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Technology to Facilitate Progress Monitoring of Infant–Toddler Growth and Development: Measuring Implementation in Community-Based Agencies

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Abstract

Despite evidence that frequent progress monitoring to identify children at-risk of delays and inform early intervention services improves child outcomes, this practice is rare in infant–toddler settings where children could benefit the most from early intervention. Using a descriptive research design within an Implementation Science framework, we evaluated how 10 community-based infant–toddler agencies implemented a standardized progress monitoring assessment using a web application to monitor children's growth and identify children at-risk for delay. An Implementation Index was developed to quantify implementation progress for each agency, which included their percent of tasks completed, and rate of task implementation over time. Staff turnover and high staff:child ratios were associated with low implementation of progress monitoring. The Implementation Index differentiated between agencies that otherwise demonstrated similar implementation rates. Implications for supporting progress monitoring and other evidence-based practices in community-based infant–toddler childcare settings are discussed.

Keywords

progress monitoring, implementation, infant–toddler, early childhood education

For over a quarter century, educators and researchers have struggled to translate scientific knowledge to local practices (Greenwood & Abbott, 2001; Joyce & Cartwright, 2020; Odom, 2009), leading to a gap between what we know works in educational settings and what is actually used. Multi-disciplinary approaches have been used to investigate the scale up and sustainability of evidence-based practices using Implementation Science (Fixsen, Naoom, Blase, Friedman, & Wallace, 2005; Supplee & Meyer, 2015). The components of Implementation Science that have been used include diffusion of practices that draw from marketing and behavioral economics (Al-Ubaydli, List, & Suskind, 2019; Allen 1956; Heath & Heath, 2007), the use of technology (Buzhardt, Abbott, Greenwood, & Tapia, 2004; Riggleman, 2020), and the development of scientifically valid measures and methods of investigating implementation (Buzhardt, Greenwood, Abbott, & Tapia, 2006; Dowling & Barry, 2020). In special education, contextual factors associated with adoption and sustained implementation of educational practices include strong administrative support (Klingner, Boardman, & McMcaster, 2013), local "champions" of the practice (Scheirer, 2005), and local and federal policies to fund resource-intensive efforts (Durlak & DuPre, 2008).

However, even with the relevant contextual factors in place, many evidence-based practices suffer from what implementation scientists refer to as the "voltage effect," whereby the effects of an intervention implemented under natural conditions are much weaker than those found in randomized control trials and other experimental conditions (Al-Ubaydli et al., 2019; Kilbourne, Neumann, Pincus, Bauer, & Stall, 2007). For example, Tibbits, Bumbarger, Kyler, and Perkins (2010) investigated the sustainability of community-based interventions to reduce adolescent violence and delinquency, and found that the majority (55%) were either no longer in operation or implementation was substantially reduced at the sites involved in the original studies. Because the effects of special education interventions are often sensitive to

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implementation fidelity, variation in implementation fidelity is often regarded as a key reason that effects are not replicated outside of the well-resourced and tightly controlled experimental trials. Understanding the mechanisms that promote or prevent implementation fidelity of a specific intervention by its targeted population can improve sustainability and scale up (McCoy, 2015). Within early childhood special education, there is a need to improve our understanding of how progress monitoring practices are implemented in infant–toddler programs, where identification of children with or at-risk for developmental delay and monitoring the effects of intervention is key to effective early intervention.

Early Intervention and Progress Monitoring

A hallmark of early intervention and prevention science is the early identification of children at-risk of delay using child data to individualize services, and making changes to services when data suggest that progress is not being made (Division for Early Childhood [DEC], 2014; National Association for Education of Young Children [NAEYC], 2018). Often referred to as *progress monitoring,* frequent assessment using standardized or curriculum-based measures helps educators identify children who may benefit from more intensive instruction, monitor progress of children receiving intervention, and make data-based intervention or curriculum changes when needed (Christ, Zopluoglu, Monaghen, & Van Norman, 2013; Stecker, Fuchs, & Fuchs, 2005). This evidence-based practice has a nearly 30-year history in K-12 (Christ et al., 2013; Foegen, Jiban, & Deno, 2007; Fuchs, Fuchs, & Compton, 2012; Stecker et al., 2005; Lee, Chung, Zhang, Abedi, & Warschauer, 2020). For example, Fuchs and colleagues (1998) found that children whose educators were randomly assigned to use progress monitoring data to individualize their reading curriculum performed significantly better on standardized reading assessments than those whose educators did not use data to inform curriculum changes (Fuchs, Fuchs, & Hamlett, l989). Using software to facilitate data collection and scoring of brief math progress monitoring assessments, (Ysseldyke & Bolt, 2007) found that students whose teachers used progress monitoring to individualize their math curriculum performed significantly better on standardized math assessments that students whose teachers did not. However, when separated by high-, medium-, and low-implementers of progress monitoring, they found that most of the gains were accounted for by students whose teachers who implemented progress monitoring at a high fidelity.

Technology to support infant–toddler progress monitoring

For infant–toddler services, progress monitoring measures need to be psychometrically sound, usable by service providers with a range of experience, and should inform the individualization of intervention services (Bagnato, McLean, Macy, & Neisworth, 2011). We developed Infant–Toddler Individual Growth and Development Indicators (IGDIs; Carta et al., 2010) to provide practitioners with psychometrically sound measures that are feasible for use in infant–toddler settings.

Despite empirical evidence that using IGDIs to monitor progress and inform intervention decisions leads to improved child outcomes (Buzhardt et al., 2011, 2018, 2020), we have limited knowledge about how adoption and implementation of these measures unfold within infant–toddler agencies outside the context of experimental studies. Infant and Toddler IGDI measures are designed to monitor growth over time to inform intervention planning and evaluation for individual children and groups of children. The measures have defined psychometric properties, are play-based, brief and repeatable, and produce actionable data to monitor development and evaluate the effects of intervention. Other IGDI measures are available for use with older children, including assessments designed for preschoolers (MyIGDIs: McConnell, McEnvoy, & Priest, 2002) and students in K-3 (Dynamic Indicators of Basic Early Literacy Skills (DIBELS): Kaminski, Cummings, Powell-Smith, & Good, 2008).

Infant and Toddler IGDI measures include the Early Communication Indicator (ECI; Greenwood et al., 2010, 2019), Early Problem-Solving Indicator (EPSI; Greenwood et al., 2006), Early Movement Indicator (EMI; Greenwood et al., 2002, 2018), and Early Social Indicator (ESI; Carta et al., 2004; Greenwood et al., 2020), each of which has normative benchmarks for children ages 6–42 months. Each IGDI has a unique set of behaviors, or *key skills*, that a certified educator scores during the six-minute play session. Scores on these key skills are combined to form a total score for each IGDI. Total scores and key skill scores can be compared to benchmark performance to help programs identify children who may need additional support and point to the area in which support is needed. Designed to be administered frequently (e.g., quarterly or more often), a child's rate of growth over time (i.e., slope) is another metric that early educators can use to compare to benchmark growth rates to determine a child's proficiency in a given area.

To facilitate data management and intervention decision making, the IGDI Online Data System and mobile application provide practitioners with meaningful information and necessary convenience and support. Specifically, the IGDI Online Data System is a critical implementation support tool that helps educators monitor the progress of individual children and groups of children, manage IGDI data, maintain user certifications, and monitor the fidelity of program-wide implementation (Buzhardt & Walker, 2010). To accommodate early educators with limited knowledge or experience with assessment administration and data analysis, the IGDI Online Data System was designed to reduce the amount of ongoing technical assistance that educators and interventionists need to interpret children's outcomes, make data-driven intervention decisions, and maintain assessments with high fidelity and reliability.

Figure 1 shows an example of a child's progress monitoring graph for the ECI generated by the Online Data System. Designed and iterated through extensive usability testing with infant–toddler practitioners and parents (Buzhardt et al., 2010), the graph illustrates the child's current communication level based on their most recent ECI assessment, their growth over time before and after intervention relative to benchmark performance based on the ECI's psychometric properties (Buzhardt et al., 2010), and general administration information. Similar graphs are generated for the child's progress on key skills for each of the IGDIs; in the case of the ECI: gestures, vocalizations, single words, and multiple words. To facilitate progress monitoring at the agency level, the Implementation Dashboard on the Online Data System's homepage (Figure 2) gives program directors aggregated information about the performance of all children in their program, as well as implementation needs, and assessment administration concerns. Each item in the dashboard is a link that provides details about each element (e.g., specific children in need of an assessment, each administration concern, etc.) to allow users to address concerns immediately. Other tools include custom group reports of children's progress, tools to facilitate reliability checks between practitioners, and training and certification information, etc. The IGDI mobile app is a companion application that allows for quick live scoring of IGDI assessments, even offline. Users tap a key skill to tally the occurences of the behavior during an assessment while a timer stops the assessment after 6 minutes have elapsed. Assessments that are scored with the mobile app are automatically uploaded to the data system when the device is connected to the internet, eliminating the need to log into the data system to enter scores as when data are collected using pen-and-paper scoring forms.

The Need to Understand Implementation Under Natural Conditions

We have conducted two randomized control trials that have demonstrated the effect of IGDI use and the Online Data System on child outcomes. In the first, Early Head Start home visitors in one midwestern state were randomly assigned to use the ECI with automated support from the Online Data System to help them interpret individual children's ECI progress monitoring data, identify language intervention

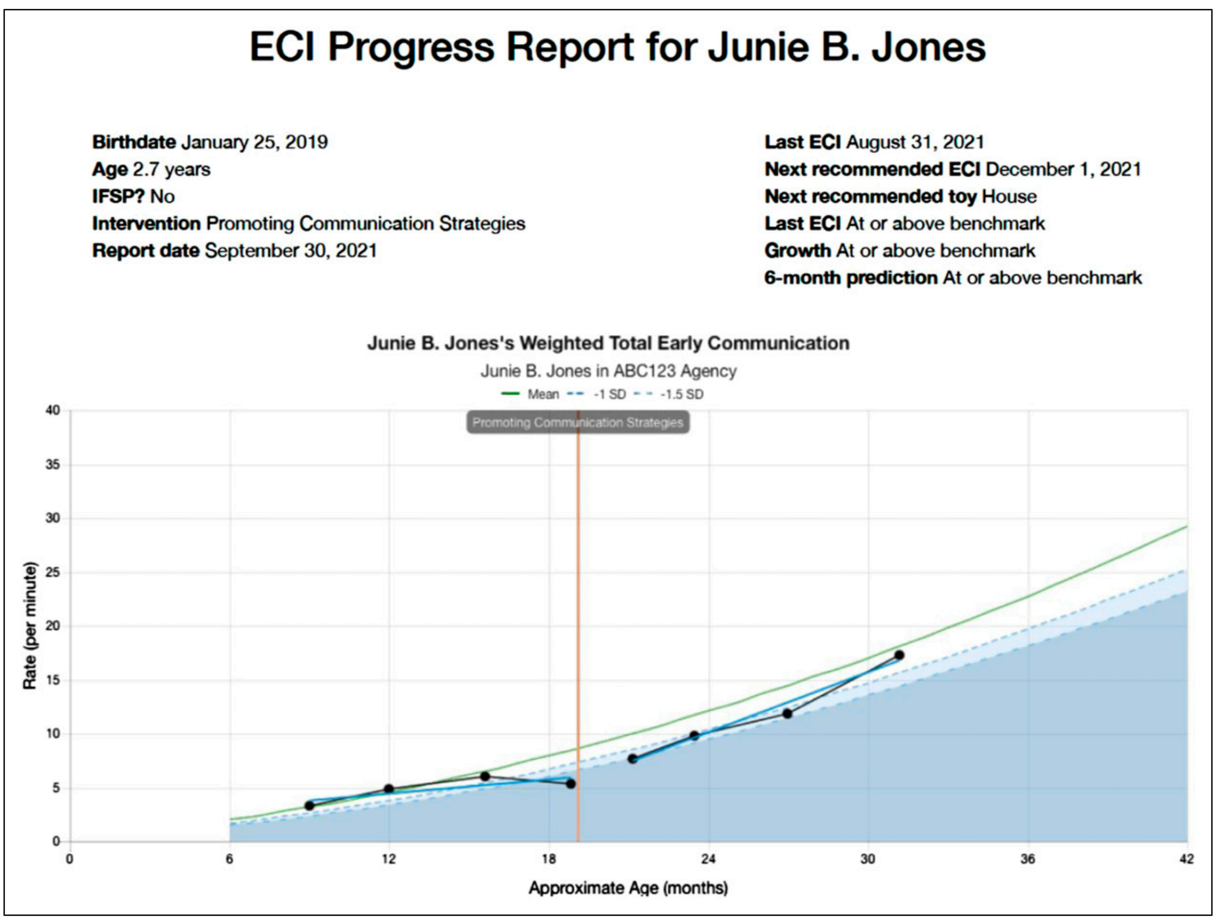

Figure 1. An IGDI progress monitoring graph generated by the Online Data System for a child's progress over time on the ECI.

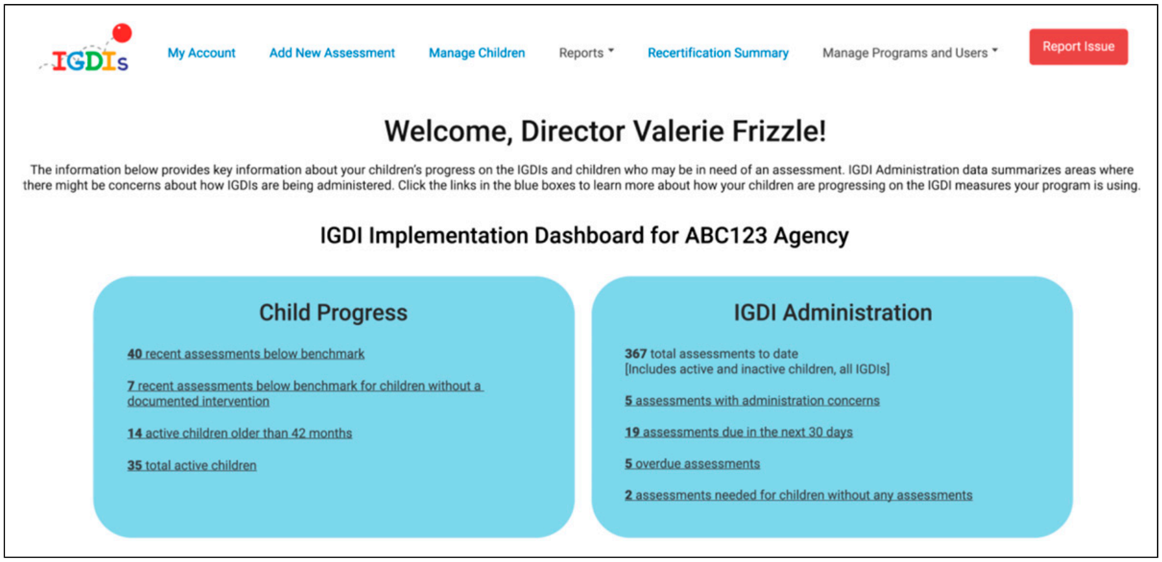

Figure 2. The implementation dashboard in the IGDI online data system.

strategies for children not making expected progress, and prompting follow-up on the use of the strategies and ongoing ECI progress monitoring (Buzhardt et al., 2011). Home visitors in both groups used the same language intervention strategies. Children whose home visitor had access to the Online Data System's decision-making guidance demonstrated significantly greater growth in expressive communication than children whose home visitor did not. We replicated these findings in a recent cluster randomized control trial across four states (Buzhardt et al., 2018, 2020) that also measured variation in the experimental group's implementation of the Online Data System's decision-making support. In this larger study, children in the experimental group whose home visitor implemented with the highest fidelity had significantly greater growth on the ECI and the Preschool Language Scale compared to the comparison group. Effect sizes on children's language growth doubled at 12-month follow-ups. Although these are promising findings, only about 38% of the experimental group home visitors implemented the ECI and Online Data System guidance with high fidelity. This highlights the need to better understand how implementation progresses over time under more natural conditions (i.e., outside of the context of a well-resourced randomized control trial), specific implementation tasks for which agencies need additional support, and agency-level variables that contribute to low rates of implementation.

Infant–toddler agencies face several challenges in implementing evidence-based progress monitoring practices. First, most agencies lack resources and infrastructure to support data collection, management, and interpretation (Akers et al., 2015; Fixsen, Blase, Metz, & Van Dyke, 2013; Walker, Carta, Greenwood, & Buzhardt, 2008), and agency staff often lack education and experience to effectively use child outcome data to inform their services (Bagnato et al., 2011; Buzhardt et al., 2010; Buzhardt, Walker, Greenwood, & Heitzman-Powell, 2012; Fixsen et al., 2013). In a recent investigation of Part C home visitors' use of Infant–Toddler IGDIs, home visitors reported that the time required to administer and score assessments was a barrier, as well as the toys needed to carry on home visits (Hughes-Belding, Luze, & Walter, 2021). High staff turnover in early childhood programs, often as high as 50% (Kwon et al., 2020), further exacerbates these barriers (Institute of Medicine and the National Research Council, 2012). Although it is critical to address factors related to high turnover (e.g., low wages, job satisfaction, few opportunities for professional advancement, and limited administrative support; Kwon et al., 2020), services and products are also needed that are less affected by high rates of staff turnover. Thus, sensitive measures are needed to document implementation of progress monitoring by early education practitioners (Buzhardt et al., 2006; Metz et al., 2013)). Without such tools, it is difficult to identify relationships between implementation efforts and outcomes, generate formative insights to support continuous quality improvement, or uncover strategies that can be shared to support sustainability at a larger scale. Thus, we developed the *IGDI Implementation Framework* (Figure 3) to operationalize implementation tasks and measure the rate at which individual agencies complete the tasks.

The aim of this study was to examine how implementation of Infant–Toddler IGDIs unfolded over time in community-based childcare agencies, identify where implementation stalled, and program characteristics related to implementation progress. This required sensitive measures of implementation progress in order to compare implementation across agencies. We evaluated implementation across 10 community-based agencies that had no prior experience with IGDIs. Also, in an effort to quantify an agency's progress across multiple

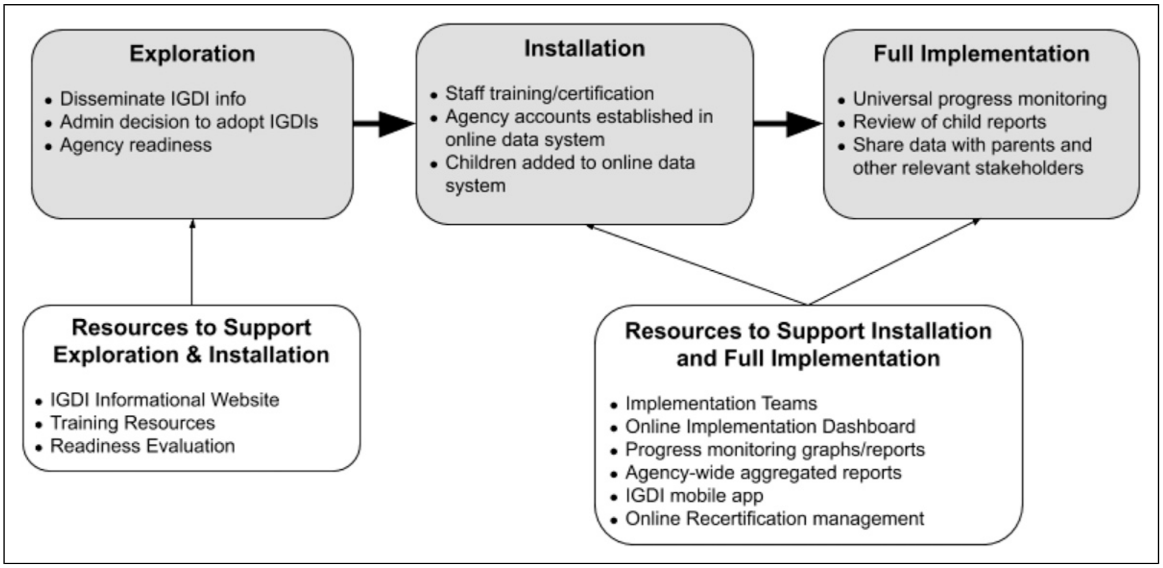

Figure 3. The IGDI Implementation Framework summarizing components of each implementation stage and the resources provided to support agencies' completion of tasks for each stage.

implementation metrics (Bast et al., 2015; Dix, Slee, Lawson, & Keeves, 2012; Dowling & Barry, 2020; Saunders, Ward, Felton, Dowda, & Pate, 2006), we developed an index score to represent each agency's progress toward full implementation. Thus, we addressed the following research questions:

1) How did implementation rate of IGDIs for progress monitoring vary between community-based infant–toddler programs?
   a) How did staff turnover and staff-to-child ratio affect implementation?
2) How did implementation vary between implementation stages: Exploration, Installation, and Full Implementation?
3) How did the Implementation Index represent each program's implementation compared to implementation rate of growth and percent of implementation tasks completed alone?

Method

Design

Using a descriptive research design (Atmowardoyo, 2018), quantitative data were analyzed to investigate how IGDIs were implemented by community-based programs under natural conditions. Data (i.e., implementation rate, implementation index) were analyzed using descriptive statistics.

Participants

Sixty-three early childhood educators (see Table 1) in 10 agencies across two midwestern states participated. As seen in Table 2, these agencies served 378 infants and toddlers who were eligible for IGDIs and 321 children older than 42 months of age for a total of 699 children ($\bar{x}$ = 60.4; range = 26–106) during the study. Five agencies chose to use the ECI measure, two chose the EMI, and three chose the EPSI. The mean child-to-staff ratio (i.e., the number of infants/toddlers for each IGDI-certified educator) was 7.65.

Procedures

Following IRB approval, we invited agencies to a meeting in which we described progress monitoring, each of the IGDI measures, and the details of the study. Agencies that chose to participate received an internet-enabled tablet to support their use of IGDIs (e.g., videotaping, entering data, viewing reports, etc.), toys necessary to administer IGDIs (each set cost $30–$50), and a $1000 stipend to compensate for the extra time engaging in research procedures (competing surveys, participating in implementation team meetings, etc.) No monetary compensation was provided to individual staff. Following Fixsen and colleagues' implementation model (Fixsen et al., 2005), IGDI Implementation tasks were categorized into one of the three stages described below.

The IGDI implementation framework. Adapted from the *Stages of Implementation* (Fixsen et al., 2005; Fixsen, Blase, Naoom, & Wallace, 2009), the *IGDI Implementation Framework* is a roadmap for an agency to move from IGDI adoption to full implementation. As illustrated in Figure 3, each implementation stage is linked to relevant resources and technology tools designed to support implementation. The specific tasks within each stage can be found in the supplemental materials.

Table 1. Early Childhood Educator Characteristics.

Variable	*n*	%
Race/ethnicity		
Euro American (white)	43	78.2
African American	4	7.3
Hispanic/Latino	4	7.3
Native American	1	1.8
Multiple Ethnicities	2	3.6
Other	1	1.8
Education level		
Less than high school	2	3.6
GED	3	5.5
High school diploma	14	25.5
Some college courses	13	23.6
Two-year degree	13	23.6
Bachelor's degree	5	9.1
Some graduate courses	4	7.3
Other	1	1.8
Early childhood education training/education		
Some early childhood training after high school	30	54.5
Child development associate credential	3	5.5
Two-year degree in education or related field	8	14.5
Bachelor's degree in education or related field	5	9.1
Some graduate courses in education or related field	5	9.1
None	3	5.5
Other	1	1.8
Early childhood Educator role		
Master/lead educator working across multiple classrooms	9	16.4
Master/lead educator working in a single classroom	28	50.9
Assistant educator working across multiple classrooms	9	16.4
Assistant educator working in a single classroom	2	3.6
Other	6	10.9

Note. Some categories do not sum to 63 because some educators chose not to answer some questions.

Table 2. Agency Characteristics.

Agency	IGDI	IGDI trained assessors	Turnover of trained assessors	Children served: 0–42 months	42+ months	Total	Children: staff[a]	Implementation progress: %	Rate
1	EPSI	3	0	50	32	82	16.67	83	0.45
2	ECI	6	1	45	50	95	7.50	93	0.57
3	ECI	4	1	15	24	39	3.75	92	0.55
4	ECI	9	0	60	25	85	6.67	97	0.64
5	EPSI	5	0	40	48	88	8.0	83	0.45
6	ECI	9	5	64	42	106	7.11	79	0.43
7	EMI	4	1	20	20	40	5.0	83	0.43
8	ECI	2	0	16	10	26	8.0	100	0.61
9	EMI	3	1	30	40	70	10	100	0.57
10	EPSI	10	0	38	30	68	3.8	93	0.57
Totals		55	9	378	321	699	N/A	N/A	N/A
Means		5.5	0.9	37.8	32.1	69.9	7.65	90.3	0.53

[a]Number of children 0–42 months of age for each IGDI trained assessor.

In the *Exploration* stage, after agency administrators learn about IGDIs and decide to adopt them for their agency (Task 1), their readiness in implementing IGDIs is assessed (Task 2). After choosing an IGDI (Task 6), they identified staff who would administer and score IGDIs (Task 5), created accounts in the data system (Task 3), and scheduled a training date for their staff (Task 4). During *Installation*, staff were trained and certified on their chosen IGDI (Task 7) and created protocols needed to successfully implement IGDIs (Tasks 10–12) informed by information from the Implementation Planning Survey completed by administrators (Task 8). At a 1-day certification workshop for each agency, staff were presented with information about IGDIs, how to administer and score each key skill, and how to use the Online Data System to interpret graphs and discuss progress reports with parents and other early childhood professionals. Each educator then scored two videos of IGDI assessments and were required to achieve 85% interobserver agreement with master codings of each video (see Buzhardt & Walker, 2010 for additional training details) (Task 9). Following the training, agencies were provided with the toys necessary to administer IGDIs (Tasks 13–15), and established an individualized plan for administering and scoring IGDIs and shared the plan with staff (Tasks 10–12, 16, 17).

During *Full Implementation,* the agency carried out plans developed in the Installation Stage to add children to the data system (Task 20), assess children based on their assessment plan (Tasks 21, 23, 24), review and interpret IGDI data for individual children (Task 18) and aggregated data for the agency as a whole (Task 22), and share data with parents and/or other stakeholders (Task 19). The IGDI Implementation Dashboard on the home page of the Online Data System served as a virtual "implementation coach" for agency staff to help them keep up with assessments and how their children are performing. The Dashboard reports an agency's current implementation data, including children in need of their first assessment, those due for a quarterly assessment, children currently performing below benchmark, and assessments with potential administration concerns (e.g., data entered more than 30 days after assessment administration, use of the same toy set for a child, etc.).

Monthly Implementation Team Meetings between agency and IGDI staff facilitated full implementation by reviewing Dashboard information, child data, and problem-solving challenges reported by the agency. The use of Implementation Teams has demonstrated promise in facilitating sustained implementation of organizational changes (Higgins, Weiner, & Young, 2012) and school-wide evidence-based practices (Sugai & Horner, 2006). General team meeting objectives included: 1) establish logistics for embedding IGDIs into an existing service model; 2) review administration progress, identify and troubleshoot barriers, 3) identify children in need of assessment; and 3) review program goals and progress of children scoring below benchmark, and those with an identified intervention or recent curriculum change. Teams set expectations for the number of IGDIs to be completed, scored, and entered in the data system between the current meeting and the next scheduled meeting and would document two or more goals. Previous goals that were partially completed or not started were added to the goals to be completed before the next meeting.

Measures

Infant–toddler educators and staff turnover. Educators completed a demographic questionnaire. Agency administrators reported staff turnover at Implementation Team Meetings. For purposes of the current study, we only report turnover of infant–toddler staff.

Child-to-staff ratio. The child-to-staff ratio was calculated by dividing the number of infants/toddlers served by the agency by the number of IGDI-certified staff at the start of the study (see Table 2).

Implementation. IGDI implementation was based on each agency's completion of the 24 tasks, which also shows the evidence we used to confirm task completion. Time was defined as the total number of weeks since the agency decided to adopt IGDIs. These data allowed us to quantify implementation using two metrics: *Percent of tasks completed* and *implementation rate*. Implementation rate was calculated by dividing the number of tasks by the total number of weeks for Total Implementation Rate (Table 2).

Implementation Index. The implementation index is a single score designed to reflect IGDI implementation progress across the stages of implementation (Exploration, Installation, and Full Implementation), while also considering an agency's staff turnover and child-to-staff ratio. As shown in equation (1) below, the Index contains the following variables: *implementation percentage*, *weighted implementation rate*, *child-to-staff ratio*, *time*, and *staff turnover*. The weighted rate (Equation (2)) was calculated by summing the rates for all three stages, with a multiplier of 2 for the Full Implementation stage, and dividing by three. The Full Implementation stage was weighted because we judged it to be the most difficult because 1) the tasks in this stage required the most effort from agency staff with the least amount of external support, 2) they required ongoing efforts (e.g., all enrolled children have been assessed in the last 90 days) compared to tasks in other stages that were completed one time (e.g., data entry plan established, IGDI plan shared with staff), and 3) this stage had the slowest implementation rate of the three stages. For the index, the square root of the child-to-staff ratio was used to avoid overrepresenting implementation for larger programs with only a few staff certified to use IGDIs. Turnover of certified IGDI staff (Weeks/[Weeks – Staff lost]) represents the time lost due to turnover through the retraining of staff or the time spent hiring replacement staff to cover classroom ratios.

$$Implementation\ Index = (Imp\%)^2 \times Rate_w \times \sqrt{\frac{Children}{Staff}} \times \frac{Weeks}{Weeks - Staff\ \ lost} \tag{1}$$

$$Rate_{Weight} = \frac{Rate_{Explore} + Rate_{Install} + 2Rate_{Implement}}{3} \tag{2}$$

Results

RQ 1: Implementation variation between agencies and relationship between staff turnover and child-to-staff ratios

Between-agency implementation variation. Table 2 shows each agency's percentage of all implementation tasks completed ($\bar{x}$ = 90.30%; range = 79%–100%), as well as their implementation rates, where a higher rate indicates faster completion of tasks over time. A visual representation of this data can be found in the supplemental materials. The mean rate was .53, meaning that agencies completed an average of .53 tasks per week (range = 0.43–0.64). Six programs achieved at least 90% implementation of all tasks, two programs reached 100%, one at 40 weeks, and the other at 42 weeks.

Because agencies varied in their completion of the Full Implementation stage, Table 3 shows the percentage of agencies that completed each Full Implementation task. Within this stage, only 40% of agencies shared child reports with parents, representing the least likely task to be completed. The only task to be completed by all agencies was entering all enrolled children into the Online Data System. Only 40% of agencies *with* turnover reviewed child reports, administered an IGDI every 90 days for all children, and completed IGDIs more frequently for children performing below benchmark, compared to 60%, 80%, and 60%, respectively, for agencies *without* turnover. A high child-to-staff ratio appeared to similarly affect administration of IGDIs every 90 days and increasing assessment frequency for children below benchmark.

Relationship between staffing and implementation. Regarding the impact of staff turnover and child-to-staff ratios on implementation, Table 2 shows that agencies with turnover (n = 5) had a lower mean completion percentage ($\bar{x}$ = 89.4; range = 79–100) than agencies with no turnover (n = 5) ($\bar{x}$ = 91.2; range = 83–100), as well as a lower implementation rate ($\bar{x}$ = 0.51; range = 0.43–0.57) than agencies with no turnover ($\bar{x}$ = 1.16; range = 0.45–0.64). Agencies with more than seven children for each certified staff person (n = 6) had a lower mean completion percentage ($\bar{x}$ = 89.67; range = 79–100) than agencies with a lower child-to-staff ratio (n = 4) ($\bar{x}$ = 91.25; range = 83–97). They also had a lower implementation rate ($\bar{x}$ = 0.51; range = 0.43–0.61) than agencies with a lower child-to-staff ratio ($\bar{x}$ = 0.55; range = 0.43–0.64).

RQ 2: Implementation variation between stages

Table 4 shows each agency's implementation progress by implementation stage, as well as turnover of certified staff in each stage. All programs completed 100% of tasks in the Exploration and Installation stages, and two programs completed 100% of tasks in the Full Implementation stage. The mean number of weeks to complete the Exploration and Installation stages was similar at 12.5 and 12.9 weeks, respectively. However, only Agencies 8 and 9 completed all Full Implementation tasks. Although agencies took longer to complete the Installation stage than Exploration, their implementation rate was nearly two times faster during Installation (1.07) compared to Exploration (0.5). This was because there were nearly twice as many tasks in the Installation stage than Exploration. The Full Implementation Stage implementation rate was the slowest of the three with a mean of 0.4 tasks completed per week (range = 0.125–1.0).

Staff turnover by implementation stage. We then compared mean completion rates between agencies with and without staff turnover during each implementation stage. Three

Table 3. Full Implementation Completion Rate.

	Completion % by agencies				
		Staff Turnover		Child-to-staff Ratio	
Task Description	All n = 10, %	Yes n = 5, %	No n = 5, %	High[a] n = 7, %	Low[a] n = 3, %
Educators have reviewed child graphs	50	40	60	67	25
Educators have shared graphs with parents	40	60	20	50	25
Enrolled children are entered into the ODS	100	100	100	100	100
Enrolled children have at least 1 completed assessment	70	60	80	67	75
The program report has been generated and reviewed	80	80	80	83	75
Enrolled children have had an IGDI in last 90 days	60	40	80	50	75
Increased frequency of IGDIs for children below benchmark	50	40	60	33	75

[a]High ratio >7; low ratio <7.

Table 4. Implementation Progress by Stage.

	Exploration			Installation			Full Implementation		
Agencies	Rate	Weeks to completion	Turnover reported	Rate	Weeks to completion	Turnover reported	Rate	% Completed (weeks)[a]	Turnover reported
1	0.67	9	0	1	12	0	0.14	43 (23)	0
2	0.6	10	0	0.93	16	0	0.3	71 (18)	1
3	0.55	11	0	0.92	13	1	0.37	78 (20)	0
4	0.5	12	0	0.86	15	0	0.63	91 (17)	0
5	0.43	14	0	1.83	7	0	0.14	43 (23)	0
6	0.38	16	0	1.83	7	1	0.1	29 (21)	4
7	0.46	13	0	0.85	14	0	0.13	33 (17)	1
8	0.4	15	0	1	12	1	0.71	100 (15)	0
9	0.55	11	0	0.58	20	0	1	100 (9)	1
10	0.43	14	0	0.92	13	0	0.5	80 (17)	0
Means	0.5	12.50		1.07	12.90		0.4	66.80 (18.60)	

[a]Percent of tasks completed and the number of weeks to reach this level of implementation.

Table 5. Implementation Index.

Rank (Agency)	Implementation index	Implementation percentage	Unweighted implementation rate	Weighted implementation rate
1 (9)	4.35	100	0.57	1.041
2 (8)	2.58	100	0.61	0.943
3 (4)	2.11	97	0.64	0.869
4 (3)	1.79	92	0.55	0.733
5 (10)	1.51	93	0.57	0.782
6 (6)	1.51	79	0.43	0.803
7 (1)	1.26	83	0.45	0.646
8 (2)	1.21	93	0.57	0.707
9 (7)	1.16	83	0.43	0.519
10 (5)	1.13	83	0.45	0.845

agencies experienced turnover during Installation, and four during Full Implementation. The four agencies with turnover during Full Implementation had a much lower mean implementation rate (0.38) and percentage of tasks completed (58.25%) than the six agencies without turnover (0.41 and 72.50%). Specifically, Agency 6, which lost four staff during Full Implementation, had the lowest completion percentage (29%) and implementation rate (0.1) during this stage (Table 4). Conversely, the three agencies that experienced turnover during Installation had a slightly higher mean implementation rate (0.92) than the seven agencies without turnover during this stage (0.89), suggesting that turnover has stronger impact on Full Implementation tasks than Installation tasks.

RQ3: Performance of the Implementation Index

Agencies with high implementation indices. An IGDI Implementation Index was calculated for each agency using the formula described in the Methods section. Table 5 ranks the 10 agencies by their Implementation Index, and includes their implementation percentage and rate for comparison. The Index score allowed more clear differentiation between agencies that otherwise had similar implementation percentages and rates. For example, at the top of the rankings in Table 5, Agency 9 had a higher Index score (4.35) than Agency 8 (2.58) despite having nearly identical percent implementation completion (100% for both) and implementation rates, 0.57 and 0.61, respectively. The index differentiated these agencies by such a large margin because Agency 9 had a higher implementation rate during Full Implementation (1.0 vs. 0.714), experienced staff turnover, and had a child-to-staff ratio that was more than twice as high as Agency 8.

Agencies with midrange implementation indices. In the middle of the index rankings, Agency 3 had a higher index than 10 and 6 because it experienced staff turnover while maintaining a relatively high implementation completion percentage at 92%. Conversely, Agency 6 reached the middle range of the rankings despite having the lowest percentage of implementation completion of all agencies, which receives the strongest weighting of any metric in the Implementation Index. Because this agency experienced the highest turnover of any agency (one staff person during Installation and four during Full Implementation), their Index increased above some agencies that completed a higher percentage of tasks.

Agencies with low implementation indices. Agencies 1, 2, 7, and 5 were at the lower end of the index rankings primarily due to their relatively low percentage of completed tasks: 83% except for Agency 2 at 93%. However, they were more clearly differentiated by their Index score due primarily to differences in their child-to-staff ratios. In fact, Agency 1 was ranked higher than Agency 2 despite a lower percentage of completed tasks (83% vs. 93%) and weighted rate (0.65 vs. 0.71) due to an unusually high child-to-staff ratio of 16.67, which was twice as high as the next agency with an 8.0 ratio. Similarly, despite Agency 5's higher weighted implementation rate, Agency 7's Index (1.16) was somewhat higher than Agency 5's (1.13) due to their staff turnover.

Discussion

We know that using progress monitoring to inform curriculum and intervention decisions for children with or at-risk for disabilities can have strong effects on child outcomes (Lee et al., 2020; Stecker et al., 2005), and that the fidelity with which progress monitoring is implemented contributes to those effects (Buzhardt et al., 2020; Ysseldyke & Bolt, 2007). However, we know little about how progress monitoring practices are implemented under natural conditions and barriers to their implementation, particularly in infant–toddler programs where these practices are much more rare than in K-12 settings (Akers et al., 2015; Hughes-Belding et al., 2021). In this study, we were able to "observe" implementation of IGDIs primarily through data logs within the online data system. Combining these data with agency-reported data about staffing and staff turnover, we were able to identify factors related to slow and/or incomplete implementation of progress monitoring. These factors included high child-to-staff ratios, and staff turnover had an acute negative effect on implementation, particularly if it occurred during the full implementation stage. This fills a gap in current knowledge about barriers to progress monitoring in early childhood (Akers et al., 2015), regardless of the measures or progress monitoring system used. Also, although the Implementation Index was developed specifically for Infant Toddler IGDIs, the index's structure could be applied to other measures as a standardized way to quantify implementation across a variety of contexts.

The primary focus of this work was to evaluate the adoption and implementation of progress monitoring practices by center-based infant–toddler service providers facilitated by web-based technology. The Online Data System allows service providers to identify children at-risk for delay in targeted areas, and manage ongoing assessments, which are rare in most infant–toddler agencies. Although our sample of agencies was too small to use inferential statistics to identify causal mechanisms, clear patterns emerged that improves our understanding of barriers to implementing progress monitoring practices in infant–toddler agencies. The three implementation measures (percentage of tasks completed, rate of completion, and an Implementation Index) were sensitive to agencies' completion of implementation tasks, the speed with which they advanced through each implementation stage, and the degree to which implementation progressed in the face of staff turnover and variation in child-to-staff ratios. All agencies completed most of the implementation tasks needed to reach full implementation. However, there was substantial variation in implementation rate between agencies and implementation stages. Agencies that experienced staff turnover and had higher child-to-staff ratios tended to complete implementation tasks at slower rates. There were at least two clear exceptions. Agencies 8 and 9 maintained average rates of implementation and achieved full implementation despite above average child-to-staff ratios and experiencing staff turnover. These agencies' ability to achieve full implementation in the face of these barriers was reflected in their high Implementation Index.

These implementation data also allowed us to identify specific tasks that agencies struggled to complete. Across all agencies, sharing data with parents was the least likely task to occur, suggesting that staff needed additional tools to support data sharing with parents, perhaps via email or other digital means. It also suggests that adding parent-level access to the Online Data System may be needed rather than relying on staff to share printed or emailed copies of child progress with parents. Staff turnover and high child-to-staff ratios appeared to have the most impact on agencies' ability to maintain a regular schedule of IGDI assessments. Since administering frequent assessments demands the most intensive efforts from staff, encouraging and providing more training for the IGDI Mobile app to score and enter assessments could help agencies maintain assessment schedules, particularly those with limited staff or that experience staff turnover.

Evaluating variation in implementation between Implementation Stages (i.e., Exploration, Installation, and Full Implementation) was important because it helped identify precisely when during the implementation process agencies had the greatest need for additional support. Agencies had the lowest implementation rate and spent the longest time in the Full Implementation stage despite having fewer tasks to complete relative to Installation. This is likely because most of the tasks in the Full Implementation stage require more effort and ongoing planning by agency staff than tasks in the other stages (e.g., all children have been assessed, sharing child progress with parents, increased assessment frequency for low-performing children, etc.). Regardless, these implementation data suggest that more implementation support is needed for this stage, and/or that more preparation is needed for these tasks in the earlier stages. This contributed to the justification for weighting this implementation stage for the implementation index.

Practical Use of the IGDI Implementation Index

Index scores that aggregate data across multiple indicators of implementation have been developed to characterize implementation of smoking cessation programs (Bast et al., 2015), school-based social-emotional interventions (Dowling & Barry, 2020), mental health initiatives (Dix et al., 2012), and health promotion interventions (Saunders et al., 2006). A unique aspect of the IGDI Implementation Index is that, in addition to implementation data, it includes agency characteristics known to impact implementation. An index such as this that considers barriers can potentially be used to improve predictions of an agency or district's ability to sustain implementation in the face of real-world challenges independent of the intervention and implementation supports (e.g., reduced labor force, state/federal budget reductions, temporary public health crises, etc.) Rather than treating these factors as "noise," the IGDI implementation index provides a more authentic indicator of implementation that may be a better predictor of ongoing implementation than measures of implementation that do not consider barriers that most early education agencies regularly experience.

Our goal in designing the index was to identify agencies in need of additional implementation support. For example, one could argue that Agency 6's index ranking (6th of 10, Table 5), which was boosted by high staff turnover, was too high given that they had the lowest implementation percentage and rate among all agencies. On the other hand, Agency 5 had a higher weighted rate than Agency 6 but a lower index because they did not experience turnover. For practical applications, when used at scale (e.g., 100+ agencies, LEAs, or districts), index cutoff scores or algorithms could be used to identify agencies at-risk of not reaching full implementation, and those that have reached full implementation but may be unlikely to sustain implementation. Similar to a screening process, an index such as this would help identify "at risk" agencies; prompting a more detailed analysis of their implementation progress, barriers they have encountered, and the support they need to get implementation back on track and increase the likelihood of sustained implementation.

Limitations

This study was not designed to make causal inferences about factors that affected implementation. The small sample size at the agency level ($n = 10$) did not allow for sufficiently powered significance testing, nor were there comparison groups to test the effects of implementation supports or agency factors such as staff turnover or child-to-staff ratios. Therefore, findings showing that agencies with higher child-to-staff ratios and staff turnover had less implementation success (i.e., lower implementation rates and completion percentages) are tenuous given the small sample size and the lack of experimental control.

Some agency variables were not measured that may have facilitated or impeded implementation progress. For example, high child-to-staff ratios and staff turnover may have been symptomatic of other problems that more directly impacted implementation, such as staff morale, salaries or other incentives. Related to this, we did not collect information about how other services provided by the agency may have impacted their work with infants and toddler. So, although the child-to-staff ratio only accounted for IGDI-certified infant–toddler staff, 45% of the children served across all agencies were older than 42 months ($n = 321$), the cutoff age for Infant–Toddler IGDIs, meaning that some infant–toddler staff may have had to spend time in preschool and/or kindergarten rooms if staff shortages occurred in those areas. Also, we did not assess "buy in" for IGDIs by staff or agency leadership, a factor commonly associated with successful implementation of evidence-practices (Buzhardt et al., 2006; Sugai & Horner, 2006). This is particularly relevant in a study such as this where the agencies received financial compensation to offset their efforts related to the research (e.g., completing surveys, ongoing communication with researcher staff throughout the study, etc.).

Future Research

Although this is the first study to our knowledge that reports how implementation of infant–toddler progress monitoring measures unfolds within infant–toddler agencies, it opens the door to other questions specific to Infant–Toddler IGDIs, as well as early childhood evidence-based practices in general. For example, although agencies have the opportunity to receive training and resources to certify their own staff after demonstrating sustained full implementation (i.e., train-the-trainer), providing this training earlier may prevent implementation dips when trained staff leave the agency. Additionally, while the implementation index allows us to identify those who are struggling with progress through the stages of implementation, more research is needed to provide a clearer picture of the variables that contribute to or hinder success. Also, more investigation is needed to explore differences based on the type of IGDI measure used, or how the use of multiple IGDIs influences implementation. Finally, there is a need to investigate the hypothesis that implementation during one stage of the framework is predictive or related to implementation in subsequent stages. Data on the relationship between these stages would make the Implementation Index functional as an early warning system to alert implementation support staff when additional technical assistance or training is needed to prevent future implementation delays or termination. Similarly, we need to know to what degree implementation performance during these first three stages is related to performance during the Sustainability stage.

Given the known challenges associated with installing, implementing, and sustaining evidence-based practices with high fidelity in early childhood education (Akers et al., 2015; Bagnato et al., 2011; Buzhardt et al., 2012; Fixsen et al., 2013; Walker et al., 2008), there is a clear need to investigate how the implementation of evidence-based practices in general progresses over time, using objective/observable evidence of implementation rather than data based primarily on practitioner self-report. Sufficiently powered studies with large enough samples of schools/agencies will allow significance testing of factors that facilitate or impede implementation at the school/agency level. Although large implementation studies of widely used education interventions (e.g., Positive Behavior Interventions and Supports; Horner & Sugai, 2015; James, Noltemeyer, Ritchie, Palmer, & Miami University, 2019) are valuable, implementation research of this nature is costly and typically requires resources that schools and intervention developers simply do not have. As web platforms increasingly become an integral component of educational interventions (Kimmons, 2020), evidence of implementation can be stored automatically in database logs of user activity, making implementation studies of this nature more practical. Our understanding of factors that promote or impede implementation of early childhood evidence-based practices will benefit from implementation frameworks that utilize valid and reliable data generated automatically, as well as carefully designed implementation index scores to help predict when schools or agencies need additional support to reduce implementation failure.

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Supplemental Material

Supplemental material for this article is available online.

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Higgins has her Master's in Child Psychology and is the lead IGDI Trainer. She has over 20 years of experience with Drs. Buzhardt and other investigators at Juniper Gardens Children's Project to develop and implement training and assessment protocols for the Infant-Toddler IGDI assessments. She also is a research project coordinator for projects involving continued research and development of the IGDIs.

Charles R. Greenwood, PhD, is a Senior Scientist at the University of Kansas. He is former Director of the Juniper Gardens Children's Project and a member of the originating team of the Individual Indicators of Growth and Development (IGDIs).

Consolver has a Bachelor's degree in Mathematics and served as a high school teacher for 1 year and worked on content development of state assessments for 7 years. He is a research coordinator across multiple research projects for IGDIs and other early childhood projects at Juniper Gardens.

Dale Walker is a Research Professor and Senior Scientist at the Juniper Gardens Children's Project, Institute for Life Span Studies at the University of Kansas. Her research focuses on identifying the effects of early experience on language development and school readiness aimed at developing interventions and measures to inform intervention with infants and young children with/without disabilities who experience socioeconomic inequity. She directs and co-directs research projects related to early communication development and intervention, progress monitoring assessment, and accountability funded by the U.S. Department of Education, Office of Special Education Programs, the Institute for Educational Science, and the National Institute for Health and Human Services Health Resources and Services Administration.

Judith Carta is a Professor of Special Education and a Senior Scientist at the Juniper Gardens Children's Project of the University of Kansas. She currently directs the Bridging the Word Gap Research Network. She has been the Principal Investigator of several multi-site research projects funded by the National Institutes of Health, the Institute of Education Sciences, Administration on Children and Families, and the Centers for Disease Control and Prevention. She has developed and validated interventions aimed at promoting parent responsiveness and children's early language development and has designed measures that practitioners can use to measure language and social growth as a function of intervention. Additional areas of her intervention research have focused on enhancing early literacy skills and social-emotional development in young children and advancing multi- tiered systems of support for young children. A key feature of her work has been the translation of research into interventions that can be scaled up for practitioners, parents from diverse cultural groups, and interdisciplinary researchers.