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ORIGINAL PAPER

Training Preservice Practitioners to Make Data-Based Instructional Decisions

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Abstract

Adapting interventions based on learner progress is paramount to the effectiveness of interventions in special education and applied behavior analysis. Although there is some research on effective methods for training practitioners to make general instructional decisions (e.g., modify an intervention) based on graphed performance data, research on training individuals to make specific decisions (e.g., how to modify an intervention) is more limited. Our purpose in this study was to evaluate the effects of a training package, consisting of a brief online training and a visual decision-making model, for increasing preservice teachers' and behavior analysts' accuracy in making specific instructional decisions based on graphed performance data. In a multiple baseline across participants design, all participants increased their decision-making accuracy on novel graphs during assessment sessions and maintained accuracy at 1-month follow-up. The implications of these findings for training and future research on data-based decision-making are discussed.

Keywords Data-based decision-making · Progress monitoring · Visual analysis · Practitioner training

Introduction

Data-based decision-making (DBDM) is integral to maximizing outcomes for individuals with disabilities (Browder et al., 2005; Fuchs et al., 1984; Stecker & Fuchs, 2000). DBDM involves the practitioner analyzing graphed performance data and determining whether the intervention should be continued, modified, or terminated (Bruhn et al., 2020). The use of data to inform instructional decisions is considered best practice (Brawley & Stormont, 2014; Ruble et al., 2018) and is included

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in preparation standards for preservice professionals in applied behavior analysis (ABA; Behavior Analyst Certification Board, 2017) and special education (Council for Exceptional Children, 2015). In addition, the Individuals with Disabilities Education Improvement Act (IDEA, 2004) requires that Individualized Education Programs (IEPs) include plans for monitoring progress towards goals and objectives so that adjustments to instruction can be made as necessary.

Researchers have made significant advancements in the development and validation of guidelines for DBDM pertaining to academic outcomes, such as reading, that are amenable to the use of standardized, curriculum-based measurement (Filderman et al., 2018; Stecker et al., 2005). These DBDM guidelines have been widely disseminated through journal articles (e.g., Lemons et al., 2014), online professional development resources (e.g., The IRIS Center, 2015), technical assistance centers (NCII, https://intensiveintervention.org/intensive-intervention), and computer applications that systematize the process of collecting and analyzing performance data related to these academic outcomes (e.g., easyCBM; Alonzo et al., 2006). However, there is limited research on, and subsequently guidelines for, DBDM as it relates to functional, social, and challenging behaviors (Bruhn et al., 2020). Practitioners' use of data to monitor the effectiveness of instruction on these outcomes is just as critical.

Practitioners who work with very young children, as well as those who work with individuals with moderate to severe disabilities, may not be addressing academic skills for which standardized data collection, analysis, and decision-making tools are ubiquitous (Bruhn et al., 2020; Ruble et al., 2018). These practitioners are more likely addressing functional, social, or challenging behaviors for which they have designed individualized objectives and data collection systems (Ruble et al., 2018). Thus, there is a need to identify effective methods for training practitioners to use DBDM with non-academic outcomes.

Despite a consensus on the importance of DBDM, many educators do not receive sufficient training on how and when to modify instruction based on data (Stormont et al., 2011). Given the inadequacy of training, it is unsurprising that researchers have also found that practitioners are unlikely to collect, graph, and use performance data to make instructional decisions (Brawley & Stormont, 2014; Grigg et al., 1989; Sandall et al., 2004). There is some evidence that when special educators are taught to use a specific DBDM protocol in their preservice training, they report continuing to implement the protocol in their classroom (Demchak & Sutter, 2019). Unfortunately, Demchak and Sutter (2019) also found inaccuracies in the teachers' use of the DBDM protocol when they analyzed work samples.

Although there is a growing literature base on training visual analysis of graphed data (e.g., O'Grady et al., 2018; Wolfe & Slocum, 2015), relatively few studies have evaluated methods of training practitioners to analyze graphs and make instructional decisions (Kipfmiller et al., 2019; Maffei-Almodovar et al., 2017). Researchers have found that a visual decision-making model (Kipfmiller et al., 2019) and behavioral skills training (BST; Maffei-Almodovar et al., 2017) can both effectively increase the accuracy of instructional decisions. However, in both studies, the researchers taught participants to make general decisions (e.g., modify the intervention) rather than specific decisions (e.g., how to modify the intervention). Practitioners not only need to decide to change an intervention that is ineffective, they also need to decide what specific changes to make considering both the data pattern and contextual variables (e.g., learner and task characteristics). Therefore, the practical utility of these findings may be limited.

Browder and colleagues (e.g., Belfiore & Browder, 1992; Browder et al., 1986) developed and evaluated comprehensive guidelines for making instructional decisions for teachers of students with moderate to severe disabilities, based on decision rules initially developed by Haring et al. (1980). The guidelines focus on trial-based or task analysis-based instructional programs and direct the practitioner to identify the data pattern and select an appropriate, specific instructional decision based on that data pattern (Browder et al., 2011). For example, if the data pattern indicates the learner is making inadequate progress, the decision is to improve antecedents (see Table 1).

Two recent studies (Jimenez et al., 2012, 2016) examined the effectiveness of training teachers to use the guidelines developed by Browder and colleagues. Jimenez et al. (2012) evaluated the effectiveness of a synchronous online training on the accuracy of special educators' decisions. The researchers measured DBDM accuracy using five experimenter-generated graphs; participants identified the data pattern and instructional decision for each graph at pre- and posttest. Jimenez et al. reported a statistically significant difference between pre- and posttest scores; however, the absence of a control group precluded them from identifying a causal relation between the training and increased scores.

In a subsequent study, Jimenez et al. (2016) used a group design to examine the effectiveness of an asynchronous online training for teaching special educators to make data-based decisions. Both groups were assigned to complete a module on data collection; only the treatment group was assigned to complete a module on the Browder et al. (2011) DBDM guidelines. The researchers measured DBDM accuracy with a pre-/posttest similar to Jimenez et al. (2012) and with a review of data from the educators' students. There was not a statistically significant difference between the two groups at posttest; the online DBDM module did not improve decision accuracy. However, the researchers did not monitor treatment fidelity, so it is not clear if the DBDM module was ineffective, or if treatment diffusion confounded the results (i.e., control participants accessed the DBDM module or treatment participants failed to complete the DBDM module).

The body of literature on training DBDM suggests that decision rules and decision-making models can support practitioners in making accurate general data-based decisions (e.g., Kipfmiller et al., 2019; Maffei-Almodovar et al., 2017), but the results have been less compelling when researchers have attempted to train practitioners to make specific data-based decisions (i.e., how to change instruction; Jimenez et al., 2016). The purpose of the current study was to address the following gaps and limitations of previous research on training DBDM: (a) limited focus on reading-related outcomes (e.g., Filderman et al., 2018; Stecker et al., 2005), (b) restricted ranges of possible decisions (e.g., Kipfmiller et al., 2019; Maffei-Almodovar et al., 2017), (c) use of non-experimental designs (Jimenez et al., 2012), and (d) lack of treatment fidelity data (Jimenez et al., 2016).

Our specific research questions were as follows:

Table 1 Browder et al. (2011) decisions and our adaptations

Data pattern	Definition	Browder et al. decision	Our decision
Mastery	The behavior is currently performed at the criterion specified in the objective	Introduce new skill	Introduce next objective and monitor maintenance
Adequate progress	The behavior is improving at a rate that suggests the learner will meet criterion during the timeframe	Make no changes	Make no changes
No progress	The behavior has not improved from baseline; the learner has not made progress towards the objective	Simplify the response (e.g., teach only one step of the task analysis)	Check treatment fidelity; if the program is being implemented with fidelity, break the skill down into smaller components. If not, provide coaching and feedback to the implementer
Inadequate progress	The behavior has improved or is improving, but the slope of the intervention data suggests the learner will not meet criterion during the timeframe	Improve antecedents (e.g., use a less intrusive prompt)	Change prompts or add teaching sessions
Inconsistent progress	The behavior is variable (i.e., fluctuating) with no detectable slope, but overall the level is improved from baseline	Improve motivation (e.g., change the reinforcer)	Check treatment fidelity; if the program is being implemented with fidelity, change the reinforcer or increase the schedule of reinforcement. If not, provide coaching and feedback to the implementer

1. What is the effect of a training package consisting of an online training and decision-making model on accuracy of identifying data patterns by preservice educators and preservice behavior analysts?
2. What is the effect of a training package consisting of an online training and decision-making model on accuracy of instructional decisions by preservice educators and preservice behavior analysts?
3. To what extent do gains in accuracy maintain 1 month following the online training?
4. To what extent do participants find the goals, procedures and outcomes of the study to be socially significant and acceptable?

Method

Participants and Setting

Participants were recruited from a graduate-level course on ABA for preservice special educators and preservice behavior analysts at a large university in the southeast United States. We did not require participants to have previous experience teaching individuals with disabilities or analyzing graphs. We excluded individuals who demonstrated accurate decision-making skills on the baseline assessment, which we defined as at least three consecutive baseline assessments at or above 80% accuracy on questions related to instructional decisions. Two individuals began the study but met this criterion during baseline and thus their participation was terminated. If an individual demonstrated accurate identification of data patterns during baseline, but did not meet our exclusion criterion for accurate decision-making during baseline, they were eligible to continue participating as the primary goal of the study was to increase accuracy of instructional decisions.

Three individuals participated in the full duration of the study. Alister was a 30-year-old white male who worked as a Registered Behavior Technician (RBT). Tegan was a 23-year-old white female who worked as an employment specialist in a postsecondary college program for individuals with disabilities. Taneka was a 24-year-old Asian female who worked as a residential counselor. Alister and Taneka were pursuing Master's of Education degrees in ABA; Tegan was pursuing Master's of Arts in Teaching in Special Education. None of the participants reported previously receiving formal instruction on analyzing graphs or making data-based decisions. Alister reported previously receiving informal instruction in these areas.

Sessions took place two to three times per week for four to 10 weeks in an office on the university campus equipped with a desk, computer and two chairs. The first intervention session was approximately 1 h long (45–50 min to complete the online training and 10 min to complete the assessment). During all other baseline and intervention sessions, the participant only completed an assessment; thus, these sessions were approximately 10 min in duration.

Materials

We designed a decision-making model (Kipfmiller et al., 2019) based on the Browder et al. (2011) data-based decision guidelines (Fig. 1). We used the Browder et al. (2011) guidelines for two primary reasons. First, they are the only published, comprehensive guidelines for DBDM for non-academic outcomes. Second, there is a sizable body of research related to these guidelines (e.g., Browder et al., 1986; Jimenez et al., 2012), some of which suggests that the implementation of these guidelines

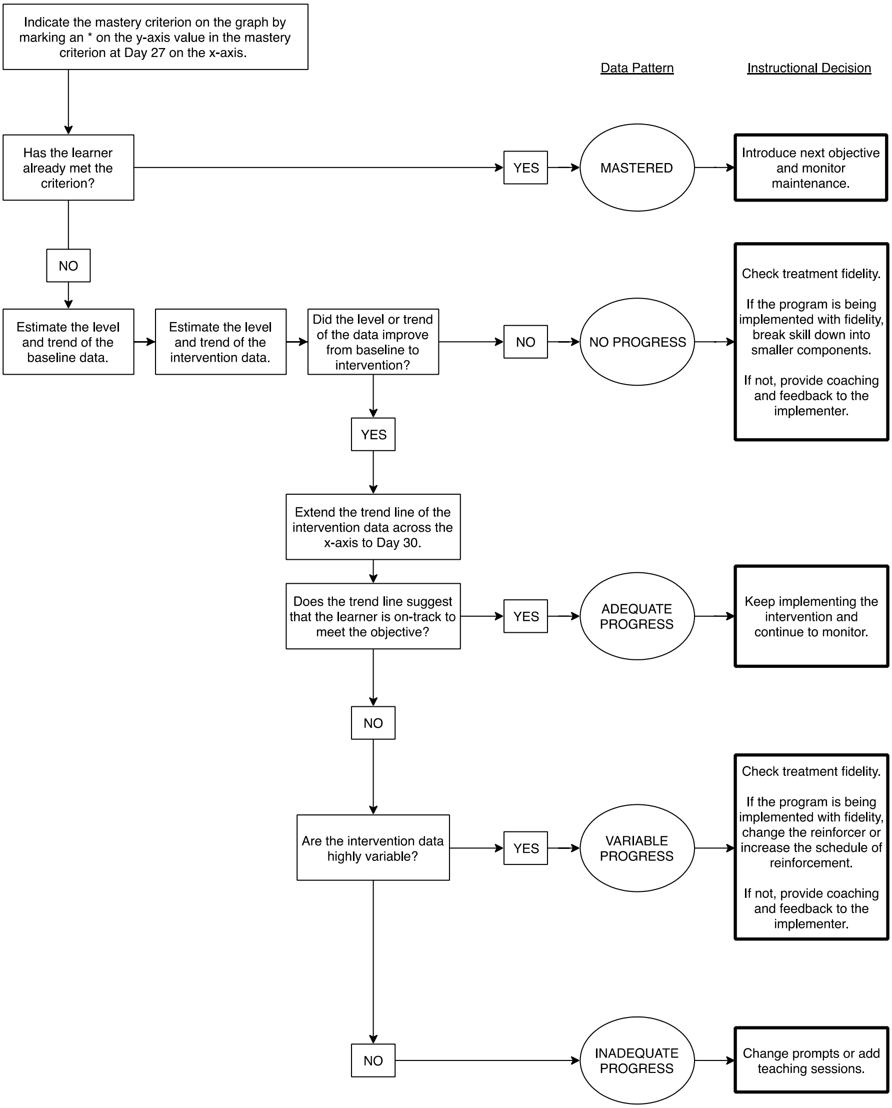

Fig. 1 Decision-making model

improves student outcomes (Browder et al., 2005). We did adapt the existing Browder et al. (2011) guidelines to acknowledge the potential role of treatment fidelity in DBDM. We added "check treatment fidelity" as an initial decision for "no progress" and "variable progress" data patterns, because these data patterns may be attributed to poor or inconsistent implementation of the treatment rather than deficiencies with the treatment itself. Participants had access to the decision-making model, which was printed on 8.5- by 11-in paper, for all intervention sessions.

We also created an interactive, online training on DBDM using Rise 360 (Articulate, 2019). All participants completed the training through the Blackboard Learning Management System on a Mac laptop connected to a display monitor.

Graph Generation and Selection

To contextualize the graphs in the study, we created 10 behavioral objectives that included functional and social outcomes. The objectives contained four elements: the individual, the behavior, the condition under which the behavior should be performed, and the mastery criterion. Five of the objectives referred to skills measured using frequency (e.g., "During independent work times, Sydney will raise her hand to gain attention from the teacher a minimum of six times per day for three consecutive days.") and five referred to skills measured using percentage (e.g., "During a game with two or more peers, Sara will indicate when it is her turn on at least 80% of opportunities for three consecutive days."). The mastery criterion varied across objectives (e.g., 80% of opportunities, at least six times per day), but the duration of required performance at the criterion was three days for all objectives.

We created graphs in Microsoft Excel using the autoregressive equation described by Wolfe and Slocum (2015). We generated graphs depicting each data pattern (i.e., no progress, inadequate progress, adequate progress, variable progress, and mastery) by manipulating the parameters of the autoregressive equation. Each graph contained five baseline data points and 10 intervention data points, with phase labels "baseline" and "treatment" and a phase change line separating the two phases. All *x*-axes were labeled "Days" and *y*-axes were labeled corresponding to the metric included in each objective (e.g., Percentage of Steps). Each graph contained 15 data points, but all *x*-axes included space for 30 data points so that participants could extend the trend line to predict future performance (see Fig. 2).

The first author generated 50 graphs for each objective, consisting of 10 graphs depicting each data pattern. This resulted in 500 initial graphs from which we selected graphs for the assessments. The second author, a doctoral student in special education holding the Board Certified Behavior Analyst (BCBA) credential, then independently evaluated each of the 500 graphs and selected the data pattern that best characterized the graph from five choices. The first author and second author agreed on 82% of graphs ($n = 410$). The graphs about which they disagreed were discarded. We repeated this procedure with two doctoral-level faculty members in special education and ABA who were also BCBAs (third and fourth authors); each evaluated half of the set (205 graphs per evaluator). Graphs that depicted mastery and adequate progress had high levels of interrater agreement among the authors,

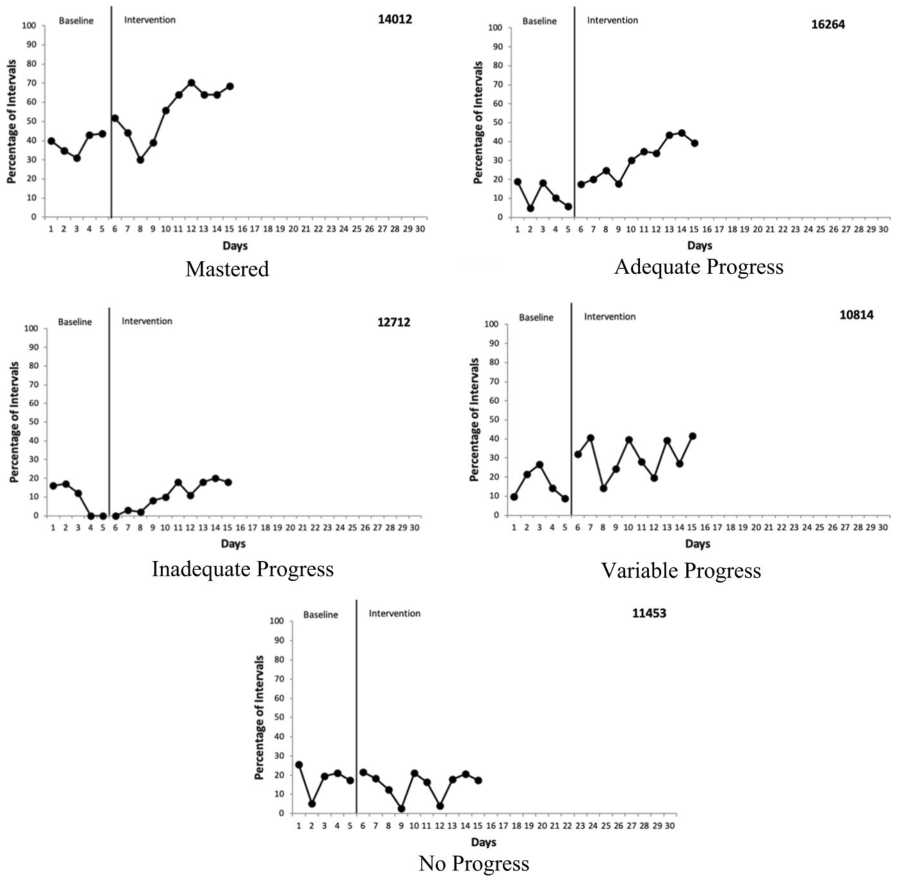

Fig. 2 Sample assessment graphs. Sample assessment graphs for Objective 1: During recess, Tasha will play on the equipment and/or verbally interact with peers during at least 60% of 2 min intervals for 3 consecutive days

whereas lower levels of interrater agreement were obtained for graphs that were intended to depict inadequate progress and variable progress. We only retained graphs with 100% agreement across three experts; the consensus response was used as the correct answer for measuring participant accuracy. This process resulted in 272 graphs across the 10 objectives and five data patterns.

Dependent Measures and Reliability

We had two dependent variables: (1) the percentage of correctly-identified data patterns and (2) the percentage of correctly-identified instructional decisions. In both cases, a correct response was defined as that which corresponded to the expert consensus produced from the previously described process for that particular graph. We measured these variables through participant responses on printed assessments.

Each assessment contained 10 graphs, each representing performance on one of our 10 objectives (described under "Graph Generation and Selection"). Of the 10 graphs, two graphs were included representing each of the five data patterns. The first author constructed each assessment by randomly assigning a data pattern to each objective, then randomly selecting one of the graphs with expert consensus that depicted that data pattern for that objective. After a graph was included in an assessment, it was removed from the pool. We produced 20 unique assessments so that participants analyzed novel graphs during each session.

We included definitions of the five data patterns on the first page of the assessment (see Table 1). Each subsequent page of the assessment consisted of an objective, a graph, and two questions pertaining to the data pattern and instructional decision. Participants answered each question by selecting one response option. The first question, "What is the data pattern?" was followed by the response options: (a) Mastery, (b) Adequate progress, (c) No progress, (d) Inadequate progress, and (e) Variable progress. The second question "What instructional decision would you make based on the data?" was followed by response options based on the adapted Browder et al. (2011) guidelines (Table 1): (a) Introduce next objective and monitor maintenance; (b) Make no changes; (c) Check treatment fidelity; if the program is being implemented with fidelity, break the skill down into smaller components. If not, provide coaching and feedback to the implementer; (d) Change prompts or add teaching sessions; and (e) Check treatment fidelity; if the program is being implemented with fidelity, change the reinforcer or increase the schedule of reinforcement. If not, provide coaching and feedback to the implementer.

All assessments were scored by entering the participants' responses into an Excel spreadsheet that automatically scored the response as correct or incorrect. We divided the number of correct responses by the total number of questions (i.e., 10) and multiplied by 100 to calculate percentage correct.

A secondary observer scored 30% of baseline and intervention assessments across all participants for the purposes of assessing reliability. We calculated point-by-point agreement by comparing the primary and secondary observers' data entry for each response in each assessment, dividing the number of agreements by the number of agreements plus disagreements, and multiplying by 100. Mean agreement for Tegan was 97% (range: 90–100%) in baseline and 97% (range: 95–100%) in intervention. Mean agreement for Alister was 100% in baseline and in intervention. Mean agreement for Taneka was 100% in both baseline and intervention. Overall agreement was 99% (range: 90–100%) in baseline and 99% (range: 95–100%) in intervention.

Experimental Design

We used a multiple baseline across participants design to evaluate the effects of the instructional package on accuracy of pattern identification and instructional decisions. The instructional package consisted of the decision-making model and a one-time, 45 min online training designed to teach participants how to apply the decision-making model.

Procedures

Baseline

During the baseline condition, participants completed one assessment per session. We told the participant to read the written instructions on the first page, which directed the participants to reference the definitions of data patterns, answer each question associated with the 10 graphs, and make one selection per question. Participants did not have access to the decision-making model, nor did they receive any training or feedback during baseline.

Intervention

Online Training

During the first session of the intervention condition, participants completed the 45 min, interactive, online training that we designed to teach participants how to use the decision-making model (see supplementary materials). The training was developed in Rise 360 (Articulate, 2019) and included didactic information about the importance of DBDM, the parts of a line graph, basic concepts in visual analysis (e.g., level, trend, and variability), and an overview of the decision-making model. The training also contained six brief video models (2–3 min each) demonstrating how to apply the decision-making model to each of the five data patterns (two video models were included for inadequate progress).

Throughout all sections of the training, we incorporated written and audio instruction as well as interactive response opportunities. Multiple-choice questions and matching questions (e.g., match the definition to the term) were included as knowledge checks and participants received immediate feedback about the accuracy of their response and an explanation of the correct response. We included other interactive response opportunities, such as labeled graphics (e.g., a line graph with numbers overlaying the features of the graph for the participant to click to see the name of the feature and a definition) and flashcards (e.g., a data path with the instruction to first estimate level, trend, or variability, then click on the data path to flip the "card" over to see the answer), that served to illustrate concepts in an interactive way, rather than to evaluate participants' acquisition of the content. The training was designed to require participants to respond to each interactive response opportunity, listen to the full duration of each audio clip, and view the full duration of each video model prior to making the next segment of the training available.

The online training concluded with a 10-question quiz in which participants applied the decision-making model to five novel graphs. The quiz consisted of two questions about each graph (What is the data pattern? and What instructional decision would you make?), with multiple-choice response options. Participants received immediate feedback about the accuracy of their responses, including an explanation of why the correct response was correct. The quiz was completed online; however, we gave participants a printed copy of the quiz so they could draw level or trend lines if they wished to do so. We did not require participants to obtain a specific score on the quiz to complete the training because we wanted to keep the training relatively brief; however, all participants responded correctly to at least 85% of quiz questions.

DBDM Model

After completing the training, participants completed an assessment using the decision-making model. Because we wanted to evaluate a streamlined and efficient training method that would not require trainer presence, there was no interaction with the researcher during the training (apart from the specific instruction described above), and the participant did not receive feedback on their accuracy.

On all subsequent intervention sessions, participants were given a copy of the decision-making model and an assessment. Participants did not access the online training after the first intervention session, and no additional instruction was provided. Participants remained in intervention until we detected a stable intervention effect via visual analysis of the level, trend, and variability of their performance.

Maintenance

One month after their final intervention session, participants completed an additional, novel assessment using the decision-making model to evaluate maintenance of accuracy over time.

Procedural Fidelity

We measured procedural fidelity for 30% of sessions in baseline and intervention phases. In baseline, a second observer measured whether the implementer provided the correct instruction, refrained from answering questions or giving feedback, and whether the primary observer delivered the correct assessment. During the first intervention session when the participant completed the training, a second observer measured whether the implementer: (1) provided the participant with a copy of the decision-making model and the quiz from the training, (2) logged the participant into Blackboard© to access the training, (3) provided a general instruction to complete the training, (4) recorded the start and end time for the completion of the training, (5) verified that the participant completed the training, and (6) ensured that the participant had a copy of the decision-making model prior to completing the assessment. Procedural fidelity for the remaining intervention sessions was identical to that in baseline, with the additional step of ensuring that the implementer gave the participant a copy of the decision-making model. Procedural fidelity was 100% across all sessions in all phases.

Social Validity

We created a questionnaire evaluating social validity of the goals, procedures, and outcomes of the study that included 11 items that participants rated on a scale from 1 (strongly disagree) to 5 (strongly agree) as well as one open-ended question. Participants were given a printed copy of the questionnaire and asked to answer questions related to the importance of analyzing graphed data and using it to inform instructional decisions. They were also asked questions related to the ease of use of both the online training and the decision-making model. Last, they were asked questions pertaining to whether the training package helped them analyze data and make instructional decisions, and whether they would continue to use the decision-making model in the future. Participants anonymously completed the questionnaire at the conclusion of the maintenance session and returned it in a sealed envelope to the third author who did not participate in sessions. All three participants completed and returned the questionnaire.

Results

Figure 3 shows the effects of the training package on correct identification of data patterns (left) and correct instructional decisions (right). Tegan and Alister accurately identified the data patterns in baseline an average of 70% and 73.5% of the time, respectively, with fairly low variability and no systematic trend. There is not a visually apparent change in level from baseline to intervention for accurate identification of data patterns for either of these participants, and both have a large amount of overlap between the two phases. Taneka accurately identified an average of 22.5% of data patterns in baseline, with a relatively stable performance below 40% correct in this phase. Following the online training, and with the use of the decision-making model, her accuracy in identifying data patterns immediately improved to 80% and remained relatively stable throughout the rest of the intervention phase. One month later, all three participants maintained accurate identification of data patterns using the decision-making model.

The right panel of Fig. 3 depicts the participants' accuracy on instructional decisions. Tegan's baseline data were low and relatively stable around a level of 30% correct. Her data demonstrate a clear and immediate level change from baseline to intervention, with correct responding fluctuating between 75 and 95% and a level around 80%. Alister's baseline data are variable, with a level around 50% and no clear trend, but one baseline session at 90%. Following the training and with the use of the decision-making model, his accuracy increased more consistently to an average of 83%. Though there is some overlap between Alister's baseline and intervention performance, his accuracy during the intervention phase is stable with all data points at or above 75% correct. Taneka's baseline data have a slight increasing trend, and the level of her final five data points in baseline was around 45%. However, her data also demonstrate a clear and immediate level change when the intervention was introduced, with a level around 80%. One

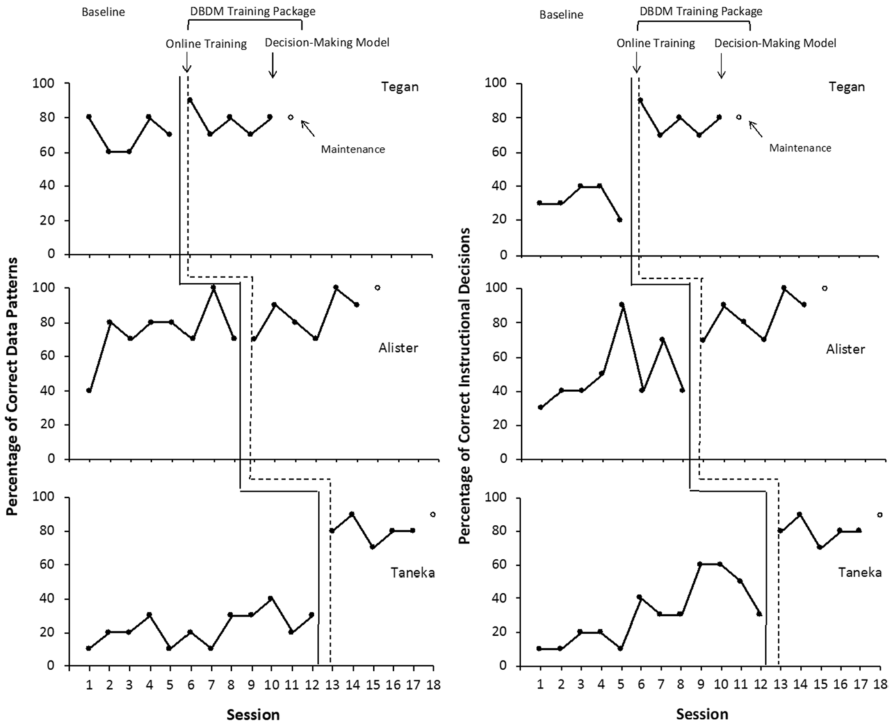

Fig. 3 Participant accuracy in identifying data patterns (Left) and in making instructional decisions (Right). Open circles represent performance on the maintenance check, which occurred 1 month following the last intervention session

month after the last intervention session, all participants identified the instructional decision at least as accurately as they had during the intervention phase.

We also analyzed the accuracy of participant responses by data pattern (Table 2). It should be noted that percentages reflect accuracy across the entire phase because each session only included two examples of each data pattern. Although accuracy increased from baseline to intervention for both pattern identification and instructional decisions for all participants on most data patterns, each participants' accuracy *decreased* from baseline to intervention for one data pattern. Specifically, Tegan and Alister demonstrated decreased accuracy on identifying a data pattern (inadequate progress and variable progress, respectively). Taneka's accuracy in making instructional decisions about graphs that depicted no progress decreased from baseline to intervention.

At the conclusion of the study, we measured participants' perceptions of the importance of DBDM, acceptability of the procedures, and significance of outcomes (see Table 3). The mean for questions related to the significance of the intervention goals was 5; the mean for questions related to the feasibility of the procedures was 4.84; and the mean for the importance of the outcomes was 4.78. Two participants provided additional comments, with both indicating the training

Table 2 Accuracy on data pattern identification and instructional decision by data pattern

Data pattern	Tegan (%)		Alister (%)		Taneka (%)	
	BL ($n=10$)	INT ($n=10$)	BL ($n=16$)	INT ($n=12$)	BL ($n=24$)	INT ($n=12$)
Data pattern identification						
Adequate progress	70	100	81	100	46	100
No progress	20	70	94	100	13	30
Inadequate progress	90	30	38	67	8	100
Variable progress	80	90	88	67	8	100
Mastered	90	100	69	83	33	70
Instructional decision						
Adequate progress	60	100	81	100	33	100
No progress	30	70	38	100	50	30
Inadequate progress	20	30	6	67	0	100
Variable progress	30	90	56	67	17	100
Mastered	100	100	69	83	54	70

BL baseline, *INT* intervention

Table 3 Results of the social validity questionnaire

Statement	Mean	Range
It is important for teachers and clinicians to know how to analyze student/client data	5	5
It is important for teachers and clinicians to know how to use student/client data to make decisions about their instruction	5	5
The online training was easy to navigate	5	5
The online training helped me learn how to analyze student/client data	5	5
The online training helped me learn how to use the decision-making model to analyze student/client data	5	5
The decision-making model helped me analyze student/client data	4.67	4–5
The decision-making model helped me make instructional decisions based on the data	4.67	4–5
The decision-making model was easy to navigate	4.67	4–5
In the future, I would use the decision-making model to make instructional decisions for my students/clients	4.67	4–5
The decision-making model increased my confidence in analyzing the data	5	5
The decision-making model increased my confidence in making instructional decisions	4.67	4–5

was helpful and one suggesting that we include instructions for drawing trendlines on the decision-making model and clarify what is meant by "highly variable" in the training.

Discussion

We conducted this study to extend previous research on training preservice practitioners to apply DBDM to measures of functional, social, or challenging behavior. Specifically, we built upon guidelines previously investigated by Jimenez et al. (2012, 2016; model developed by Browder et al., 2011), and upon the decision-making model developed by Kipfmiller et al. (2019). We developed a training package consisting of a 45 min online training that incorporated elements of BST (i.e., descriptions, modeling, rehearsal, and feedback) and the adapted decision-making model. Three preservice practitioners completed the training and applied the model to researcher-generated graphs during subsequent sessions. We visually analyzed data within a multiple baseline across participants design and concluded there was a functional relation between the DBDM training package and accurate instructional decisions; however, there was not a functional relation between the DBDM training package and accurate data pattern identification.

The present study extends previous research on training DBDM in a number of ways. Our decision-making model (Fig. 1) guided participants through more complex decisions than previous studies, including five possible data patterns and five corresponding instructional decisions. Additionally, our assessment included a larger number of contextualized graphs than previous research (e.g., multiple instructional domains, multiple measurement systems, and objectives with varying mastery criteria). We used an experimental single-case design and found that, following intervention, there was an immediate change in participants' accuracy of making instructional decisions despite the complexity of required decisions. Furthermore, we ruled out treatment diffusion as a threat to internal validity by maintaining 100% procedural fidelity across observed sessions.

We hypothesize that two primary features of our DBDM training package resulted in participants' increased instructional decision-making scores. First, the online training included components of BST, a training method that has been validated across the broader literature on training ABA practitioners (Parsons et al., 2012) and was included in previous DBDM research (Maffei-Almodovar et al., 2017). Second, the decision-making model included step-by-step instructions for visual analysis of the graphed data and then directed users to the corresponding data pattern and instructional decisions (Kipfmiller et al., 2019). Thus, the decision-making model likely functioned as a task analysis that supported individuals in making accurate instructional decisions. Our results replicate the findings of Kipfmiller et al. (2019), who demonstrated that a flowchart improved front-line employees' accuracy of basic data-based decisions (e.g., terminate program, modify program). We also extended that work by demonstrating that a brief training and decision-making model can increase accuracy in making more specific decisions (e.g., change prompts, increase schedule of reinforcement) that are appropriate for practitioners who supervise RBTs and other direct support professionals (e.g., special education teachers and BCBAs).

We did not conduct a component analysis of our intervention package, and thus cannot draw conclusions about the separate effects of the online training and decision-making model. Previous research suggests that a decision-making model alone can increase accuracy of data-based decisions for some participants (Kipfmiller et al., 2019). However, the Kipfmiller et al. (2019) study included one-phase graphs (i.e., treatment only) and a universal mastery criterion. Thus, we hypothesized that some training would be necessary for participants to effectively use our decision-making model given the complexity of the graphs, decisions, and model in the current study. Future research could investigate the conditions under which the online training or decision-making model are necessary or sufficient to produce accurate decision-making. For example, the decision-making model alone may be sufficient for an individual with previous experience in visual analysis, but not for an individual without that history. In addition, future research could evaluate whether the elements of the intervention package have differential effects on decision-making at different points in time. For example, the online training may produce immediate changes in decision-making; conversely, the model may be responsible for more long-term effects.

Unlike previous studies on DBDM, we measured participants' accuracy on two dependent variables: data pattern identification and instructional decision. During baseline, two participants (Tegan and Alister) consistently performed better on questions related to data pattern identification than on questions related to instructional decision, which may be attributed to our provision of definitions of the data patterns or to an instructional history related to analyzing line graphs. We chose to retain them in the study given their low and variable accuracy in making instructional decisions during baseline, and they both demonstrated visually apparent improvements in instructional decisions during the intervention phase. However, their high accuracy on pattern identification in baseline precluded us from demonstrating a functional relation for this dependent variable. Future research may consider including more participants with response patterns similar to Taneka, who demonstrated low baseline performance on both aspects of DBDM (pattern identification and instructional decision), to allow for a full evaluation of experimental control related to DBDM.

It is somewhat interesting to note the similarity between all participants' accuracy on questions related to data pattern identification and instructional decisions in the intervention phase. In all intervention sessions, participants' accuracy on data pattern identification questions and instructional decision questions was identical. In other words, when participants incorrectly identified the data pattern for a given graph, they also incorrectly identified the instructional decision. This is perhaps unsurprising because we trained participants to identify the data pattern and then select the corresponding instructional decision for that data pattern; the decision-making model moves directly from a data pattern to a decision. This finding suggests that, in our model, decision errors need to be remediated at the level of pattern identification. In other words, within our model, accurate identification of data patterns is a prerequisite to accurate instructional decisions; thus, we hypothesize that more stable responding may be achieved by fine-tuning the visual analysis training.

In addition to our primary findings, we measured maintenance of decision-making accuracy 1 month post-intervention. Maintenance data indicate that participants' accuracy levels remained at or above intervention levels across both dependent measures. While these results should be interpreted with caution given that we only collected one maintenance probe, and only 1 month following the intervention, these results are promising given that previous studies on training DBDM have not evaluated maintenance following training. It is important to note that participants may have accessed content related to visual analysis or instructional decisions during the break between intervention and maintenance assessments; however, we ensured that they did not have access to either component of our training package during that time.

Finally, we measured the social significance of our goals, procedures, and results with post-intervention surveys. All three participants responded favorably (ratings of "agree" or "strongly agree") to all social validity items. These results suggest that, overall, the participants perceived that the components of this study were socially significant. Readers should note that this finding may be limited to preservice practitioners. Because we designed our training package with feasibility in mind, we hypothesize that in-service practitioners could complete a relatively brief online training (45 min) and use a one-page visual support such as ours when making instructional decisions in applied settings. Nonetheless, validation of this hypothesis is an important next step in this research line.

Limitations

There are limitations to our findings that should be acknowledged. First, we recognize that DBDM is a complex and multi-faceted process that is often informed by contextual variables that are not captured in a graph or by our decision-making model. For example, a skilled practitioner is likely to also consider factors such as learner characteristics, difficulty of the skill, and anecdotal data related to learner performance when making an instructional decision—and to engage in DBDM on an ongoing basis. The intervention package we developed and evaluated in this study is an initial attempt at a systematic method for training preservice or novice practitioners to make sound data-based instructional decisions—not to supplant a skilled practitioners' consideration of other relevant factors. Given the importance and complexity of DBDM, we hope that our preliminary work serves as a foundation for additional research in this area.

Second, two individuals who were initially eligible for participation met our exclusion criterion for accurate decisions during baseline assessments, and one participant's (Alister) data were highly variable during baseline. We attempted to control for a potential testing threat by including different graphs in each session; nonetheless, these data patterns suggest that a testing threat may have been present for those individuals. In other words, repeatedly completing the assessment may have inadvertently resulted in some participants learning the correct answers. While some DBDM group design research indicates that testing may not be a threat with only two administrations of the test (Brodhead & Truckenmiller, 2021), it is possible that the continuous measurement used in our single-case design study produced a testing threat. Future research may use the multiple probe design to remedy this concern.

Third, we provided definitions of the data patterns on the front of the assessment, and it is possible that the definitions of data patterns were sufficient for Tegan and Alister to correctly identify many of the data patterns in baseline. In contrast, Tane-ka's baseline data suggest that the definitions alone did not evoke her accurate identification of the data patterns. We elected to provide definitions of the data patterns to control for the possibility of low accuracy being a result of different interpretations of potentially subjective terms like "adequate" and "inadequate." We view the inclusion of those definitions as providing a more rigorous evaluation of the effects of our training package on data pattern identification. Nonetheless, future studies may parse this out and evaluate baseline performance prior to exposing participants to written definitions of data patterns.

Third, we acknowledge that our assessment conditions were contrived, despite their improvement upon previous research. We used fictitious data, and an important next step would be to evaluate generalization of DBDM skills to real data collected within applied settings. Also, participants responded by answering multiple-choice questions with fairly broad instructional implications. For example, if the data pattern indicated variable progress, the corresponding instructional decision was to: (1) check fidelity and (2) if fidelity was high, change the reinforcer or schedule of reinforcement. Our assessment data indicate that participants could correctly select this decision; however, requiring participants to apply the decision was outside the scope of this study. Thus, for this example, we cannot say whether participants would be able to accurately collect fidelity data, select an effective reinforcer, or design a schedule of reinforcement.

Implications for Future Research

We recommend three primary and related avenues for future research on training practitioners to implement DBDM. First, our results indicate that certain data patterns—namely, inadequate progress and variable progress—may be difficult to discriminate. These graphs produced more disagreements among our experts and more errors by the participants. Future studies on DBDM may focus on developing trainings that target these more difficult discriminations.

Second, we recommend that future research focus on developing trainings and models that specifically target the moreinvestigations focus on development of an ecologically valid assessment that more closely approximates DBDM in the real world. Such an assessment might include scenarios that describe the learner, intervention, and context in more detail, and open-ended responses that require participants to generate even more specific decisions (e.g., increasing or decreasing a prompt level).

Second, DBDM researchers must work to establish the validity of the instructional decisions included in decision-making models. We adapted the instructional decisions in our model from the guidelines described by Browder et al. (2011). Although there is some evidence that student progress improves when teachers use these specific guidelines (Belfiore & Browder, 1992), more current research is needed to support a direct link between specific decisions and improvements in outcomes. As previously discussed, DBDM is a complex skill that requires a practitioner to consider myriad factors, and a comprehensive decision-making framework will need to incorporate other contextual variables. Ultimately, the goal of DBDM is to improve learner outcomes, and validation of instructional decisions is integral to support the long-term significance of this research.

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Ethical Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. The University of South Carolina Institutional Review Board approved the procedures in this study.

Informed Consent Informed consent was obtained from all individual participants included in the study.

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