, and *coaching and supervision* subscales are the result of respondents recognizing these factors as inherently linked to the familiar functions of an administrator. With this familiarity, they are able to assess themselves and their administrative peers on data use for DDDM. On the contrary, the mid-range ratings on the *technical* and *adaptive leadership* subscales may be the result of respondents associating these factors with the functions of top-level leaders and perhaps have fewer opportunities to witness DDDM or are less familiar with what it looks like in practice. Because many implementation frameworks, especially the *AIF Drivers*, accentuate the importance of strong leadership in efforts to implement change, innovations, and EBPs (Aarons, Ehrhart, Farahnak, & Sklar, 2014; Fixsen et al., 2005; Fixsen et al., 2009; Lyons et al., 2018), these lingering questions

make it imperative to continue studying leadership and to ascertain exactly what leadership means in the context of early childhood programs and their implementation and DDDM efforts.

Another unique finding from the middle ranking subscale group is the presence of the *decision support data system* subscale. While the other two *Organizational* construct based subscales were among the top ranking group, the *decision support data systems* subscale ranked at the bottom of the middle group in sixth place. This finding fits within the key takeaways of a recent report from the Early Childhood Data Collaborative that exposed a current lack of comprehensive early childhood data systems for the purposes of supporting policy decisions and understanding links between program quality and outcomes (King, Perkins, Nugent, & Jordan, 2018). Moreover, the Early Childhood Data Collaborative found home visiting programs as the least likely of early childhood programs to link data (King et al., 2018). Given that the majority of the program administrator respondents in this study came from home visiting programs, the issue of comprehensive decision support data systems appears to be a real and present need. This presents yet another possibility for the strategic partnerships suggested earlier between implementation scientists, social work researchers, and the practice field to conceptualize and identify best practices for data system development (Bellamy et al., 2008; Bertram et al., 2015; Fischer et al., 2014; Okypch and Yu, 2014).

It may also be worth considering if the relatively low ranking of the *decision support data system* subscale is logically linked to the low rankings of the *staff selection, training,* and *performance assessment* subscales. Indeed, the developers of the *AIF Drivers* and scholars alike express favor in decision support data systems that include complete data related to staff performance and fidelity and suggest that DDDM is not possible without it (Fixsen et al., 2015; Zweig et al., 2015). It may be that the limitations of program data systems in terms of what data

they contain and what meaningful reports they provide is contributing to their lower use of data in other subscale factor areas. Consistent with the compliance-centric use of data discussed elsewhere in the literature (Zwieg et al., 2015), it could be that data systems are designed predominantly around compliance and accountability to external entities and are missing elements for tracking other practical decision data (e.g., *staff selection* and *training*). Furthermore, these conclusions are theoretically sound given the assumption of the that implementation drivers intersect, integrate, and influence one another (Fixsen et al., 2005; Fixsen et al., 2009).

Summary of high, medium, and low subscale rankings. The effort to categorize EC-DDDM's subscales into high, mid-range, and low ranking groups was worthwhile as it led to the revelation of meaningful patterns, which may not have been discovered otherwise. Specifically, it exposed three distinct patterns for each of the three construct levels. First, *Organizational* based subscales related to *systems intervention* and *facilitative administration* were prevalent the highest scoring group, leading the researcher to suggest that administrators largely understand the importance of data to justify their programs' worthiness. Second, *Competency* based items dominated the lowest scoring group. Thus, this finding suggests less readiness for DDDM during hiring, training, and performance assessment process. Despite their dominance of the lowest scoring group, one *Competency* based subscale, *coaching*, ranked among highest and led to the speculation that program administrator respondents were more familiar with their roles as coaches, supervisors, or managers. Third, *Leadership* based subscales coalesced in the middle, and as such, the readiness for DDDM at the leadership level is less clear. While this categorization did unveil individual differences between these subscales and

drivers, it also confirmed how, taken as a whole, organizations operate within multi-faceted and multi-level contexts (Guerrero et al., 2018; Weiner, 2009).

RQ2: Is the Active Implementation Drivers Framework an effective guide for understanding organizational readiness for DDDM?

At a conceptual level, this study examined the extent to which the *AIF Drivers* are an effective guide for understanding organizational data use and DDDM. At a practical level, the study attempted to discover initial evidence for the validity of the newly developed EC-DDDM instrument. While acknowledging no single study can establish an instrument's complete validity (Streiner & Kottner, 2014), the researcher evaluated the initial validation of EC-DDDM based on Goodwin's (2002) recommendation to consider the accumulation of evidence across five validity categories: 1) evidence based on test content, 2) evidence based on response processes, 3) evidence based on internal structure, 4) evidence based on other variables, and 5) evidence based on consequences of testing. To this end, the study findings suggest initial evidence of EC-DDDM's validity as well as evidence of the *AIF Drivers* as an underlying factor structure for measuring organizational readiness for DDDM. Specifically, there is support for three of the five aspect categories based on its test content, its internal structure, and the relationships between external variables (i.e., demographics and program characteristics) and the instrument's subscale factors. A discussion of each of these three evidence categories now follows.

Evidence of test content validity. The first evidence for validity of the EC-DDDM involves the concept of test content validity. Test content validity raises questions around the extent to which the content of an instrument relates to the content domain (Goodwin, 2002) and translates to this study in terms of how well the content of the EC-DDDM questionnaire related

to the concepts and practices of data use in early childhood programs. The evaluation of an instrument from experts is also recommended (Goodwin, 2002; Grant & Davis, 1997). The selection process for the panel of experts was critical and emphasized finding experts with relevant backgrounds, training, experience, and qualifications in the various content areas of the study as well as those with practical experience to evaluate the burden of completing the instrument to the final sample of respondents (Grant & Davis, 1997). Another key part of the selection process involved the number of panelists needed. Grant and Davis (1997) suggested the number of panelists should be predicated on the range of content areas in need of a given study. Seven members were selected for this study given their wide range of distinct, relevant, and overlapping knowledge bases. These knowledge bases included those familiar with implementing evidence-based early childhood programs, those with backgrounds in instrument development and validation, those familiar with early childhood research and evaluation, and those familiar with the theoretical implementation framework used to guide survey development.

Instrument development was an iterative process that provided an important opportunity for refinement and revision. Three iterations occurred between the researcher and panel of experts. Development began with the researcher writing DDDM-based statements corresponding to each of the nine *AIF Drivers* (Fixsen et al., 2005; Fixsen et al., 2009). To refine the instrument, the researcher distributed the questionnaire to a panel of seven experts who provided content feedback relating to the instrument's understandability, usefulness, length, and completeness. Panelists included two social work academics familiar with the study, two applied research with backgrounds in instrument development and early childhood program research and evaluation, two state-level leads and funders of statewide early childhood programs, and one early childhood program administrator. Based on this feedback, the researcher revised, removed,

and added several items as well as definitions for commonly misunderstood terms (i.e., coach and coaching). See Appendix B to view the final instrument used in this study.

Reflecting on this approach and existing literature on validity standards, there is reasonable evidence of EC-DDDM's test content validity. First, generation of the initial item list for the EC-DDDM was consistent with recommendations to base item development on relevant theory (Holmbeck & Devine, 2009). Second, the approach used for the EC-DDDM followed recommendations to develop and refine the instrument over a series of iterations involving a panel of experts to review and provide feedback on content (Goodwin, 2002; Holmbeck & Devine, 2009). And third, the approach to selecting panelists to review the EC-DDDM aligned with the *Standards for Educational and Psychological Testing*, which suggest having panelists with a wide-range of practical, theoretical, and empirical expertise (Goodwin, 2002; Holmbeck, 2009). In retrospect, developing the instrument through this particular process served as the bedrock of the entire study as it gave the researcher an opportunity to hear others' perspectives on the potential usefulness and shortcomings of the original EC-DDDM items. These iterative feedback loops led to a critical evaluation of EC-DDDM's content and ultimately, a final instrument tailored for its target respondents.

Evidence of internal structure validity. The second, and perhaps strongest, evidence of validity present in this study is based on the internal factor structure of the instrument. This type of evidence is related to construct validity and addresses questions about the relationships and match between instrument items and their underlying constructs (Goodwin, 2002). It is often associated with confirmatory factor analysis as an analytical method that may contribute to the validity evidence of an instrument (Goodwin, 2002; Holmbeck & Devine, 2009). The findings from the confirmatory factor analyses conducted for this study indicated a goodness of fit for

both 3-factor and 9-factor models as specified. Furthermore, there is reasonable evidence to suggest that all factors in both models met or exceeded commonly accepted levels of internal consistency (Nunnally, 1978; Taber, 2018). As such, the analysis of the initial use of the EC-DDDM instrument provided evidence supporting the proposition that *AIF Drivers* act as an underlying factor structure for organizational data use and readiness for DDDM in a sample of early childhood program administrators.

When the 3-factor and 9-factor models are compared, the 9-factor model better fits the data overall. That suggests that data use and DDDM emerges from the nine distinct factors identified in the *AIF Drivers* and aligns with both theoretical assumptions and empirical research on measurement development. Theoretically, the 9-factor model as a better fit makes sense as *AIF Drivers* assumes successful implementation requires the presence of each of the nine component drivers to some degree (NIRN, n.d.). Furthermore, while empirical research on instruments based intentionally on implementation drivers is rare, the fit of the 9-factor model for the EC-DDDM is similar to the factor analysis of the *Implementation Components Questionnaire (ICQ)*, which also confirmed the drivers as its underlying factor structure (Ogden et al., 2012). All things considered, the findings of the confirmatory factor analysis combined with their consistency with theory and previous research make a strong case for EC-DDDM's construct validity.

Evidence of concurrent validity based on relationships with external variables. The third kind of validity evidence found in this study is associated with concurrent validity and involves examining the relationships between external variables and the instrument (Goodwin, 2002). Goodwin (2002) argued for the importance of this type of validity analysis to understand the extent to which scores obtained from an instrument correlate with other variables in ways one

might or might not expect. Because this study sought to understand whether or not there were relationships between the EC-DDDM results and demographics and program characteristics of the respondents, the study presented an opportunity to assess concurrent validity through a series of bivariate analyses to compare group differences and correlations between demographics and program characteristic and the subscale scores of the instrument. These bivariate analyses found no statistically significant relationships or practically significant relationships in terms of effect size between demographics, program characteristics, and subscale factor scores on the EC-DDDM.

The importance of this finding is encouraging to EC-DDDM's concurrent validity case and should not be overlooked. While demographic and program characteristic data can change, these variables usually remain fixed and are less responsive to change over time (LeCroy, 2019). As a result, actual relationships with these kinds of fixed variables make it difficult to measure the effect of change over time on a behavior or outcome or understand how to design programs or make decisions based on them (LeCroy, 2019). In the context of this study, the fact that none of these demographic or program characteristic variables appear to have a substantial relationship to readiness for DDDM supports the case for the instrument's concurrent validity. Moreover, because the findings of the confirmatory factor analysis suggest the *AIF Drivers* are a fitting factor structure, the EC-DDDM subscales and items provide a more practical framework for organizations to base decision-making processes. For an example of this, consider what a program might do to change, encourage, or improve data use in its practice. It seems far more reasonable, and ethical, that a program may be better situated to change its behaviors around data use by making adjustments in its hiring or training processes than it would be to assume that

hiring a particular service provider based on fixed factors such as gender, age, or race would lead effective DDDM.

Summary of validity assessment. While this study is the first use and assessment of the validity of the EC-DDDM, the findings offer evidence to support its validity in the areas of test content validity, internal structure validity, and concurrent validity. As such, it appears there is reasonable initial evidence supporting the *AIF Drivers* as an effective framework for guiding the measurement and understanding of readiness for DDDM in early childhood programs.

RQ3: How are demographic characteristics or program characteristics of early childhood program administrators related to factors of readiness for DDDM?

A thorough search of both scholarly and gray literature produced no studies that attempted to understand the relationships between program administrators' personal demographics (e.g., age, race, gender, education), program characteristics (e.g., program type, size, and staffing), and data use in early childhood programs. To the best of this researcher's knowledge, this study is the first of its kind to pose such a question. However, this study found no credible evidence of relationships between demographics and program characteristics and the nine summative subscale scores of the EC-DDDM. The results of 72 bivariate analyses between all variables studied returned non-statistically significant findings, and, moreover, an analysis of effect sizes suggested that the relationships would have been small at best had there been any statistically meaningful results. At least for now, it is concluded that readiness for DDDM is unrelated to respondent and program characteristics. Considering the literature cited earlier, this lack of evidence for these types of relationships may be encouraging. After all, demographic and characteristic variables are unlikely to change (LeCroy, 2019), difficult for programs to control, and ultimately lead to ethical questions regarding to how to use the information in socially just

manners. Despite this encouraging finding, it is important to note the respondent sample lacked diversity. The vast majority of respondents were white women working in home visiting programs. To fully understand how demographic and program characteristics relate to DDDM, a larger and more diverse sample is needed.

Additionally, these findings lead to further speculation of what other variables may be more precisely related to data use and DDDM and should be considered for future research. To this question, two suggestions are offered. The first suggestion is that further investigation should examine the relationships between the subscale scores themselves. It may be reasonable to hypothesize, for example, that higher data use by programs in certain areas leads to higher levels of data use in other areas. After all, it has been suggested both conceptually and empirically that the implementation drivers have compensatory effects for one another (Collins-Camargo et al., 2011; Fixsen et al., 2005; Fixsen et al., 2009). Does data use at the leadership level relate to data use in competency factors such as hiring, training, and coaching? Does data use in early program processes like hiring predict data use in training and performance assessment processes that occur later? Further examination of the relationships between these subscales may elucidate answers these questions.

The second suggestion is that future studies should devote time to understanding the individual variability of certain organizational practices and decisions related to data. It could be that data use and DDDM requires the right combination of people, tools, plans, activities, and timing in order to occur. Strengthening this claim is literature on the five dimensions of capacity in non-profit organizations, which emphasizes the importance of human resources, financial stability and sufficiency, infrastructure, planning and development, and networks of external partnerships (Hall et al., 2003; Misener & Doherty, 2009). Furthermore, a new line of inquiry

known as “precision prevention science” is emerging with the explicit aim of identifying the active ingredients of change (Supplee, Parekh, & Johnson, 2018). Looking to these frameworks for guidance may offer a conceptual foundation for building studies that seek to understand the relationships, correlates, and predictors of DDDM.

Limitations

In light of these encouraging findings and discussions, the study experienced a number of general limitations related to its research design. For starters, it is cross-sectional and lacks evidence of EC-DDDM’s usefulness over time. Because implementation occurs the course of several years in some instances (Fixsen et al., 2015; Ogden et al., 2012), this study cannot say how readiness for DDDM changes over time and what factors ebb and flow throughout the program implementation lifecycle. Longitudinal studies could help identify patterns in these trends over time and may support the test-retest reliability of using EC-DDDM multiple times.

The study is also limited with respect to its sample. It focused on one specific respondent population (i.e., early childhood program administrators) and used non-probability sampling techniques to engage them (Rubbin & Babbie, 1993). There was a rationale for engaging program administrators specifically given their multitude of program roles and responsibilities; however, this approach is less generalizable and may have contributed to a sample that lacked demographic diversity, especially as it relates to race and gender (Rubbin & Babbie, 1993). Moreover, even though the sample size for this study was determined adequate, it is on the lower end of what is recommended (Mundform et al., 2005; Worthington & Whittaker, 2006). The risks associated with this limitation include the potential for unstable results due to higher margins of error and a sample that is not fully representative of the target population (DeVellis, 2003). Future studies should engage in efforts to recruit both a larger sample and a more diverse

sample. In terms of a larger sample, such efforts may involve recruiting participants on a national scale, and perhaps even internationally, rather than the more regional and relationship-based approach used in this study. For more diverse samples, future studies should also recruit participants at other levels of the organizational hierarchy such as direct service providers, executive leadership, and even families served to compare and contrast how they rate program data practices.

One final general limitation with this study is that its exclusive quantitative design constrains any commentary on why program administrators report more agreement with some factors or items than others. For example, even if theoretically supported, the previous discussion regarding respondents identifying more strongly with their roles as administrators or coaches rather than their roles as leaders is speculative. Future studies should attempt to disentangle the extent to which these results are a product of their familiarity of their own data practices, their perceptions about their roles and responsibilities to encourage data use and build a culture of DDDM, and their social desire to appear in agreement with data practices of their assumed identities. Perhaps future research could combine responses to the EC-DDDM with qualitative follow ups with participants to gain a deeper understanding of how respondents perceive data use and why respondents rated items in particular ways. Also, future studies should consider the relationship between scores on certain factors. For instance, low scores on the data system items may have contributed to low scores on some of the *Competency Driver* based items around staff selection, training, and performance assessment. This particular example was also a point of emphasis in the previous discussion that, while theoretically-based, is not confirmable within the limits of this study's exclusive quantitative design.

Limitations of test content validity evidence. Even though the use of panelists within this study supports the case for EC-DDDM's content validity, there were three limitations with respect to how the researcher utilized the panel. First, the EC-DDDM development process only included eight people, the researcher and seven panelists. While three individuals had experience as early childhood program administrators, involving more representatives of the target population in instrument development may have refined and tailored the EC-DDDM even further. Gathering this feedback could improve acceptability, appropriateness, and usability of EC-DDDM. Second, the selection and recruitment of panelists were based largely on the researcher's knowledge of and professional relationships with each of the panelists. It is not possible to ascertain if this introduced some bias into their review. To guard against this problem, the researcher discussed panel representation with a mentor to vet the process. Third, only two of the seven panelists were included in reviewing the final iteration of the EC-DDDM. Even though two panelists agreed that the researcher incorporated feedback from all panelists in the final instrument, it is unknown if the remaining panelists would agree. However, given that a number of these panelists are focused on implementing and delivering programs to children and families rather than implementation research, it is important to reflect on the practicality and feasibility of asking panelists to obligate time for additional reviews, especially when they did so voluntarily without compensation. Thus, with this study, the researcher chose to move forward with a limited number of panelists reviewing the final instrument. With these considerations in mind, researchers conducting similar studies are encouraged to consider how they will recruit diverse panel members, include them in the later iterations of the instrument development process, and ensure panelists are compensated for their efforts.

Limitations of internal structure evidence. As stated earlier in this discussion, evidence of the internal structure of EC-DDDM may provide the strongest evidence of its validity insofar as it is obtainable and reportable through factor analyses; however, Goodwin (2002) cautions against relying exclusively on it when examining validity. Furthermore, the sample responding to this study is limited in terms of its size, reach, and diversity. Similar studies on larger and more diverse samples may result in different findings related to internal structures and are worthy of replicate investigation.

Of particular importance to this researcher is the mindfulness of designing and validating an instrument that genuinely helps early childhood programs advance their work. As noted by Thorndike (1997), just because an instrument may have factorial validity does not necessarily mean the instrument has practical or substantive utility in the real world. While the results of this initial study and feedback from panelists are promising, it is yet to be seen whether or not this instrument will contribute in this way. Future work in this area should build in feedback mechanisms with respondents to understand their perspectives on its utility.

Limitations of relationships with external variables evidence. This study is not without its limitations related to the evidence it produced with external variable relationships and comparisons. These limitations may hinder the study's understanding of EC-DDDM's criterion and construct validity. As it pertains to criterion validity, the bivariate analyses conducted are correlational in nature rather than predictive and are not generalizable beyond the study sample (Goodwin, 2002). Future studies should assess criterion validity by examining the relationship between the EC-DDDM and implementation and client outcomes. As for its limitations with construct validity, no convergent or divergent validity tests were conducted to enhance an understanding of the study's findings in relation to similar or different constructs (Goodwin,

2002). Any prospective studies should incorporate additional measures of constructs that are similar (i.e., convergent studies) or dissimilar (i.e., discriminant studies) to the constructs and factors measured in the EC-DDDM.

Implications for Early Childhood Practice

Even though there are limitations associated with this study, it also gave rise to a number of notable implications for practice and research. Despite the substantial amount of implementation theory and research developments suggesting that certain components, factors and capacities may support and influence DDDM, no measure of DDDM in early childhood programs had been developed (Albers et al, 2017; Barwick et al., 2011; Children's Defense Fund—Minnesota, 2017; Fearing et al., 2014; Fischer et al., 2014; Graff et al., 2010; Kimber et al., 2012; McCrae et al., 2014; Metz et al., 2015; Salverson et al., 2015. Accordingly, the development of the EC-DDDM provides the early childhood practice landscape an assessment platform of sorts on which to understand their own programs' readiness for DDDM and identify areas of strength or opportunities for improvement within their own practice. Programs' use of EC-DDDM early and often throughout program implementation may help organizations identify strengths and needs for additional supports across implementation drivers and understand the patterns of various factors over time. Circling back to the dimensions of capacity (Hall et al., 2003; Misener & Doherty, 2009), these opportunities may be general in nature such as acknowledging a lack of a proper data system infrastructure or may be more innovation-specific including fostering buy-in and champions to lead DDDM efforts. In other words, the EC-DDDM is a theoretically-grounded and research-supported outline of activities, behaviors, and roles that can be used in early childhood programs to inform opportunities for DDDM. In its own way, the use of the EC-DDDM in a real practice setting is a pathway to data-driven

decision-making in and of itself. Research backs this proposition as Lyons and colleagues (2018) acknowledged this same implication as it pertains to the development of strategic implementation measures for the uptake of EBPs in the education sector.

Implications for Social Work Research

The creation of a new measure for practice grounded in a pragmatic implementation framework is rather timely. At the most recent Annual Conference of the Society for Social Work Research (SSWR), a keynote speaker highlighted a need for social work scholars to create new measures in an effort to address limited progress being made in the evidence base for social work practice (LeCroy, 2019). Rather than rely on conventional psychometric theories, LeCroy (2019) urged social work researchers to embrace a new 'socialworkmetric' paradigm with the potential to discover and advance evidence-based social work. It is peculiar, and perhaps not coincidental, that LeCroy (2019) traces his concerns with measurement, and explicitly *mismeasurement*, back to his time as a researcher exploring the potential evidence base for an early childhood home visitation program.

Without a doubt, LeCroy's words resonate strongly with the focus of this research. In many way, this study serves as an observable application of his ideas and provide a welcome boost to the importance of this study. Paying it forward, the researcher hopes the lessons learned from the EC-DDDM's development and initial validation will model this process and engender enthusiasm for the development of future 'socialworkmetric' tools. Specifically, three key lessons learned here could support future research endeavors. First, EC-DDDM's development demonstrates the usefulness of *AIF Drivers* as a guide for structuring instrument development. While others have shown the practical application of *AIF Drivers* for structuring and supporting implementation generally (Metz & Bartley, 2012), this study deepens the use of the framework

by applying it to a feasible measure. Second, even though validation is an ongoing process that is ultimately based on the merit of accumulated evidence, initial validation studies are crucial to discovering evidence as a means to understanding theoretical constructs and inform practice in the social and human services (Cork, Detmer, & Friedman, 1998; Kimberlin & Winterstein, 2008; Krysik & LeCroy, 2012). Third, the involvement of a diverse panel of reviewers was essential to vetting the EC-DDDM and tailoring its content for the target population. Engaging panelists combined with the importance of their contribution makes this key lesson particularly salient because it reinforces the need for more applications of community-based participatory action approaches as a mechanism for bridging the gap between research and practice (Wallerstein & Duran, 2010).

In addition to these prospects, several suggestions for future research were identified earlier in this discussion chapter. The commonalities amongst these suggestions intersect at the proposition that no single study will be sufficient for determining EC-DDDM's validity (Streiner & Kottner, 2014). Continued critical examination of the instrument's validity as well as future studies examining the two other aspects of validity not addressed here is recommended. These include evidence related to response processes such as activities to engage a more diverse sample to understand how responses differ across subgroups and analyses of individual responses through qualitative interviewing of respondents (Goodwin, 2002). Future validation studies should also consider the evidence related to the long term consequences of responding to the questionnaire (Goodwin, 2002). What are the proximal, intermediate, or long term benefits and unanticipated effects of using this instrument? Does taking the questionnaire result in change? Is change linear and upward or is iterative and up and down? While this initial study showed

promise for EC-DDDM's validity, it is but one study, and future research should further the case for or against its use.

Conclusion

Harnessing the use of data to demonstrate program effectiveness, establish lines of accountability, and implement evidence-based programs and interventions is a present demand of social welfare and human service organizations (Coultan et al, 2015). Even though literature suggests the mobilization and management of an organization's data and knowledge may serve as a mechanism for change and improvement (Dill & Shera, 2015; Austin et al., 2008), social and human service organizations are not widely engaging with their data in ways that inform practice and policy decisions (Coultan et al., 2015). Early childhood service organizations, in particular, face requirements to use data and evidence to support decision-making, while having little research that offers best practices for data use in early childhood and limited programmatic capacity to collect and process data in ways that support decision-making (Yazejian & Bryant, 2013). Ultimately, DDDM in early childhood programs is about more than just what data are collected, how data are stored, and how data are analyzed (Zweig et al., 2015). DDDM involves a more complex, multi-dimensional understanding of how staff competency, organizational structures, and leadership dynamics emerge, combine, and interact across program hierarchies. This study sought to increase this understanding and uncovered evidence to make sense of this complexity with the help of the *Active Implementation Framework* and its nine component drivers. Findings from this study provide initial quantitative evidence that developing an instrument around the nine distinct *AIF Drivers* serves as an initial fit for understanding data use and DDDM in early childhood programs. These findings are particularly noteworthy within the

context of their alignment with theory, existing empirical literature, and recent calls for the development of strong measurements.

At the end of it all, this work is about creating a world where all children and families are afforded opportunities to thrive and pursue a life of value. Early childhood programs are often the first to target and serve society's most vulnerable children and families, and they deserve to be equipped with tools that help them advance these efforts. As social work researchers, we owe it to programs to bring forth the best evidence and tools to facilitate sound decision-making. Most importantly, families deserve the best we have to offer. As social workers, we owe it to families to make the best decisions possible in these pursuits.

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Appendix A

Email Invitation for Program Administrators to Complete EC-DDDM

Hello,

You are receiving this email because you've been identified as an early childhood program administrator in (STATE'S NAME). My name is Jared Barton, and my colleagues and I support the data efforts of a number of early childhood program initiatives including initiatives in (STATE'S NAME). I am writing to ask for your valued time completing this 10 to 15 minute survey. The University of Kansas School of Social Welfare is conducting research to develop a tool to measure readiness for data-driven decision-making. Your insight into your program's use of data for decision-making is important for this research.

Please click this link to participate in the survey:
Survey for Early Childhood Data Driven Decision Making

What is the purpose of survey?

1) To explore how early childhood programs use data for decision-making;
2) To understand gaps and capacity issues within early childhood programs for data-driven decision-making; and
3) To identify factors that lead to data-driven decision-making and.

What can you expect? The survey is broken into several pages, and on each page there are between 4 and 8 statements with a 5-point agreement scale. The survey will take about 15 minutes and is completely anonymous and won't ask for your name or contact info about you or your program. Survey results will be presented in a summary format that prevents the identification of any and all individuals.

Who should complete the survey?
Any program administrator of an early childhood program or organization is welcome to take this survey including directors, supervisors, program managers, and coordinators. Participants should be at least 18 years of age or older.

What is the outcome of this research? I hope to use the information learned from this study to begin crafting specific tools, tips, training, and technical assistance materials to help organizations make better use of their data. That could mean identifying gaps in current data usage, the development of new or improved reports, and targeted tip sheets translating data usage into real world practice.

Thank you for your consideration and your participation! If you need any additional information concerning the study, please feel free to contact us by phone or email.

Please click this link to participate in the survey:
Survey for Early Childhood Data Driven Decision Making

Appendix B

Final Early Childhood Data-Driven Decision-Making (EC-DDDM) Instrument

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Information about this survey for Early Childhood Data Driven Decision Making

The School of Social Welfare at the University of Kansas supports the practice of protection for human subjects participating in research. The following information is provided for you to decide whether you wish to participate in the present study. You should be aware that even if you agree to participate, you are free to withdraw at any time without penalty.

We are conducting this study to better understand the use of data in early childhood programs to support decision-making. This will entail your completion of a survey. Your participation should take less than 15 minutes to complete. The content of the survey should cause no more discomfort than you would experience in your everyday life.

Although participation may not benefit you directly, we believe that the information obtained from this study will help us gain a better understanding of how early childhood programs use data to support decision-making and the factors that lead to data-driven decision-making in early childhood programs. This research could lead to improved tools and technical assistance practices provided to programs regarding data use and decision-making.

Your participation is strictly voluntary and if at any time during the survey you wish to discontinue, simply close the survey. No identifying information will be collected with this survey and your responses cannot be traced or associated back to you. It is possible, however, with internet communications that, though intent or accident, someone other than the intended recipient may see your responses. If you would like additional information concerning this study before or after it is completed, please feel free to contact us by phone or mail.

Completion of this survey indicates your willingness to take part in this study and that you are at least 18 years old. If you have any additional questions about your rights as a research participant, you may call (785) 864-7429 or write the Human Research Protection Program (HRPP), University of Kansas, 2385 Irving Hill Road, Lawrence, Kansas 66045-7563, email irb@ku.edu.

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Page 1 of 11

Please continue to the next page to begin this survey.

Next Page >>

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Resize font

Page 2 of 11

Selection and Hiring

The following statements are about data use in your program's hiring practices. Please select answers to the following statements that best describe your program.

Hiring of early childhood service providers for our program includes assessment of applicants' skills and experience related to using data.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset
Data gathered during the hiring process about applicants' experience and skills are used to inform training needs of new hires.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset
Our program relies primarily on the gut feelings and opinions of the hiring team to hire new staff.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset
Our program uses data on past employee performance to inform our hiring practices (e.g., job descriptions, interview questions, recruitment materials).	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset
Hiring teams use data to make adjustments to recruitment materials (e.g., job descriptions, interview questions, job announcements) during the hiring process.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset

<< Previous Page Next Page >>

Training

10% Complete

The following statements are about data use in your program's training practices. Please select answers to the following statements that best describe your program.

Trainers make adjustments to training plans based on data gathered from assessments or evaluations of current staff performance.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

Trainers make adjustments to training plans based on assessment data gathered on new staff during the hiring process.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

Trainers customize training plans based on reviews of child and family level data collected by our program.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

Trainers give staff PRE-training knowledge and skills tests to identify opportunities for targeted training.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

After training, trainers give staff POST-test knowledge and skills tests to identify opportunities to improve future trainings.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

After training, trainers provide coaches and/or supervisors with feedback and POST-test results to aid in future coaching and/or supervision efforts.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

Training sessions include activities to help staff understand how to use data to support decision-making in practice.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

<< Previous Page Next Page >>

Coaching and Supervision

20% Complete

The following statements are about data use in your program's coaching and supervision practices. Please select answers to the following statements that best describe your program.

What is coaching? Coaching involves the ongoing development and guidance of service providers on the job. It may occur during supervision or separate from supervision.

What are coaches? Coaches provide service providers with ongoing development and guidance on the job. Depending on your program, supervisors may serve as coaches or coaches may be other individuals.

Coaches and/or program supervisors access multiple data sources to inform decision-making (e.g., child and family records, observation data, performance assessment data).	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree	reset
Coaches and/or program supervisors understand the data requirements of our program's desired outcomes.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree	reset
Coaches and/or program supervisors use data to craft personalized coaching plans for individual service providers.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree	reset
Coaches and/or program supervisors have access to data across multiple levels of our work (e.g., child, family, and provider-level records).	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree	reset
Coaches and/or program supervisors understand how to use our program's data system to support decision-making.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree	reset
Supervision or coaching sessions include activities to help staff understand how to use data in their practice to support decision-making.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree	reset

<< Previous Page Next Page >>

Performance Assessment

30% Complete

The following statements are about data use in your program's performance reviews and performance evaluation practices. Please select answers to the following statements that best describe your program.

Performance assessments and evaluations of program service providers include reviews of child and family data to verify provider performance.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

Our program uses child and family level data to set realistic performance targets and goals.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

Data collected for performance assessment are linked to intended outcomes of the program.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

Program supervisors use their own discretion to evaluate the performance of individual service providers.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

<< Previous Page Next Page >>

Systems Intervention

40% Complete

The following statements are about your program's use of data for purposes which may be external to your organization. Please select answers to the following statements that best describe your program.

Using data is necessary to generate support for our program from those outside our organization.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset
Data helps us decide where we allocate our time and resources for advocacy.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset
To strengthen our case for funding, we include data on program results and child and family level outcomes into grants and funding proposals.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset
Using data is critical to demonstrate our worth to external stakeholders.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset
Data helps our program reduce external threats (e.g., funding cuts or competing programs) to our program's sustainability.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset
We have the data it takes to communicate our program's impact on children and families to stakeholders outside our organization.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset

<< Previous Page Next Page >>

Facilitative Administration

50% Complete

The following statements are about your program's use of data in its administrative practices. Please select answers to the following statements that best describe your program.

Our program's administrators model data-driven decision-making for staff to see examples of it in practice.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset
Program administrators speak about data in terms that program staff can understand.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset
Using data to support decision-making is a part of our program's culture.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset
Information on program results are shared with staff across our program.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset
Program administrators encourage staff to use data for continous quality improvement (CQI).	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset
The use of data has helped my program make better decisions.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset
Our program will improve if we continously review program data.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset
Our organization invests resources (e.g., money, time) into improving the quality of data collection.	1-Strongly disagree 2-Disagree 3-Neither agree or disagree 4-Agree 5-Strongly agree reset

<< Previous Page Next Page >>

Data Systems

60% Complete

The following statements are about your program's data system. Please select answers to the following statements that best describe your program.

My program has an electronic data system that meets our program's needs.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

Data entered into our system are relevant to the goals of our program.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

Even though we put data into our system, we cannot get data out in meaningful reports.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

Staff are adequately trained to use the parts of the data system which support their specific work.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

Our data system supports decision-making in a variety of program activities (e.g., training, coaching, supervision, reporting, practice, policy-making).

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

When needed, our data system is updated to ensure its relevance to our program's work.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

My program analyzes data by relevant subgroups (e.g., outcomes by race, age group, etc.)

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

reset

<< Previous Page Next Page >>

Technical Leadership

70% Complete

The following statements are about how leaders at your organization support or facilitate data use. Please select answers to the following statements that best describe your program.

Leaders in my organization have the technical skills needed to use data for strategic planning.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

react

Leaders have emerged within my program in terms of promoting or 'championing' data use in our program.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

react

Leaders seek feedback from program staff regarding challenges using data.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

react

Leaders in my organization are directly involved in determining the data needed to demonstrate program impact.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

react

Leaders at my organization review program results and child and family data to stay informed of program performance.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

react

Leaders include data as a part of their rationale for implementing changes or policies in our organization.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

react

<< Previous Page Next Page >>

Adaptive Leadership

80% Complete

The following statements are about how leaders at your organization support or facilitate data use. Please select answers to the following statements that best describe your program.

Leaders create an organizational culture which values data and encourages its use for decision-making.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

react

Leaders in our organization have a clear vision of the long term impact of our work supported with data.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

react

Leaders at our organization are willing to adapt messages and modify plans as data emerge.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

react

Leaders are competent in interpreting data to inform decisions that make sense for our program.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

react

When data doesn't tell us what we expect, leaders in my organization respond in ways that instill confidence in the program's future.

- 1-Strongly disagree
- 2-Disagree
- 3-Neither agree or disagree
- 4-Agree
- 5-Strongly agree

react

<< Previous Page Next Page >>

Demographics and Program Characteristics

90% Complete

What is your age?

What is your race?

PLEASE CHECK ALL THAT APPLY

- American Indian or Alaska Native
- Asian
- Black or African American
- Native Hawaiian
- White
- Other

Are you Hispanic or Latino?

- No
- Yes

reset

What is your gender identity?

- Female
- Male
- Gender non-conforming/non-binary
- Prefer not to answer

reset

What is your highest level of education completed?

- Less than high school
- High school graduate or GED
- Some college
- Bachelors degree
- Masters degree or higher

reset

Please enter your degree type or college major (e.g., early childhood education, social work, psychology, etc.)

How many years of work experience do you have in early childhood programming?

What type of early childhood program do you serve in?

- ○ Preschool or Other Center-based Early Childhood Education Program
- ○ Home Visiting Program or Other Home-based Program
- ○ Parenting Groups
- ○ Maternal-Child Health Program
- ○ Other

reset

Approximately how many families does your program serve in a given year?

Approximately how many staff does your program have?

What family populations does your program serve or target?

- ☐ Low income families
- ☐ Pregnant or parents under 21 years old
- ☐ Households with history of substance use or abuse
- ☐ Households with history of child abuse or neglect
- ☐ Non-English speaking families
- ☐ Other

What outcomes does your program focus on?

PLEASE CHECK ALL THAT APPLY

- ☐ Prevention of child abuse and neglect
- ☐ Child development
- ☐ School and kindergarten readiness
- ☐ Maternal health
- ☐ Infant and child health
- ☐ Family economic self-sufficiency

<< Previous Page Submit

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Appendix C

Polychoric correlation Coefficients between Observed Variables

	selection_1	selection_2	selection_3	selection_4	selection_5
selection_1	1				
selection_2	0.459	1			
selection_3	0.28	0.293	1		
selection_4	0.334	0.287	0.251	1	
selection_5	0.269	0.266	0.226	0.716	1
training_1	0.242	0.329	0.064	0.353	0.349
training_2	0.4	0.563	0.216	0.292	0.313
training_3	0.335	0.307	0.206	0.336	0.407
training_4	0.23	0.105	0.193	0.17	0.151
training_5	0.218	0.134	0.173	0.094	0.119
training_6	0.35	0.268	0.202	0.219	0.321
training_7	0.349	0.063	0.103	0.178	0.201
coaching_1	0.268	0.229	0.179	0.388	0.364
coaching_2	0.28	0.242	0.23	0.35	0.43
coaching_3	0.361	0.321	0.254	0.302	0.352
coaching_4	0.161	0.097	0.101	0.232	0.284
coaching_5	0.297	0.181	0.304	0.286	0.431
coaching_6	0.318	0.142	0.174	0.311	0.259
perf_assess_1	0.274	0.203	0.307	0.388	0.349
perf_assess_2	0.28	0.226	0.227	0.24	0.32
perf_assess_3	0.186	0.131	0.214	0.165	0.249
perf_assess_4	0.031	0.184	0.34	0.222	0.134
sys_intervention_1	0.157	0.177	0.055	0.12	0.209
sys_intervention_2	0.177	0.097	0.117	0.062	0.271
sys_intervention_3	0.248	0.263	0.089	0.114	0.141
sys_intervention_4	0.173	0.101	0.039	-0.005	0.142
sys_intervention_5	0.184	0.094	0.002	0.14	0.18
sys_intervention_6	0.245	0.052	-0.006	0.051	0.055
facil_admin_1	0.374	0.412	0.225	0.287	0.373
facil_admin_2	0.331	0.357	0.226	0.353	0.421
facil_admin_3	0.326	0.349	0.307	0.24	0.39
facil_admin_4	0.211	0.31	0.152	0.137	0.19
facil_admin_5	0.293	0.292	0.23	0.122	0.209
facil_admin_6	0.287	0.127	0.228	0.2	0.253
facil_admin_7	0.221	0.174	-0.003	0.122	0.138
facil_admin_8	0.283	0.231	0.158	0.17	0.251
decision_support_1	0.175	-0.117	0.104	-0.017	-0.033
decision_support_2	0.172	0.028	0.115	-0.018	0.134
decision_support_3	-0.091	-0.18	0.075	0.004	0.007
decision_support_4	0.366	0.285	0.276	0.109	0.075
decision_support_5	0.317	0.089	0.263	0.083	0.172
decision_support_6	0.176	-0.142	0.103	0.027	0.11
decision_support_7	0.185	0.118	0.092	-0.046	0.217
technical_1	0.235	0.297	0.195	0.213	0.379
technical_2	0.252	0.148	0.114	0.11	0.272
technical_3	0.352	0.346	0.257	0.292	0.343

	selection_1	selection_2	selection_3	selection_4	selection_5
technical_4	0.209	0.259	0.104	0.176	0.273
technical_5	0.3	0.265	0.258	0.224	0.292
technical_6	0.231	0.259	0.268	0.234	0.346
adaptive_1	0.246	0.269	0.284	0.257	0.403
adaptive_2	0.294	0.222	0.365	0.29	0.432
adaptive_3	0.183	0.266	0.309	0.275	0.415
adaptive_4	0.315	0.297	0.303	0.286	0.388
adaptive_5	0.307	0.256	0.309	0.247	0.372

	training_1	training_2	training_3	training_4	training_5	training_6
selection_1						
selection_2						
selection_3						
selection_4						
selection_5						
training_1	1					
training_2	0.675	1				
training_3	0.6	0.539	1			
training_4	0.204	0.216	0.213	1		
training_5	0.126	0.173	0.209	0.73	1	
training_6	0.336	0.326	0.451	0.575	0.637	1
training_7	0.205	0.169	0.416	0.259	0.327	0.401
coaching_1	0.483	0.414	0.394	0.06	0.183	0.262
coaching_2	0.319	0.293	0.405	0.012	0.164	0.249
coaching_3	0.402	0.317	0.421	0.144	0.209	0.317
coaching_4	0.301	0.174	0.299	0.1	0.102	0.097
coaching_5	0.404	0.284	0.487	0.128	0.19	0.263
coaching_6	0.321	0.294	0.42	0.215	0.226	0.296
perf_assess_1	0.172	0.27	0.328	0.251	0.283	0.291
perf_assess_2	0.276	0.3	0.439	0.158	0.331	0.356
perf_assess_3	0.232	0.157	0.377	0.156	0.284	0.335
perf_assess_4	0.18	0.184	0.057	0.046	0.035	0.068
sys_intervention_1	0.348	0.289	0.282	0.032	0.197	0.137
sys_intervention_2	0.336	0.29	0.299	0.106	0.149	0.231
sys_intervention_3	0.3	0.27	0.191	0.062	0.059	0.132
sys_intervention_4	0.324	0.153	0.181	0.024	0.102	0.165
sys_intervention_5	0.227	0.173	0.251	-0.051	0.131	0.159
sys_intervention_6	0.039	0.094	0.194	0.14	0.173	0.243
facil_admin_1	0.314	0.4	0.41	0.181	0.232	0.432
facil_admin_2	0.338	0.335	0.327	0.038	0.159	0.284
facil_admin_3	0.416	0.452	0.413	0.153	0.249	0.383
facil_admin_4	0.339	0.284	0.32	0.144	0.155	0.239
facil_admin_5	0.406	0.455	0.387	0.007	0.094	0.236
facil_admin_6	0.415	0.279	0.357	0.23	0.249	0.285
facil_admin_7	0.266	0.231	0.387	-0.004	0.163	0.102
facil_admin_8	0.372	0.223	0.409	0.109	0.082	0.28
decision_support_1	0.064	-0.04	0.01	0.118	0.158	0.181
decision_support_2	0.126	0.108	0.155	0.127	0.127	0.194
decision_support_3	0.086	-0.081	-0.039	0.006	-0.05	-0.071
decision_support_4	0.176	0.286	0.196	0.086	0.183	0.291

	training_1	training_2	training_3	training_4	training_5	training_6
decision_support_5	0.252	0.286	0.37	0.196	0.264	0.307
decision_support_6	0.168	0.069	0.177	0.237	0.266	0.15
decision_support_7	0.138	0.195	0.209	0.185	0.234	0.363
technical_1	0.312	0.296	0.35	0.122	0.245	0.343
technical_2	0.274	0.156	0.284	0.107	0.122	0.233
technical_3	0.322	0.313	0.326	0.222	0.18	0.383
technical_4	0.294	0.214	0.215	0.237	0.216	0.278
technical_5	0.37	0.288	0.353	0.155	0.159	0.266
technical_6	0.334	0.378	0.368	0.185	0.186	0.217
adaptive_1	0.381	0.297	0.356	0.162	0.247	0.387
adaptive_2	0.326	0.292	0.336	0.23	0.198	0.35
adaptive_3	0.281	0.307	0.379	0.152	0.141	0.259
adaptive_4	0.396	0.366	0.45	0.271	0.283	0.431
adaptive_5	0.282	0.234	0.314	0.31	0.256	0.364

	coaching_1	coaching_2	coaching_3	coaching_4	coaching_5
selection_1					
selection_2					
selection_3					
selection_4					
selection_5					
training_1					
training_2					
training_3					
training_4					
training_5					
training_6					
training_7					
coaching_1	1				
coaching_2	0.72	1			
coaching_3	0.588	0.548	1		
coaching_4	0.515	0.6	0.493	1	
coaching_5	0.663	0.82	0.728	0.701	1
coaching_6	0.554	0.604	0.623	0.532	0.762
perf_assess_1	0.505	0.429	0.508	0.321	0.405
perf_assess_2	0.542	0.459	0.572	0.42	0.576
perf_assess_3	0.456	0.349	0.444	0.391	0.467
perf_assess_4	0.15	0.095	0.163	0.087	0.081
sys_intervention_1	0.522	0.434	0.251	0.255	0.307
sys_intervention_2	0.356	0.341	0.22	0.347	0.35
sys_intervention_3	0.599	0.537	0.408	0.468	0.376
sys_intervention_4	0.526	0.527	0.405	0.379	0.388
sys_intervention_5	0.512	0.445	0.304	0.192	0.381
sys_intervention_6	0.338	0.316	0.47	0.329	0.4
facil_admin_1	0.503	0.483	0.632	0.206	0.52
facil_admin_2	0.565	0.583	0.52	0.259	0.532
facil_admin_3	0.572	0.597	0.61	0.441	0.624
facil_admin_4	0.494	0.529	0.448	0.305	0.43
facil_admin_5	0.463	0.488	0.411	0.3	0.464
facil_admin_6	0.485	0.539	0.476	0.431	0.57

	coaching_1	coaching_2	coaching_3	coaching_4	coaching_5
facil_admin_7	0.597	0.499	0.41	0.306	0.42
facil_admin_8	0.361	0.399	0.339	0.318	0.379
decision_support_1	0.255	0.229	0.276	0.311	0.349
decision_support_2	0.365	0.389	0.273	0.363	0.396
decision_support_3	0.194	0.189	0.126	0.29	0.303
decision_support_4	0.32	0.362	0.399	0.268	0.399
decision_support_5	0.228	0.27	0.412	0.325	0.416
decision_support_6	0.164	0.173	0.116	0.234	0.258
decision_support_7	0.276	0.302	0.224	0.184	0.201
technical_1	0.41	0.4	0.598	0.328	0.532
technical_2	0.341	0.442	0.493	0.415	0.539
technical_3	0.397	0.443	0.517	0.313	0.413
technical_4	0.208	0.254	0.391	0.185	0.21
technical_5	0.354	0.421	0.438	0.305	0.485
technical_6	0.305	0.368	0.473	0.312	0.461
adaptive_1	0.435	0.417	0.568	0.252	0.48
adaptive_2	0.403	0.439	0.571	0.367	0.588
adaptive_3	0.459	0.542	0.459	0.373	0.463
adaptive_4	0.403	0.463	0.489	0.416	0.558
adaptive_5	0.311	0.386	0.445	0.232	0.437

	perf_assess_1	perf_assess_2	perf_assess_3	perf_assess_4
selection_1				
selection_2				
selection_3				
selection_4				
selection_5				
training_1				
training_2				
training_3				
training_4				
training_5				
training_6				
training_7				
coaching_1				
coaching_2				
coaching_3				
coaching_4				
coaching_5				
coaching_6				
perf_assess_1	1			
perf_assess_2	0.675	1		
perf_assess_3	0.6	0.756	1	
perf_assess_4	0.261	0.293	0.22	1
sys_intervention_1	0.198	0.36	0.172	-0.081
sys_intervention_2	0.263	0.486	0.321	0.031
sys_intervention_3	0.332	0.405	0.322	0.14
sys_intervention_4	0.232	0.34	0.313	0.126
sys_intervention_5	0.301	0.263	0.315	0.091
sys_intervention_6	0.411	0.497	0.472	0.127

	perf_assess_1	perf_assess_2	perf_assess_3	perf_assess_4
facil_admin_1	0.475	0.567	0.429	0.281
facil_admin_2	0.336	0.407	0.301	0.148
facil_admin_3	0.358	0.544	0.491	0.3
facil_admin_4	0.244	0.364	0.279	0.133
facil_admin_5	0.276	0.406	0.357	0.092
facil_admin_6	0.378	0.56	0.433	0.257
facil_admin_7	0.319	0.451	0.389	0.104
facil_admin_8	0.211	0.29	0.402	0.022
decision_support_1	0.212	0.306	0.274	-0.033
decision_support_2	0.329	0.39	0.341	0.04
decision_support_3	0.204	0.27	0.207	0.258
decision_support_4	0.266	0.313	0.253	0.137
decision_support_5	0.297	0.432	0.411	0.05
decision_support_6	0.102	0.336	0.306	0.066
decision_support_7	0.296	0.306	0.213	-0.052
technical_1	0.351	0.588	0.502	0.239
technical_2	0.29	0.507	0.472	0.161
technical_3	0.349	0.37	0.351	0.107
technical_4	0.315	0.324	0.35	0.17
technical_5	0.363	0.424	0.373	0.325
technical_6	0.343	0.422	0.368	0.279
adaptive_1	0.377	0.498	0.349	0.146
adaptive_2	0.427	0.585	0.47	0.26
adaptive_3	0.37	0.445	0.301	0.138
adaptive_4	0.337	0.526	0.5	0.153
adaptive_5	0.295	0.373	0.432	0.043

	sys_inter_1	sys_inter_2	sys_inter_3	sys_inter_4	sys_inter_5	sys_inter_6
selection_1						
selection_2						
selection_3						
selection_4						
selection_5						
training_1						
training_2						
training_3						
training_4						
training_5						
training_6						
training_7						
coaching_1						
coaching_2						
coaching_3						
coaching_4						
coaching_5						
coaching_6						
perf_assess_1						
perf_assess_2						
perf_assess_3						
perf_assess_4						
sys_intervention_1	1					
sys_intervention_2	0.681	1				

	sys_inter_1	sys_inter_2	sys_inter_3	sys_inter_4	sys_inter_5	sys_inter_6
sys_intervention_3	0.652	0.544	1			
sys_intervention_4	0.697	0.505	0.767	1		
sys_intervention_5	0.568	0.427	0.572	0.742	1	
sys_intervention_6	0.21	0.343	0.577	0.552	0.475	1
facil_admin_1	0.338	0.351	0.35	0.371	0.36	0.422
facil_admin_2	0.332	0.274	0.401	0.366	0.342	0.298
facil_admin_3	0.344	0.477	0.506	0.465	0.451	0.471
facil_admin_4	0.435	0.311	0.56	0.574	0.496	0.483
facil_admin_5	0.324	0.279	0.536	0.582	0.474	0.331
facil_admin_6	0.423	0.474	0.52	0.507	0.458	0.43
facil_admin_7	0.506	0.409	0.65	0.665	0.664	0.461
facil_admin_8	0.337	0.425	0.388	0.381	0.392	0.407
decision_support_1	0.116	0.123	0.336	0.262	0.153	0.404
decision_support_2	0.209	0.31	0.447	0.393	0.293	0.461
decision_support_3	-0.023	0.051	0.175	0.105	0.107	0.134
decision_support_4	0.206	0.191	0.256	0.24	0.182	0.234
decision_support_5	0.215	0.384	0.22	0.304	0.259	0.4
decision_support_6	0.128	0.185	0.18	0.267	0.151	0.298
decision_support_7	0.214	0.268	0.348	0.22	0.252	0.248
technical_1	0.335	0.4	0.382	0.391	0.336	0.479
technical_2	0.347	0.493	0.407	0.438	0.464	0.448
technical_3	0.134	0.222	0.278	0.224	0.257	0.378
technical_4	0.235	0.318	0.432	0.338	0.327	0.406
technical_5	0.182	0.363	0.434	0.347	0.32	0.363
technical_6	0.309	0.447	0.467	0.341	0.287	0.401
adaptive_1	0.406	0.41	0.341	0.373	0.378	0.333
adaptive_2	0.297	0.401	0.406	0.409	0.427	0.438
adaptive_3	0.394	0.423	0.389	0.386	0.408	0.314
adaptive_4	0.298	0.459	0.414	0.364	0.351	0.427
adaptive_5	0.172	0.304	0.366	0.357	0.287	0.371

	facil_admin_1	facil_admin_2	facil_admin_3	facil_admin_4
selection_1				
selection_2				
selection_3				
selection_4				
selection_5				
training_1				
training_2				
training_3				
training_4				
training_5				
training_6				
training_7				
coaching_1				
coaching_2				
coaching_3				
coaching_4				
coaching_5				
coaching_6				
perf_assess_1				

	facil_admin_1	facil_admin_2	facil_admin_3	facil_admin_4
perf_assess_2				
perf_assess_3				
perf_assess_4				
sys_intervention_1				
sys_intervention_2				
sys_intervention_3				
sys_intervention_4				
sys_intervention_5				
sys_intervention_6				
facil_admin_1	1			
facil_admin_2	0.635	1		
facil_admin_3	0.766	0.714	1	
facil_admin_4	0.438	0.634	0.606	1
facil_admin_5	0.509	0.585	0.659	0.613
facil_admin_6	0.641	0.53	0.696	0.574
facil_admin_7	0.512	0.472	0.552	0.492
facil_admin_8	0.479	0.459	0.556	0.579
decision_support_1	0.24	0.312	0.221	0.363
decision_support_2	0.313	0.245	0.326	0.478
decision_support_3	0.094	0.095	0.135	0.085
decision_support_4	0.382	0.491	0.468	0.444
decision_support_5	0.461	0.312	0.483	0.431
decision_support_6	0.133	0.153	0.209	0.368
decision_support_7	0.292	0.178	0.267	0.332
technical_1	0.666	0.564	0.757	0.611
technical_2	0.606	0.487	0.67	0.462
technical_3	0.472	0.517	0.596	0.488
technical_4	0.465	0.455	0.489	0.391
technical_5	0.602	0.528	0.586	0.493
technical_6	0.53	0.583	0.685	0.559
adaptive_1	0.643	0.572	0.691	0.607
adaptive_2	0.587	0.508	0.74	0.554
adaptive_3	0.494	0.574	0.626	0.625
adaptive_4	0.538	0.618	0.685	0.582
adaptive_5	0.529	0.51	0.6	0.546

	facil_admin_5	facil_admin_6	facil_admin_7	facil_admin_8
selection_1				
selection_2				
selection_3				
selection_4				
selection_5				
training_1				
training_2				
training_3				
training_4				
training_5				
training_6				
training_7				
coaching_1				

	facil_admin_5	facil_admin_6	facil_admin_7	facil_admin_8
coaching_2				
coaching_3				
coaching_4				
coaching_5				
coaching_6				
perf_assess_1				
perf_assess_2				
perf_assess_3				
perf_assess_4				
sys_intervention_1				
sys_intervention_2				
sys_intervention_3				
sys_intervention_4				
sys_intervention_5				
sys_intervention_6				
facil_admin_1				
facil_admin_2				
facil_admin_3				
facil_admin_4				
facil_admin_5	1			
facil_admin_6	0.566	1		
facil_admin_7	0.584	0.595	1	
facil_admin_8	0.583	0.509	0.434	1
decision_support_1	0.308	0.382	0.287	0.278
decision_support_2	0.469	0.495	0.425	0.345
decision_support_3	0.026	0.271	0.098	-0.072
decision_support_4	0.553	0.314	0.332	0.331
decision_support_5	0.438	0.491	0.318	0.379
decision_support_6	0.318	0.38	0.198	0.382
decision_support_7	0.278	0.268	0.247	0.157
technical_1	0.528	0.563	0.453	0.53
technical_2	0.516	0.573	0.492	0.468
technical_3	0.49	0.428	0.272	0.543
technical_4	0.364	0.39	0.367	0.491
technical_5	0.555	0.473	0.413	0.505
technical_6	0.537	0.533	0.441	0.439
adaptive_1	0.521	0.599	0.449	0.566
adaptive_2	0.55	0.641	0.39	0.539
adaptive_3	0.494	0.55	0.435	0.475
adaptive_4	0.525	0.573	0.437	0.584
adaptive_5	0.512	0.501	0.356	0.562

	decision_support_1	decision_support_2	decision_support_3
selection_1			
selection_2			
selection_3			
selection_4			
selection_5			
training_1			
training_2			

	decision_support_1	decision_support_2	decision_support_3
training_3			
training_4			
training_5			
training_6			
training_7			
coaching_1			
coaching_2			
coaching_3			
coaching_4			
coaching_5			
coaching_6			
perf_assess_1			
perf_assess_2			
perf_assess_3			
perf_assess_4			
sys_intervention_1			
sys_intervention_2			
sys_intervention_3			
sys_intervention_4			
sys_intervention_5			
sys_intervention_6			
facil_admin_1			
facil_admin_2			
facil_admin_3			
facil_admin_4			
facil_admin_5			
facil_admin_6			
facil_admin_7			
facil_admin_8			
decision_support_1	1		
decision_support_2	0.793	1	
decision_support_3	0.502	0.517	1
decision_support_4	0.395	0.369	-0.021
decision_support_5	0.501	0.598	0.386
decision_support_6	0.66	0.669	0.316
decision_support_7	0.322	0.417	0.218
technical_1	0.24	0.336	0.102
technical_2	0.192	0.272	0.133
technical_3	0.25	0.391	0.067
technical_4	0.176	0.224	0.042
technical_5	0.233	0.451	0.148
technical_6	0.184	0.394	0.247
adaptive_1	0.225	0.338	0.087
adaptive_2	0.283	0.436	0.196
adaptive_3	0.19	0.357	0.199
adaptive_4	0.279	0.391	0.112
adaptive_5	0.307	0.433	0.108

	decision_support4	decision_support5	decision_support6	decision_support7
selection_1				
selection_2				
selection_3				
selection_4				
selection_5				
training_1				
training_2				
training_3				
training_4				
training_5				
training_6				
training_7				
coaching_1				
coaching_2				
coaching_3				
coaching_4				
coaching_5				
coaching_6				
perf_assess_1				
perf_assess_2				
perf_assess_3				
perf_assess_4				
sys_intervention_1				
sys_intervention_2				
sys_intervention_3				
sys_intervention_4				
sys_intervention_5				
sys_intervention_6				
facil_admin_1				
facil_admin_2				
facil_admin_3				
facil_admin_4				
facil_admin_5				
facil_admin_6				
facil_admin_7				
facil_admin_8				
decision_support_1				
decision_support_2				
decision_support_3				
decision_support_4	1			
decision_support_5	0.519	1		
decision_support_6	0.35	0.538	1	
decision_support_7	0.34	0.368	0.327	1
technical_1	0.453	0.444	0.269	0.235
technical_2	0.37	0.463	0.182	0.21
technical_3	0.457	0.362	0.221	0.265
technical_4	0.292	0.373	0.223	0.265
technical_5	0.441	0.405	0.314	0.146
technical_6	0.398	0.482	0.289	0.239
adaptive_1	0.322	0.478	0.261	0.237
adaptive_2	0.293	0.496	0.317	0.174

	decision_support4	decision_support5	decision_support6	decision_support7
adaptive_3	0.307	0.4	0.207	0.279
adaptive_4	0.443	0.534	0.325	0.184
adaptive_5	0.355	0.497	0.407	0.207

	technical_1	technical_2	technical_3	technical_4	technical_5	technical_6
selection_1						
selection_2						
selection_3						
selection_4						
selection_5						
training_1						
training_2						
training_3						
training_4						
training_5						
training_6						
training_7						
coaching_1						
coaching_2						
coaching_3						
coaching_4						
coaching_5						
coaching_6						
perf_assess_1						
perf_assess_2						
perf_assess_3						
perf_assess_4						
sys_intervention_1						
sys_intervention_2						
sys_intervention_3						
sys_intervention_4						
sys_intervention_5						
sys_intervention_6						
facil_admin_1						
facil_admin_2						
facil_admin_3						
facil_admin_4						
facil_admin_5						
facil_admin_6						
facil_admin_7						
facil_admin_8						
decision_support_1						
decision_support_2						
decision_support_3						
decision_support_4						
decision_support_5						
decision_support_6						
decision_support_7						
technical_1	1					
technical_2	0.673	1				

	technical_1	technical_2	technical_3	technical_4	technical_5	technical_6
technical_3	0.653	0.527	1			
technical_4	0.554	0.655	0.501	1		
technical_5	0.676	0.618	0.634	0.583	1	
technical_6	0.683	0.613	0.591	0.627	0.822	1
adaptive_1	0.774	0.577	0.602	0.525	0.672	0.677
adaptive_2	0.723	0.61	0.601	0.503	0.704	0.716
adaptive_3	0.565	0.485	0.635	0.4	0.62	0.679
adaptive_4	0.749	0.604	0.706	0.527	0.805	0.759
adaptive_5	0.6	0.489	0.682	0.443	0.644	0.636

	adaptive_1	adaptive_2	adaptive_3	adaptive_4	adaptive_5
selection_1					
selection_2					
selection_3					
selection_4					
selection_5					
training_1					
training_2					
training_3					
training_4					
training_5					
training_6					
training_7					
coaching_1					
coaching_2					
coaching_3					
coaching_4					
coaching_5					
coaching_6					
perf_assess_1					
perf_assess_2					
perf_assess_3					
perf_assess_4					
sys_intervention_1					
sys_intervention_2					
sys_intervention_3					
sys_intervention_4					
sys_intervention_5					
sys_intervention_6					
facil_admin_1					
facil_admin_2					
facil_admin_3					
facil_admin_4					
facil_admin_5					
facil_admin_6					
facil_admin_7					
facil_admin_8					
decision_support_1					
decision_support_2					
decision_support_3					
decision_support_4					

	adaptive_1	adaptive_2	adaptive_3	adaptive_4	adaptive_5
decision_support_5					
decision_support_6					
decision_support_7					
technical_1					
technical_2					
technical_3					
technical_4					
technical_5					
technical_6					
adaptive_1	1				
adaptive_2	0.789	1			
adaptive_3	0.782	0.755	1		
adaptive_4	0.713	0.814	0.753	1	
adaptive_5	0.602	0.734	0.708	0.79	1

Appendix D

Descriptive Statistics of One-Way ANOVA Tests

						95% Confidence Interval			
Subscale	*Race Group*	*N*	*M*	*S.D.*	*S.E.*	*Lower Bound*	*Upper Bound*	*Min.*	*Max.*
SELECTION	White	151	17.66	3.16	0.26	17.15	18.17	7	25
	Non-White	18	17.61	3.11	0.73	16.07	19.16	12	21
	Total	169	17.66	3.15	0.24	17.18	18.13	7	25
TRAINING	White	147	23.29	4.52	0.37	22.55	24.02	10	33
	Non-White	17	23.59	4.46	1.08	21.30	25.88	15	31
	Total	164	23.32	4.50	0.35	22.62	24.01	10	33
COACHING	White	150	24.30	3.52	0.29	23.73	24.87	9	30
	Non-White	18	25.78	3.15	0.74	24.21	27.35	20	30
	Total	168	24.46	3.50	0.27	23.92	24.99	9	30
PERFORM-ANCE ASSESSMENT	White	152	14.24	2.65	0.22	13.81	14.66	6	20
	Non-White	18	14.56	2.59	0.61	13.27	15.85	10	18
	Total	170	14.27	2.64	0.20	13.87	14.67	6	20
SYSTEMS INTERVEN-TION	White	149	25.26	3.17	0.26	24.75	25.77	17	30
	Non-White	18	26.22	2.86	0.67	24.80	27.64	20	30
	Total	167	25.37	3.14	0.24	24.89	25.85	17	30
FACILITA-TIVE ADMINI-STRATION	White	142	32.37	4.42	0.37	31.64	33.11	20	40
	Non-White	18	33.72	3.23	0.76	32.11	35.33	29	40
	Total	160	32.53	4.31	0.34	31.85	33.20	20	40
DECISION SUPPORT DATA SYSTEM	White	147	25.20	4.42	0.36	24.48	25.92	12	34
	Non-White	18	26.50	4.45	1.05	24.29	28.71	17	34
	Total	165	25.35	4.43	0.34	24.67	26.03	12	34
TECHNICAL LEADERSHIP	White	148	23.00	3.93	0.32	22.36	23.64	11	30
	Non-White	17	24.71	3.79	0.92	22.76	26.65	15	30
	Total	165	23.18	3.94	0.31	22.57	23.78	11	30
ADAPTIVE LEADERSHIP	White	151	19.44	3.55	0.29	18.87	20.01	6	25
	Non-White	18	19.89	2.81	0.66	18.49	21.28	11	24
	Total	169	19.49	3.48	0.27	18.96	20.01	6	25

Subscale	*Ethnicity Group*	*N*	*M*	*S.D.*	*S.E.*	*95% Confidence Interval*		*Min.*	*Max.*
						Lower Bound	*Upper Bound*		
SELECTION	Non-Hispanic/ Non-Latino	155	17.78	3.04	0.24	17.30	18.26	7	25
	Hispanic/Latino	15	17.20	4.49	1.16	14.71	19.69	8	24
	Total	170	17.73	3.18	0.24	17.25	18.21	7	25
TRAINING	Non-Hispanic/Non-Latino	153	23.54	4.36	0.35	22.85	24.24	10	33
	Hispanic/Latino	13	21.54	5.91	1.64	17.97	25.11	13	30
	Total	166	23.39	4.51	0.35	22.69	24.08	10	33
COACHING	Non-Hispanic/Non-Latino	153	24.63	3.52	0.28	24.07	25.20	9	30
	Hispanic/Latino	15	22.80	2.93	0.76	21.18	24.42	18	27
	Total	168	24.47	3.50	0.27	23.94	25.00	9	30
PERFORM-ANCE ASSESSMENT	Non-Hispanic/Non-Latino	156	14.40	2.60	0.21	13.99	14.82	6	20
	Hispanic/Latino	15	13.00	2.65	0.68	11.53	14.47	10	19
	Total	171	14.28	2.63	0.20	13.88	14.68	6	20
SYSTEMS INTERVEN-TION	Non-Hispanic/Non-Latino	153	25.51	3.08	0.25	25.02	26.00	18	30
	Hispanic/Latino	15	24.13	3.18	0.82	22.37	25.90	17	28
	Total	168	25.39	3.10	0.24	24.91	25.86	17	30
FACILITA-TIVE ADMINI-STRATION	Non-Hispanic/Non-Latino	148	32.79	4.07	0.33	32.13	33.45	20	40
	Hispanic/Latino	13	29.54	5.94	1.65	25.95	33.13	22	39
	Total	161	32.53	4.32	0.34	31.86	33.20	20	40
DECISION SUPPORT DATA SYSTEM	Non-Hispanic/Non-Latino	151	25.49	4.43	0.36	24.78	26.20	12	34
	Hispanic/Latino	15	24.27	4.10	1.06	22.00	26.54	17	32
	Total	166	25.38	4.40	0.34	24.71	26.05	12	34
TECHNICAL LEADERSHIP	Non-Hispanic/Non-Latino	151	23.30	3.77	0.31	22.70	23.91	11	30
	Hispanic/Latino	15	21.40	4.79	1.24	18.75	24.05	12	29
	Total	166	23.13	3.89	0.30	22.54	23.73	11	30
ADAPTIVE LEADERSHIP	Non-Hispanic/Non-Latino	155	19.60	3.35	0.27	19.07	20.13	6	25
	Hispanic/Latino	15	18.07	4.35	1.12	15.66	20.48	11	25
	Total	170	19.46	3.46	0.27	18.94	19.99	6	25

Subscale	*Education Group*	*N*	*M*	*S.D.*	*S.E.*	*95% Confidence Interval*		*Min.*	*Max.*
						Lower Bound	*Upper Bound*		
SELECTION	Less than college education	17	17.41	2.76	0.67	15.99	18.83	12	22
	Bachelor's degree	83	17.67	3.32	0.36	16.95	18.40	7	25
	Master's degree or higher	70	17.81	3.13	0.37	17.07	18.56	8	24
	Total	170	17.71	3.18	0.24	17.22	18.19	7	25
TRAINING	Less than college education	16	24.00	4.68	1.17	21.51	26.49	13	29
	Bachelor's degree	83	22.96	4.70	0.52	21.94	23.99	10	31
	Master's degree or higher	66	23.79	4.25	0.52	22.74	24.83	11	33
	Total	165	23.39	4.51	0.35	22.70	24.09	10	33
COACHING	Less than college education	17	24.29	3.58	0.87	22.45	26.14	18	30
	Bachelor's degree	82	24.18	3.54	0.39	23.40	24.96	15	30
	Master's degree or higher	69	24.99	3.48	0.42	24.15	25.82	9	30
	Total	168	24.52	3.52	0.27	23.99	25.06	9	30
PERFORM-ANCE ASSESSMENT	Less than college education	17	13.47	3.02	0.73	11.92	15.02	6	18
	Bachelor's degree	84	14.55	2.35	0.26	14.04	15.06	6	20
	Master's degree or higher	70	14.16	2.85	0.34	13.48	14.84	8	20
	Total	171	14.28	2.64	0.20	13.88	14.68	6	20
SYSTEMS INTERVEN-TION	Less than college education	17	25.59	3.16	0.77	23.96	27.21	18	30
	Bachelor's degree	83	25.45	3.20	0.35	24.75	26.14	17	30
	Master's degree or higher	68	25.32	3.06	0.37	24.58	26.06	19	30
	Total	168	25.41	3.12	0.24	24.94	25.89	17	30
FACILITA-TIVE ADMINI-STRATION	Less than college education	16	32.63	4.50	1.13	30.23	35.02	24	39
	Bachelor's degree	78	32.44	4.73	0.54	31.37	33.50	20	40
	Master's degree or higher	67	32.63	3.82	0.47	31.70	33.56	24	40
	Total	161	32.53	4.32	0.34	31.86	33.21	20	40
DECISION SUPPORT DATA SYSTEM	Less than college education	17	26.18	4.56	1.11	23.83	28.52	17	33
	Bachelor's degree	82	25.63	4.30	0.47	24.69	26.58	12	34

	Master's degree or higher	67	24.76	4.52	0.55	23.66	25.86	16	34
	Total	166	25.34	4.41	0.34	24.66	26.01	12	34
TECHNICAL LEADERSHIP	Less than college education	16	22.31	4.05	1.01	20.16	24.47	15	30
	Bachelor's degree	82	23.61	3.42	0.38	22.86	24.36	16	30
	Master's degree or higher	68	22.88	4.44	0.54	21.81	23.96	11	30
	Total	166	23.19	3.93	0.30	22.58	23.79	11	30
ADAPTIVE LEADERSHIP	Less than college education	16	18.69	3.84	0.96	16.64	20.73	11	23
	Bachelor's degree	84	19.73	3.22	0.35	19.03	20.42	11	25
	Master's degree or higher	70	19.36	3.71	0.44	18.47	20.24	6	25
	Total	170	19.48	3.48	0.27	18.95	20.00	6	25

Subscale	*Number of Families Served Group*	*N*	*M*	*S.D.*	*S.E.*	*95% Confidence Interval*		*Min.*	*Max.*
						Lower Bound	*Upper Bound*		
SELECTION	60 or fewer families	55	17.84	3.24	0.44	16.96	18.71	10	25
	61 to 199 families	51	17.29	2.72	0.38	16.53	18.06	8	23
	200 or more families	61	17.95	3.53	0.45	17.05	18.85	7	24
	Total	167	17.71	3.20	0.25	17.22	18.20	7	25
TRAINING	60 or fewer families	55	22.56	4.92	0.66	21.23	23.89	13	31
	61 to 199 families	50	23.26	4.48	0.63	21.99	24.53	10	33
	200 or more families	58	24.28	4.10	0.54	23.20	25.35	11	33
	Total	163	23.39	4.54	0.36	22.68	24.09	10	33
COACHING	60 or fewer families	56	24.50	3.09	0.41	23.67	25.33	17	30
	61 to 199 families	50	24.26	3.58	0.51	23.24	25.28	15	30
	200 or more families	59	24.78	3.88	0.51	23.77	25.79	9	30
	Total	165	24.53	3.52	0.27	23.99	25.07	9	30
PERFORM-ANCE ASSESSMENT	60 or fewer families	56	14.04	2.34	0.31	13.41	14.66	6	20
	61 to 199 families	51	14.24	2.36	0.33	13.57	14.90	8	19
	200 or more families	61	14.64	3.02	0.39	13.87	15.41	6	20
	Total	168	14.32	2.61	0.20	13.92	14.71	6	20
SYSTEMS INTERVEN-TION	60 or fewer families	55	25.25	3.38	0.46	24.34	26.17	17	30
	61 to 199 families	51	25.02	3.32	0.46	24.09	25.95	18	30
	200 or more families	59	25.86	2.72	0.35	25.16	26.57	18	30
	Total	165	25.40	3.14	0.24	24.92	25.88	17	30
FACILITA-TIVE ADMINI-STRATION	60 or fewer families	51	32.35	4.34	0.61	31.13	33.57	22	40
	61 to 199 families	46	31.43	3.89	0.57	30.28	32.59	24	39
	200 or more families	61	33.46	4.53	0.58	32.30	34.62	20	40
	Total	158	32.51	4.34	0.35	31.83	33.20	20	40
DECISION SUPPORT DATA SYSTEM	60 or fewer families	54	24.98	4.80	0.65	23.67	26.29	12	34
	61 to 199 families	50	25.24	4.08	0.58	24.08	26.40	16	32
	200 or more families	59	25.88	4.27	0.56	24.77	26.99	14	34
	Total	163	25.39	4.39	0.34	24.71	26.07	12	34
TECHNICAL LEADERSHIP	60 or fewer families	54	22.78	4.10	0.56	21.66	23.90	12	30
	61 to 199 families	51	22.31	4.07	0.57	21.17	23.46	11	30
	200 or more families	58	24.34	3.46	0.45	23.44	25.25	16	30
	Total	163	23.19	3.95	0.31	22.58	23.80	11	30
ADAPTIVE LEADERSHIP	60 or fewer families	56	19.20	3.28	0.44	18.32	20.08	11	25
	61 to 199 families	51	19.20	3.82	0.54	18.12	20.27	6	25
	200 or more families	60	20.03	3.37	0.44	19.16	20.90	11	25
	Total	167	19.50	3.49	0.27	18.96	20.03	6	25

Subscale	*Number of Staff Group*	*N*	*M*	*S.D.*	*S.E.*	*95% Confidence Interval*		*Min.*	*Max.*
						Lower Bound	*Upper Bound*		
SELECTION	5 or fewer staff	64	17.56	3.09	0.39	16.79	18.33	8	25
	6 to 14 staff	44	17.84	3.34	0.50	16.83	18.86	10	24
	15 or more staff	60	17.83	3.26	0.42	16.99	18.68	7	24
	Total	168	17.73	3.20	0.25	17.24	18.22	7	25
TRAINING	5 or fewer staff	63	22.73	4.88	0.61	21.50	23.96	10	31
	6 to 14 staff	44	23.61	4.67	0.70	22.19	25.03	13	33
	15 or more staff	57	24.02	3.98	0.53	22.96	25.07	11	30
	Total	164	23.41	4.54	0.35	22.72	24.11	10	33
COACHING	5 or fewer staff	64	24.16	3.41	0.43	23.30	25.01	17	30
	6 to 14 staff	43	25.35	2.89	0.44	24.46	26.24	21	30
	15 or more staff	59	24.36	3.97	0.52	23.32	25.39	9	30
	Total	166	24.54	3.51	0.27	24.00	25.07	9	30
PERFORM-ANCE ASSESSMENT	5 or fewer staff	65	14.06	2.47	0.31	13.45	14.67	6	20
	6 to 14 staff	44	14.98	2.39	0.36	14.25	15.70	10	20
	15 or more staff	60	14.13	2.86	0.37	13.39	14.87	6	19
	Total	169	14.33	2.61	0.20	13.93	14.72	6	20
SYSTEMS INTERVEN-TION	5 or fewer staff	64	25.13	3.38	0.42	24.28	25.97	18	30
	6 to 14 staff	43	26.00	3.20	0.49	25.02	26.98	17	30
	15 or more staff	59	25.31	2.81	0.37	24.57	26.04	18	30
	Total	166	25.42	3.14	0.24	24.93	25.90	17	30
FACILITA-TIVE ADMINI-STRATION	5 or fewer staff	62	32.03	4.08	0.52	31.00	33.07	23	40
	6 to 14 staff	38	32.76	4.41	0.72	31.31	34.21	22	40
	15 or more staff	59	32.93	4.59	0.60	31.74	34.13	20	40
	Total	159	32.54	4.34	0.34	31.86	33.22	20	40
DECISION SUPPORT DATA SYSTEM	5 or fewer staff	63	25.57	4.39	0.55	24.47	26.68	16	34
	6 to 14 staff	42	25.26	4.54	0.70	23.85	26.68	12	34
	15 or more staff	59	25.29	4.31	0.56	24.16	26.41	14	34
	Total	164	25.39	4.37	0.34	24.72	26.06	12	34
TECHNICAL LEADERSHIP	5 or fewer staff	63	22.46	3.98	0.50	21.46	23.46	12	30
	6 to 14 staff	43	23.26	4.07	0.62	22.00	24.51	11	30
	15 or more staff	58	23.97	3.71	0.49	22.99	24.94	15	30
	Total	164	23.20	3.94	0.31	22.59	23.81	11	30
ADAPTIVE LEADERSHIP	5 or fewer staff	65	19.05	3.21	0.40	18.25	19.84	11	25
	6 to 14 staff	44	19.73	4.25	0.64	18.44	21.02	6	25
	15 or more staff	59	19.86	3.12	0.41	19.05	20.68	11	25
	Total	168	19.51	3.48	0.27	18.98	20.04	6	25

Subscale	*Program Type Group*	*N*	*M*	*S.D.*	*S.E.*	*95% Confidence Interval*		*Min.*	*Max.*
						Lower Bound	*Upper Bound*		
SELECTION	Other program type	56	17.82	3.07	0.41	17.00	18.64	8	24
	Home visiting program	115	17.69	3.23	0.30	17.09	18.28	7	25
	Total	171	17.73	3.17	0.24	17.25	18.21	7	25
TRAINING	Other program type	55	24.09	4.36	0.59	22.91	25.27	11	30
	Home visiting program	111	23.05	4.57	0.43	22.19	23.91	10	33
	Total	166	23.40	4.52	0.35	22.71	24.09	10	33
COACHING	Other program type	56	23.86	4.04	0.54	22.77	24.94	9	30
	Home visiting program	113	24.80	3.19	0.30	24.20	25.39	17	30
	Total	169	24.49	3.51	0.27	23.95	25.02	9	30
PERFORM-ANCE ASSESSMENT	Other program type	56	13.48	3.13	0.42	12.64	14.32	6	20
	Home visiting program	116	14.67	2.27	0.21	14.25	15.09	8	20
	Total	172	14.28	2.63	0.20	13.89	14.68	6	20
SYSTEMS INTERVEN-TION	Other program type	55	24.75	3.26	0.44	23.87	25.63	18	30
	Home visiting program	114	25.71	3.03	0.28	25.15	26.27	17	30
	Total	169	25.40	3.13	0.24	24.92	25.87	17	30
FACILITA-TIVE ADMINI-STRATION	Other program type	55	32.45	4.50	0.61	31.24	33.67	20	40
	Home visiting program	107	32.57	4.23	0.41	31.76	33.38	22	40
	Total	162	32.53	4.31	0.34	31.86	33.20	20	40
DECISION SUPPORT DATA SYSTEM	Other program type	55	24.24	4.29	0.58	23.08	25.40	14	34
	Home visiting program	112	25.87	4.37	0.41	25.05	26.68	12	34
	Total	167	25.33	4.40	0.34	24.66	26.00	12	34
TECHNICAL LEADERSHIP	Other program type	54	23.04	3.79	0.52	22.00	24.07	13	30
	Home visiting program	113	23.23	3.99	0.38	22.49	23.97	11	30
	Total	167	23.17	3.92	0.30	22.57	23.77	11	30
ADAPTIVE LEADERSHIP	Other program type	55	19.40	3.06	0.41	18.57	20.23	12	25
	Home visiting program	116	19.52	3.66	0.34	18.84	20.19	6	25
	Total	171	19.48	3.47	0.27	18.96	20.00	6	25

Appendix E

Statistics of One-Way ANOVA and Welch-ANOVA Tests

Race Groups by Subscale

Subscale Score		*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*	Eta-Squared (η^2)
SELECTION	Between Groups	.042	1	.042	.004	.948	.000
	Within Groups	1664.053	167	9.964			
	Total	1664.095	168				
TRAINING	Between Groups	1.395	1	1.395	.069	.794	.000
	Within Groups	3296.118	162	20.346			
	Total	3297.512	163				
COACHING	Between Groups	35.097	1	35.097	2.895	.091	.017
	Within Groups	2012.611	166	12.124			
	Total	2047.708	167				
PERFORM-ANCE ASSESSMENT	Between Groups	1.635	1	1.635	.234	.630	.001
	Within Groups	1175.918	168	7.000			
	Total	1177.553	169				
SYSTEMS INTERVEN-TION	Between Groups	14.816	1	14.816	1.505	.222	.009
	Within Groups	1623.903	165	9.842			
	Total	1638.719	166				
FACILITATIVE ADMINI-STRATION	Between Groups	29.071	1	29.071	1.568	.212	.010
	Within Groups	2928.829	158	18.537			
	Total	2957.900	159				
DECISION SUPPORT DATA SYSTEM	Between Groups	26.932	1	26.932	1.378	.242	.008
	Within Groups	3186.378	163	19.548			
	Total	3213.309	164				
TECHNICAL LEADERSHIP	Between Groups	44.374	1	44.374	2.896	.091	.017
	Within Groups	2497.529	163	15.322			
	Total	2541.903	164				
ADAPTIVE LEADERSHIP	Between Groups	3.283	1	3.283	.270	.604	.002
	Within Groups	2026.930	167	12.137			
	Total	2030.213	168				

Ethnicity Groups by Subscale

Subscale Score		*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*	Eta-Squared (η^2)
SELECTION	Between Groups	4.611	1	4.611	0.454	0.501	.003
	Within Groups	1706.942	168	10.160			
	Total	1711.553	169				
TRAINING	Between Groups	48.121	1	48.121	2.380	0.125	.014
	Within Groups	3315.205	164	20.215			
	Total	3363.325	165				
COACHING	Between Groups	45.948	1	45.948	3.806	0.053	.022
	Within Groups	2003.903	166	12.072			
	Total	2049.851	167				
PERFORM-ANCE ASSESSMENT	Between Groups	26.969	1	26.969	3.979	0.048	.023
	Within Groups	1145.558	169	6.778			
	Total	1172.526	170				
SYSTEMS INTERVEN-TION	Between Groups	25.883	1	25.883	2.716	0.101	.016
	Within Groups	1581.969	166	9.530			
	Total	1607.851	167				
FACILITATIVE ADMINI-STRATION	Between Groups	126.387	1	126.387	7.027	0.009	.042
	Within Groups	2859.738	159	17.986			
	Total	2986.124	160				
DECISION SUPPORT DATA SYSTEM	Between Groups	20.422	1	20.422	1.055	0.306	.006
	Within Groups	3174.668	164	19.358			
	Total	3195.090	165				
TECHNICAL LEADERSHIP	Between Groups	49.498	1	49.498	3.311	0.071	.020
	Within Groups	2451.587	164	14.949			
	Total	2501.084	165				
ADAPTIVE LEADERSHIP	Between Groups	32.155	1	32.155	2.709	0.102	.016
	Within Groups	1994.133	168	11.870			
	Total	2026.288	169				

Education Groups by Subscale

Subscale Score		*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*	Eta-Squared (η^2)
SELECTION	Between Groups	2.374	2	1.187	0.116	0.890	.001
	Within Groups	1702.920	167	10.197			
	Total	1705.294	169				
TRAINING	Between Groups	31.472	2	15.736	0.770	0.465	.009
	Within Groups	3309.922	162	20.432			
	Total	3341.394	164				
COACHING	Between Groups	25.134	2	12.567	1.013	0.365	.012
	Within Groups	2046.771	165	12.405			
	Total	2071.905	167				
PERFORM-ANCE ASSESSMENT	Between Groups	18.210	2	9.105	1.312	0.272	.015
	Within Groups	1166.316	168	6.942			
	Total	1184.526	170				
SYSTEMS INTERVEN-TION	Between Groups	1.155	2	0.577	0.059	0.943	.001
	Within Groups	1627.506	165	9.864			
	Total	1628.661	167				
FACILITATIVE ADMINI-STRATION	Between Groups	1.461	2	0.730	0.039	0.962	.000
	Within Groups	2988.601	158	18.915			
	Total	2990.062	160				
DECISION SUPPORT DATA SYSTEM	Between Groups	41.434	2	20.717	1.064	0.347	.013
	Within Groups	3173.674	163	19.470			
	Total	3215.108	165				
TECHNICAL LEADERSHIP	Between Groups	33.202	2	16.601	1.077	0.343	.013
	Within Groups	2512.009	163	15.411			
	Total	2545.211	165				
ADAPTIVE LEADERSHIP	Between Groups	16.195	2	8.097	0.665	0.515	.008
	Within Groups	2032.211	167	12.169			
	Total	2048.406	169				

Number of Families Served Groups by Subscale

Subscale Score		*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*	Eta-Squared (η^2)
SELECTION	Between Groups	13.236	2	6.618	0.644	0.526	.008
	Within Groups	1684.968	164	10.274			
	Total	1698.204	166				
TRAINING	Between Groups	83.917	2	41.958	2.066	0.130	.025
	Within Groups	3248.733	160	20.305			
	Total	3332.650	162				
COACHING	Between Groups	7.372	2	3.686	0.294	0.745	.004
	Within Groups	2027.756	162	12.517			
	Total	2035.127	164				
PERFORM-ANCE ASSESSMENT	Between Groups	11.109	2	5.555	0.812	0.446	.010
	Within Groups	1129.171	165	6.843			
	Total	1140.280	167				
SYSTEMS INTERVEN-TION	Between Groups	21.268	2	10.634	1.078	0.343	.013
	Within Groups	1598.332	162	9.866			
	Total	1619.600	164				
FACILITATIVE ADMINI-STRATION	Between Groups	109.376	2	54.688	2.972	0.054	.037
	Within Groups	2852.099	155	18.401			
	Total	2961.475	157				
DECISION SUPPORT DATA SYSTEM	Between Groups	24.379	2	12.190	0.630	0.534	.008
	Within Groups	3094.271	160	19.339			
	Total	3118.650	162				
TECHNICAL LEADERSHIP	Between Groups	125.687	2	62.844	4.191	0.017	.050
	Within Groups	2399.417	160	14.996			
	Total	2525.104	162				
ADAPTIVE LEADERSHIP	Between Groups	26.937	2	13.468	1.108	0.333	.013
	Within Groups	1992.812	164	12.151			
	Total	2019.749	166				

Number of Staff Groups by Subscale

Subscale Score		*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*	Eta-Squared (η^2)
SELECTION	Between Groups	2.977	2	1.488	0.144	0.866	.002
	Within Groups	1705.970	165	10.339			
	Total	1708.946	167				
TRAINING	Between Groups	51.978	2	25.989	1.267	0.284	.015
	Within Groups	3301.827	161	20.508			
	Total	3353.805	163				
COACHING	Between Groups	39.553	2	19.776	1.614	0.202	.019
	Within Groups	1997.730	163	12.256			
	Total	2037.283	165				
PERFORM-ANCE ASSESSMENT	Between Groups	25.436	2	12.718	1.889	0.154	.022
	Within Groups	1117.664	166	6.733			
	Total	1143.101	168				
SYSTEMS INTERVEN-TION	Between Groups	20.811	2	10.405	1.056	0.350	.013
	Within Groups	1605.508	163	9.850			
	Total	1626.319	165				
FACILITATIVE ADMINI-STRATION	Between Groups	26.952	2	13.476	0.712	0.492	.009
	Within Groups	2954.533	156	18.939			
	Total	2981.484	158				
DECISION SUPPORT DATA SYSTEM	Between Groups	3.375	2	1.688	0.087	0.917	.001
	Within Groups	3115.649	161	19.352			
	Total	3119.024	163				
TECHNICAL LEADERSHIP	Between Groups	68.592	2	34.296	2.245	0.109	.027
	Within Groups	2459.768	161	15.278			
	Total	2528.360	163				
ADAPTIVE LEADERSHIP	Between Groups	23.472	2	11.736	0.967	0.382	.012
	Within Groups	2002.504	165	12.136			
	Total	2025.976	167				

Program Type Groups by Subscale

Subscale Score		*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*	Eta-Squared (η^2)
SELECTION	Between Groups	0.681	1	0.681	0.067	0.796	.000
	Within Groups	1710.945	169	10.124			
	Total	1711.626	170				
TRAINING	Between Groups	39.538	1	39.538	1.949	0.165	.012
	Within Groups	3326.221	164	20.282			
	Total	3365.759	165				
COACHING	Between Groups	33.037	1	33.037	2.703	0.102	.016
	Within Groups	2041.176	167	12.223			
	Total	2074.213	168				
PERFORM-ANCE ASSESSMENT	Between Groups	53.507	1	53.507	8.039	0.005	.045
	Within Groups	1131.534	170	6.656			
	Total	1185.041	171				
SYSTEMS INTERVEN-TION	Between Groups	34.554	1	34.554	3.580	0.060	.021
	Within Groups	1611.884	167	9.652			
	Total	1646.438	168				
FACILITATIVE ADMINI-STRATION	Between Groups	0.485	1	0.485	0.026	0.872	.000
	Within Groups	2989.861	160	18.687			
	Total	2990.346	161				
DECISION SUPPORT DATA SYSTEM	Between Groups	97.968	1	97.968	5.196	0.024	.031
	Within Groups	3110.918	165	18.854			
	Total	3208.886	166				
TECHNICAL LEADERSHIP	Between Groups	1.362	1	1.362	0.088	0.767	.001
	Within Groups	2545.944	165	15.430			
	Total	2547.305	166				
ADAPTIVE LEADERSHIP	Between Groups	0.513	1	0.513	0.042	0.837	.000
	Within Groups	2048.166	169	12.119			
	Total	2048.678	170				

Program Type and Performance Assessment Subscale Welch-ANOVA Statistics

Welch	*Statistic**	*df1*	*df2*	*Sig.*
Performance Assessment	6.464	1	83.983	.013

Note: *Asymptotically F distributed