INVESTIGATING THE EFFICACY OF AN INTERACTIVE COMPUTER-BASED TRAINING PACKAGE AND DECISION-MAKING MODEL ON THE ACCURATE IDENTIFICATION OF DATA-BASED INSTRUCTIONAL DECISIONS BY APPLIED BEHAVIOR ANALYSIS GRADUATE STUDENTS

by

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(Under the Direction of Kevin Ayres)

ABSTRACT

Board-certified behavior analysts (BCBAs) are entrusted with employing data-based decision-making (DBDM), a best-practice and proven approach that fosters client progress. Previous research implications have found low interrater agreement on visual analysis of single case design graphs, conducted by BCBAs. Inaccurate visual analysis results in erroneous clinical decisions, thus limiting client progress. This study aimed to expand on the foundational work of Wolfe et al. (2023), through employing an interactive computer-based training and decision-making model (DMM) to increase pre-service BCBAs accuracy in identifying instructional decisions. The implications of this study suggest the intervention was effective, across all participants. Moreover, in the absence of the DMM during the 1-month post intervention participants maintained high levels of accuracy in identifying instructional decisions. Limitations found in conducting this study and future research considerations are described.

INDEX WORDS: Data-based decision-making, Data-based decision-making training, Pre-service behavior analyst training, Visual analysis training, Progress monitoring training, Applied behavior analysis graduate student training.

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DEDICATION

I dedicate this to my boys, Nathaniel and Benjamin. Nathaniel, thank you for teaching me how to slow down, live in the moment, and appreciate the little things. Benjamin, your curiosity and creativity inspire me to try new things. You two give me purpose and drive me to become a better person, every day. I am so grateful to be your mom and would not have it any other way. To my husband Chris, thank you for always supporting my endeavors, thank you for being the best partner I could hope for in life, and for being the amazing father you are to the boys. You are invaluable to me. I love you. Mama, I appreciate the support you readily provide for the boys. Thank you for being flexible and willing to help us, always. This was possible because of you. We love you and appreciate all you do for us. I would also like to dedicate this to all the parents and caregivers of individuals with disabilities. Don't give up hope and allow external influences to dictate your loved ones' trajectory. Take control, do your research, be persistent, and keep advocating for your loved one and those that aren't able to do so for themselves. Know your loved one appreciates you and all your efforts, even if they aren't yet able to communicate it to you yet. Also, know it is not selfish to seek respite, when you need it. Lastly, don't forget to be kind to yourself.

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CHAPTER 1

INTRODUCTION

Visual analysis entails a systematic process of evaluating graphed data to detect data patterns and characteristics, informing behavior analysts on making implications on the efficacy of behavioral interventions. Visual analysis allows for formative assessments and progress monitoring, which allows interventionists to be responsive, proactively involved in their learner's progress and for the manipulation of the intervention to provide the most significant result for the individuals receiving them. The process of formatively graphing and conducting visual analysis are critical components of conducting data-based decision-making (DBDM) (Ledford & Gast, 2018). DBDM is a gold-standard approach employed by scientist-practitioners (Barlow et al., 1984; Ledford & Gast, 2018), such as behavior analysts, where such professionals can make data-informed decisions concerning the effect of interventions through the comprehensive practice of visual analysis, with the intent to promote a targeted effect. DBDM can be used to intervene on a variety of behaviors, to include those that require instructional interventions. Instructional DBDM can be employed by professionals working with clients on instructional goals or skill acquisition. DBDM lends itself as a perceptive approach behavior analysts may employ to ultimately foster the enhancement of client progress.

Board-certified behavior analysts (BCBAs) commonly provide services to learners in a variety of contexts, including clinical and educational contexts. Irrespective of the context, BCBAs are mandated to provide ethical treatment approaches in accordance with the Behavior Analyst Certification Board (BACB) ethics code. The BACB requires the practice of DBDM. The BACB ethics code 2.17 requires that BCBAs collect client data, graphically display the data collected, summarize data through the process of visual analysis, and use the data to make decisions on the effectiveness of the intervention (Behavior Analyst Certification, 2020). DBDM allows BCBAs to make objective decisions in the best interest of clients, through informing decisions based on inarguable data, and not on subjective reasoning. When serving clients in educational contexts, BCBAs are not only obligated to abide by the BACBs ethics code, they are additionally mandated to comply with nationally enforced education laws, such as the Individuals with Disabilities Education Improvement Act (IDEIA, 2004) and the No Child Left Behind Act (NCLB, 2002). These education laws require that school-based interventions for students be based on evidence-based practices (EBP). Both the IDEIA act (IDEIA, 2004) and the NCLB act (NCLB, 2002) place an emphasis on data-driven decision-making within educational contexts including multidisciplinary professionals collaborating to work towards an objective for students. Furthermore, In recent years there has been a widespread effort across the United States adopting the multi-tiered system of supports (MTSS), which encompasses response to intervention (RTI). RTI is a data-driven approach to identify students that require intervention early on, providing a system to conduct progress monitoring, and inform if interventions require modifications, through DBDM (Al Otaiba et al., 2019).

Ninci et al. (2015) analyzed 19 studies where professionals including BCBAs were asked to conduct visual analysis on SCD graphs. A mean proportion agreement of .76 was found across the studies analyzed. One of the studies evaluated by Ninci et al. (2015) was the Lieberman et al. (2011) study, which assessed 36 experts' ability to conduct visual analysis to infer on the presence of a functional relation on 16 multiple baseline design graphs. The participants were review board members of the *Journal of Behavioral Education*, the *Education and Treatment of Children*, and the *Journal of Applied Behavior Analysis*, which publishes SCD research data. The mean proportion agreement in the inference of the presence of a functional relation, across the experts was .40. Inaccurate inference on the efficacy of an intervention or on the presence of a functional relation is concerning, as it may result in misinformed data interpretation (Hojnoski et al., 2009. Considering the levels of disagreement in conducting visual analysis across experts, it is relevant to equip preservice BCBAs with the appropriate training to ensure they are competent in their abilities to conduct visual analysis, thus in accurately conducting DBDM. It is imperative that BCBAs accurately conduct DBDM, as inaccurate DBDM may result in BCBAs making erroneous instructional decisions that do not align with student data (e.g., Demchak & Sutter, 2019). It is important to note that the better performing groups evaluated in Ninci et al., (2015) were those that were provided with a visual aid to supplement respondent decision-making.

Through a comparison study O'Grady et al. (2020) evaluated how efficient and effective various forms of instruction are in teaching visual analysis of AB graphs to university students including: (a) didactic instruction with the opportunity to pause, (b) didactic instruction without the opportunity to pause, (c) computer-based training, and a (d) no training group (i.e., control group). Moreover, the training prepared students to determine if an overall change has occurred between baseline and treatment, as it relates to trend, variability, and level. The implications of O'Grady et al. (2020), resulted in no statistical differences across groups, supporting that computer-based training can be just as effective as didactic instruction in teaching university students with no prior experience how to conduct visual analysis.

McCammon et al. (2024) conducted a comparison study to train university students how to conduct DBIDM. The two groups compared were a group provided with a DMM alone and no supplemental training and a group provided with supplemental online training along with a DMM. The implications of the study were that both conditions were just as effective in increasing accurate instructional decisions made by preservice teachers, suggesting that the DMM alone can be an effective intervention for professionals to reference to conduct accurate DBIDM, however that identification of specific data patterns would benefit from the supplemental online training (McCammon et al. 2024).

The DBDM guidelines originally developed by Haring et al. (1980), were adapted by Browder et al. (1986) which was developed to provide specific directions to educators of students with extensive support needs, such as individuals with ASD. The guidelines cater towards programs that are task analysis-based or trial-based (Wolfe et al., 2023). This approach has resulted in an increase in the efficiency and effectiveness of teachers' implementation of DBIDM and more importantly has resulted in increased student progress (McCammon et al., 2024; Browder et al., 2005). Although there is a body of research where researchers have employed decision-making models that prompt educators to modify treatment, they do not specify how the educator should modify treatment (e.g. check procedural fidelity, if treatment is being implemented as intended, change the reinforcer). Although there is an existing body of research on training practitioners on how to conduct visual analysis, there are few that teach practitioners how to analyze graphs and make instructional decisions (Wolfe et al., 2023; Kipfmiller et al., 2019; Mafei-Almodovar et al., 2017). Moreover, the existing body of research that instructs preservice professionals on how to conduct DBDM primarily works with preservice educators and limited research addresses preservice BCBAs professional development in conducting DBDM. Although BCBAs receive training on conducting visual analysis through their university programs, exploring alternative methods of instruction on DBDM that lend themselves to be effective and feasible is relevant. Moreover, it is significant that preservice BCBAs are provided with the tools to feel confident in their abilities to implement specific instructional decisions for their future clients.

Wolfe et al. (2023) aimed to evaluate the effects of a training package, consisting of an interactive computer-based online training and data-based instructional DMM, based on the guidelines prescribed by Browder et al. (2011), which outlines specific instructional decisions that should be made for students living with disabilities such as ASD. Although there was no visually apparent change in the levels of data pattern identification, the DBDM training was effective in increasing the primary targeted behavior (i.e. accurate instructional decision identification) across the participants. The participants were all graduate-level students which included preservice special education teachers and preservice BCBAs. While there was a functional relation between the intervention package developed by Wolfe et al. (2023) and the primary dependent variable of identifying accurate instructional decisions, some of the self-reported limitations included: (1) the multiple baseline design characteristic of continuous measurement potentially led to participants learning the answers through the repeated exposure (i.e. through the continuous measurement, a characteristic specific to multiple baseline designs), (2) generalization measures including real learner data were not included, and (3) there was greater disagreement among experts with inadequate progress and variable progress graphs.

The current study attempted to address these limitations by: (1) employing a multiple probe design to combat the potential testing threat, (2) conducting generalization probes using real learner data from the students that the participants' case managed in their practicum setting, and (3) by attempting to generate inadequate and variable progress graphs that are more distinguishable – in accordance to the DMM and definition table (Wolfe et al., 2023; Browder et al., 2011).

Purpose Statement

The purpose of this study is to contribute to the limited research addressing effective and feasible approaches for pre-service professional development relating to data-based instructional decision-making. More specifically, this study aims to test the efficacy of a practical and feasible training package consisting of an interactive online training and DMM, on increasing the accuracy in identification of instructional decisions by pre-service BCBAs (i.e. applied behavior analysis graduate students). This study is an attempt to build upon the foundational work of Wolfe et al. (2023). Through employing the same intervention developed by Wolfe et al. (2023). This study aims to answer the following research questions:

Research Question 1: What are the effects of the DBDM training package consisting of a DMM and the DBDM interactive computer-based training on the accurate identification of data patterns and data-based instructional decisions for first-year ABA graduate students?

Research Question 2: Do the gains in data pattern identification and instructional decisions maintain and generalize to contextualized student data in the absence of DMM and materials at 1- month post-intervention?

Research Question 3: How acceptable and socially significant do the participants find the intervention and its outcomes?

Research Question 4: How acceptable and socially significant do the experts find the DMM and the competency of conducting data-based decision-making?

CHAPTER 2

METHOD

Participants

The opportunity to participate in this study was extended to first year applied behavior analysis (ABA) graduate students from a southeastern university by email. Participation incentives were not offered, except for the possibility of increasing their competency in visual analysis and instructional decision-making. Seven participants expressed interest in the opportunity, consenting to participate, and ultimately four remained for the entirety of the study based on the inclusion criteria. To be considered for inclusion in this study, participants were expected to be first-year ABA graduate students, having no involvement in concurrent studies that may contribute to possible attrition - due to scheduling conflicts, moreover participants would be excluded upon scoring seventy percent in accuracy in the primary dependent variable (i.e. identification of instructional decision, based on data pattern depicted in AB graphs) for three consecutive sessions during baseline would be excluded. The three participants that were excluded had already consented and were actively participating in another study.

All the participants were enrolled in a practicum course where they were active case managers for preschool students with intellectual disabilities. The participants were responsible for updating instructional materials as required, based on student performance. The case managers were not instructed on how to conduct data-based instructional decision-making prior to intervention, however the participants had completed an introductory course to ABA, where they were introduced to fundamental visual analysis characteristics and concepts (e.g., within-phase characteristics of trend, level, variability) prior to this study. The participants (see Table 1) were teachers in their practicum placement, which was a southeastern university-based clinical preschool setting. The participants all had experience working with neuroatypical children, including clients diagnosed with autism spectrum disorder (ASD) - even prior to starting their ABA programed practicum course.

A questionnaire was disseminated to participants to collect experience and demographic information pertaining to the participants, The questionnaire included multiple choice questions, with other or write-in options – to allow for open responding, and a “prefer not to say” option. The information gathered included: (1) age, (2) gender identity (i.e. woman, man, non-binary, agender, prefer not to say, genderqueer or genderfluid, muxe, two-spirit, and other), (3) diagnosis, (4) degrees and certifications, (5) RBT and BCaBA certification status and years certified, (6) experience in teaching (i.e. what contexts they worked in, description of learners worked with, clinical experience, or ABA related experience).

Antoinette was a twenty-two-year-old White and Asian American woman who held a Bachelor of Science (B.S.) in psychology with a minor in biology. Antoinette was a registered behavior technician (RBT), having held her certification for three years prior to the start of this study. Antoinette was employed based out of a behavioral therapy clinic, serving children with intellectual disabilities in classroom, home, and clinical settings. Genevieve was a twenty-three-year-old Asian American woman who held an Associate of Science (A.S.) and a B.S. in psychology. Genevieve previously worked at a special needs school, as a child development specialist for toddlers with special needs for the duration of a year. Sebastian was a twenty-one-year-old Black man with a B.S. in psychology and a B.S. in human services. Sebastian had been certified as an RBT for one year, working based out of a behavioral therapy clinic that primarily had children diagnosed with ASD as clients. Josephine was a twenty-two-year-old White woman holding a B.S. in psychology, also certified as a RBT for two and a half years. Josephine worked primarily with children diagnosed with ASD, based out of a behavioral therapy clinic, within the clinic, home, and school settings.

Table 1 Participants' Demographics and Experience

Participant	**Antoinette**	**Genevieve**	**Sebastian**	**Josephine**
Age	22	22	21	22
Gender Identity (Pronouns)	Woman (She, her, hers, herself)	Woman (She, her, hers, herself)	Man (He, him, his, himself)	Woman (She, her, hers, herself)
Race/Ethnicity Identity	White or European and Asian or Asian American	Asian or Asian American	Black or African American	White or European
Education Background	B.S. psychology with a minor in biology	A.S. and B.S. psychology	B.S. psychology and human services	B.S. psychology
RBT Yes or No (years certified)	Yes (3)	No	Yes (1)	Yes (2.5)
BCaBA Yes or No (years certified)	No	No	No	No
Experienced Contexts	School, home, clinic	School	School, home, clinic	School, home, clinic
Last profession title held	RBT	Child development specialist	RBT	RBT

Setting

Sessions were conducted in university-based classrooms, containing tables, chairs, a podium and smart board. Sessions were held three to four times per week, contingent on the participants' availability. Participants were allotted twenty minutes (i.e. one minute per question) to complete assessments, irrespective of the condition, and one hour to complete the interactive training. The participants took an average of five minutes to complete assessments and thirty minutes to complete the training.

Materials

A university-based e-learning center platform was employed to compose the assessments that were used to evaluate the participants' competency in the dependent variables (i.e. identification of data pattern and instructional decision), in collecting agreement data from expert reviewers, also being referenced in the collection of reliability data through the auto-grading feature. Each assessment was composed of twenty questions (i.e. two opportunities to respond to the five possible data patterns and instructional decisions), two per graph (i.e. "Identify the data pattern in phase II (intervention)." and "Based on the data pattern in phase II (intervention), what instructional decision should be made?"). Every question included a behavioral objective that was measured by percentage (i.e. skills requiring multiple steps or task analysis). The ten SCD AB graphs used in generated using an Excel™ spreadsheet formulated with a modified version of the first-order autoregressive model employed in Fisher et al. (2003), as employed in Wolfe and Slocum (2015), Kipfmiller et al. (2019), and in Wolfe et al. (2023). Using the autoregressive equation, the parameters were manipulated to generate graphs depicting five possible data patterns including: mastered, no progress, adequate progress, variable progress, and inadequate progress (see Fig. 2). Each graph included five baseline data points, ten intervention data points, general phase labels (i.e., baseline and treatment), a phase change line between conditions, and with the x-axis extending to thirty days following interventions (i.e. thirty days was the targeted timeline to meet mastery criterion), allowing participants to visualize a trend line.

Three experts, board-certified behavior analysts with at least one year of fieldwork experience, were recruited by email to ensure the graphs developed using the autoregressive model were externally valid (i.e. if the data depicted were likely to be encountered by professionals) and to collect agreement on the accurate data pattern and the instructional decision that corresponded to the identified data pattern as prescribed in the DMM provided to them (see Fig. 1). Only graphs in which 100% agreement was obtained across two experts were retained for assessments, additionally graphs that experts identified to be not externally valid (i.e. unrealistic) were excluded. AB graphs were generated using the formulated spreadsheet and agreed upon, to compose 21 assessments (see Fig. 2). Each assessment provided participants with two opportunities to respond for every data pattern and instructional decision (e.g. two opportunities to identify the data pattern and instructional decision for “mastered”, etc.).

Similar to the agreement findings in Wolfe et al. (2023), lower levels of interrater agreement were found among experts were inadequate progress and variable progress graphs. A questionnaire was disseminated to expert reviewers following their participation as expert reviewers, providing a measure of social validity on the dependent and independent variable, also providing demographical information, pronoun preference and insight on how prepared they felt by their educational experience in the implementation of DBDM.

Table 2 Expert reviewers' Demographics and Experience

Expert Reviewer	**Noel**	**Ingrid**	**Amy**
Age	26	31	25
Gender Identity (Pronouns)	Man (He, him, his, himself)	Woman (She, her, hers, herself)	Woman (She, her, hers, herself)
Race/Ethnicity Identity	White or European	White or European	White or European
Education Background	B.S.Ed. Special education, B.A. Spanish language and culture, and M.Ed. Special education	B.S. Family and consumer sciences, M.A. Teaching (birth to kindergarten)	B.S.Ed. Special education, minor in Spanish, M.Ed. Special education
Years certified as a BCBA	2 years	5 years	1 year and 6 months
Diagnosis (Age diagnosed)	ASD (24) and ADHD (12)	n/a	n/a
Experienced Contexts	Clinical and school	Clinical and school	Clinical and school
Last profession title held	University-based Clinic BCBA and doctoral candidate	University-based Clinic BCBA	University-based Clinic BCBA and doctoral candidate
Experienced in DBDM	Yes	Yes	Yes

Fig. 1 Decision-making model (Wolfe et al., 2023; Browder et al., 2011)

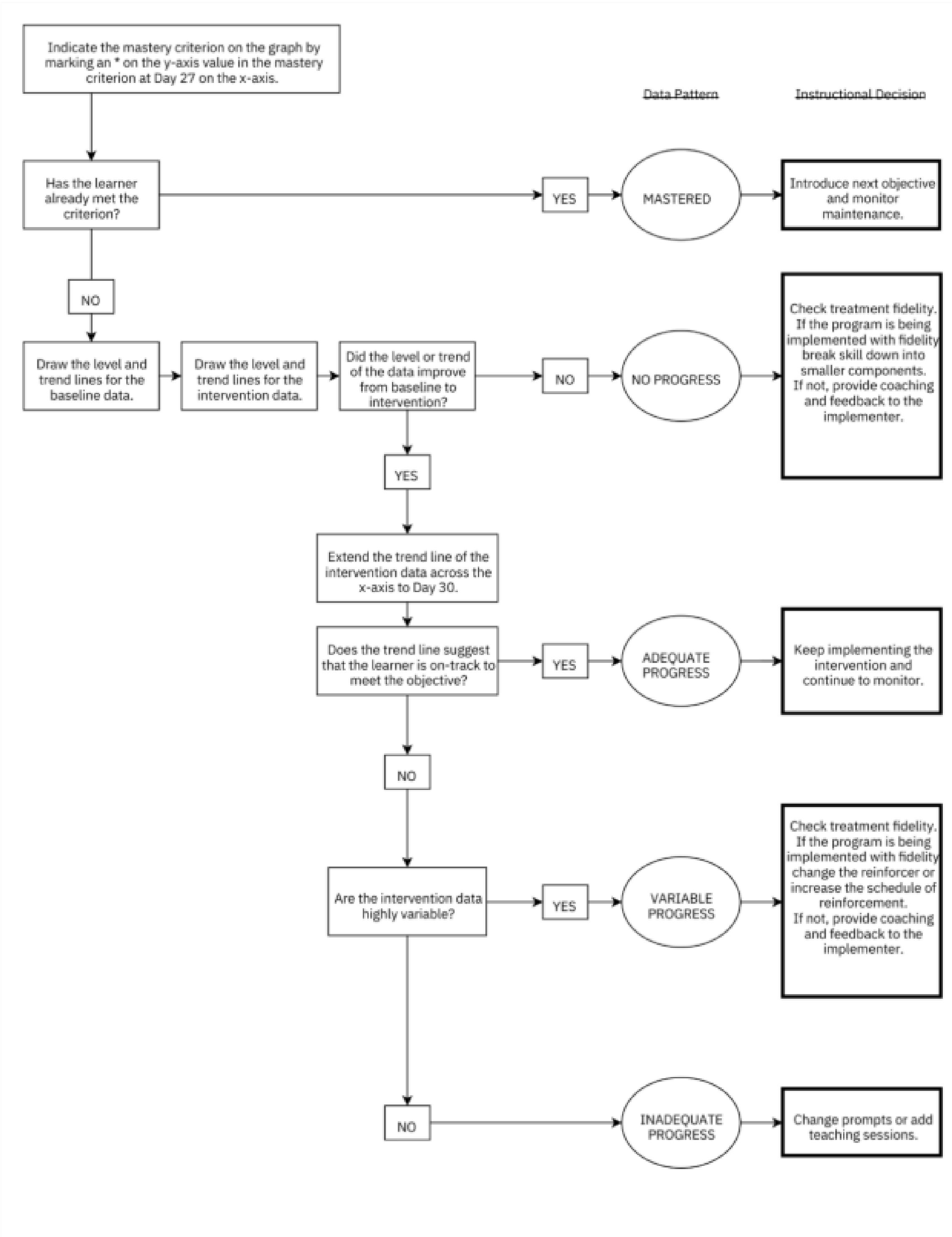
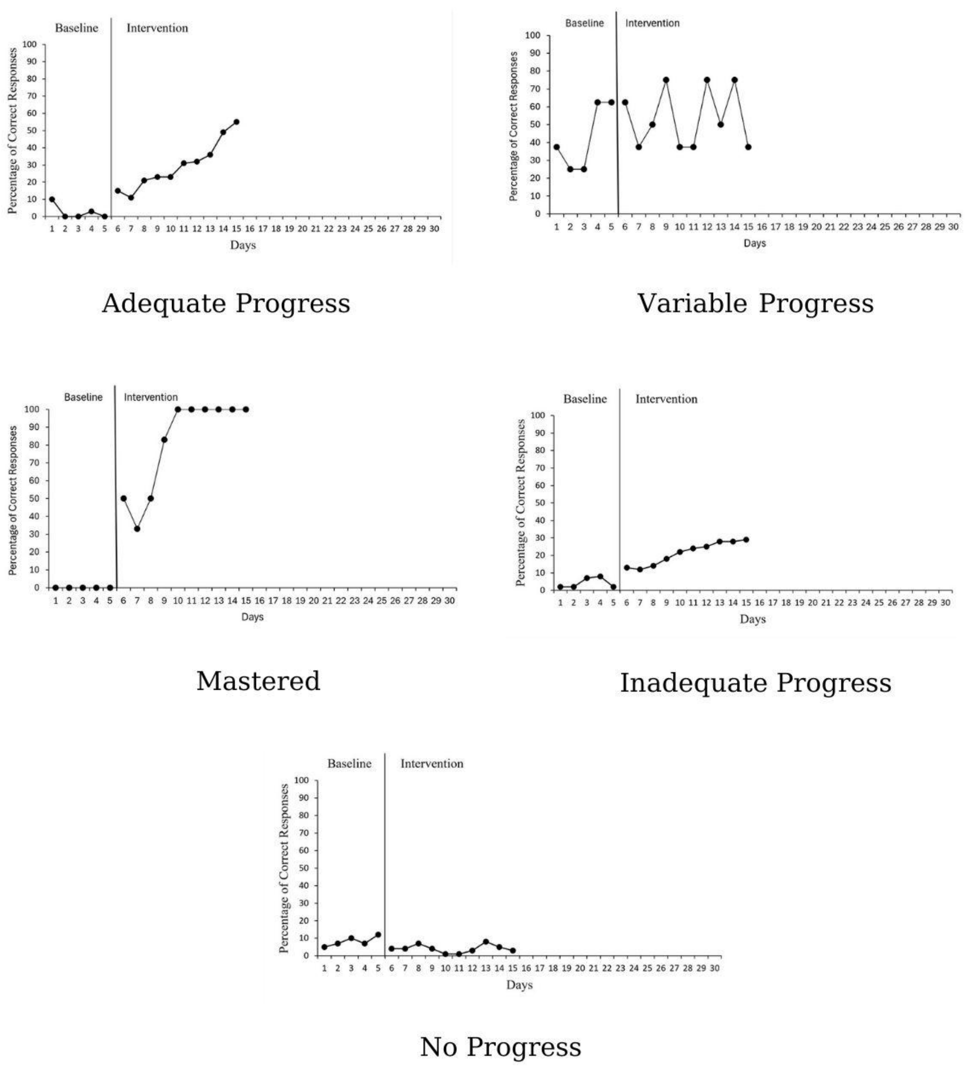


Table 3 Definition table and instructional decisions (Wolfe et al., 2023; Browder et al., 2011)

Data pattern	Definition	Instructional decision
Mastered	The behavior is currently performed at the criterion specified in the objective.	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.	Keep implementing the intervention and continue to monitor.
No Progress	The behavior has not improved from baseline; the learner has not made progress towards the objective.	Check treatment fidelity. If the program is being implemented with fidelity, break 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.	Change prompts or add teaching sessions.
Variable Progress	The behavior is variable (i.e., fluctuating) with no detectable slope, but overall, the level is improved from baseline.	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.

Fig. 2 Sample assessment graphs



Additional assessments were generated using graphs composed of real client data of which were case managed by the participants in their practicum setting and previous learners in their practicum setting – employed to measure generalization across conditions and ongoingly through maintenance probes. The participants were required to bring their personal laptops to access the assessments and the interactive training modules. With the exception of maintenance sessions, the participants were provided with printed copies of the graphs, along with a twelve-inch translucent ruler, and a writing utensil, to aid them in the estimation of the level and trend of the data sets for all sessions. Additional graphs and assessments were created, using real-data from client data at the university-based preschool setting, of which was the participants' prescribed practicum placement. One of the experts that provided agreement for the hypothetical data, volunteered to provide additional agreement on the graphs depicting real student data. resulting in sufficient graphs agreed on to generate additional assessments for maintenance sessions.

Response Definitions

The primary dependent variable in this study was the percentage of accurate instructional decisions (e.g., mastered: introduce next objective and monitor maintenance). The secondary dependent variable was the percentage of accurate data pattern identification (i.e., mastered, variable progress, no progress, adequate progress, inadequate progress). A correct response is defined as a response selection that is equivalent to the expert consensus obtained through the agreement process previously described. Refer to the definition table (Table 4) and DMM (Fig.1) for response definitions and descriptions of data patterns. An incorrect response is defined as an alternative response that is not aligned with the expert consensus and the DMM.

Interrater Agreement

Point-by-point agreement was used to calculate agreement for every response opportunity (i.e. twenty questions), by dividing the sum of agreements by the sum of agreements plus disagreements and multiplying the quotient by one hundred to obtain the percentage of agreement. Volunteers were recruited to provide interrater agreement on participant responses, including second-year ABA graduate students, a special education doctoral candidate, and a university faculty member with a Ph. D in special education. Training on how to score assessments was provided to raters through behavioral skills training (BST). Interrater agreement data was collected across all participants and conditions. Interrater agreement was collected for 34% of baseline sessions, 41.7% of intervention sessions, and 35% of maintenance sessions. Interrater agreement was 99.55% during baseline, 100% during intervention, and 100% during maintenance.

Procedural Fidelity

The researcher's procedural fidelity was measured by volunteer observers that agreed to measure the researcher's fidelity in conducting sessions as planned (i.e. as determined by pre-established necessary steps or a task analysis contingent on the phase or condition). Secondary observers were selected randomly, based on their availability. The reviewers included second-year ABA graduate students, a special education doctoral candidate, and a university faculty member with a Ph. D in special education. BST was employed to teach volunteers how to collect fidelity data and to clarify the procedural steps across conditions. The researcher's procedural fidelity was calculated by dividing the number of the researcher's correct steps implemented by the total number of steps (i.e. the sum of correct steps and incorrect steps implemented), followed by multiplying the quotient obtained by one hundred, to attain the percentage of accurate implementation of procedural steps. The secondary observers included four second-year graduate students in the ABA program and two BCBAs. Procedural fidelity was collected for 40.63% of baseline sessions, resulting in a 99.44% fidelity score. During baseline observers scored the researcher's implementation or lack thereof on the following steps: (1) The researcher provided the participant with a print-out of the graphs corresponding to the assigned assessment, a ruler, and a writing utensil. (2) The researcher provided the participant with access to the correct assessment as predetermined by the counterbalanced assessment table. (3) The researcher provided a general prompt for the participant to complete the assessment., (4) The researcher did not provide the participant with any prompt, feedback, or additional materials other than those mentioned in step one, and (5) The researcher verified that the participant completed the assessment. Procedural fidelity was collected for 54.17% of intervention sessions, resulting in a 100% fidelity score. During intervention, the steps scored were: (1) The researcher provided the participant with the instructional decision-making model and data pattern definitions handout, print-out of the graphs corresponding to the assigned assessment, a ruler, and a writing utensil., (2) The researcher provided the participant with access to the correct assessment as predetermined by the counterbalanced assessment table., (3) The researcher provided a general prompt for the participant to complete the assessment., and (4) The researcher verified that the participant completed the assessment. Procedural fidelity was collected for 35% of maintenance sessions, resulting in a 100% fidelity score. The same steps implemented during baseline were implemented during maintenance sessions, with the exception of the provision of materials (i.e. printout of graphs, translucent ruler, and writing utensil).

Experimental Design

A multiple probe across participants design was used to evaluate the effect of the DBDM training package including the DBDM interactive computer-based training and DMM (Wolfe et al., 2023; Browder et al., 2011) on the accurate identification of data patterns and instructional decisions made by ABA graduate students. In an effort to reduce bias, such as the potential effects the order of assessments would have on participants' performance, the assessments used to measure participants accurate responses were predetermined by a counterbalanced schedule, using a balanced Latin square generator (Bradley, 1958). Employing the Latine square generator to counterbalance assessment order allowed for systematic randomization, also ensuring that participants would not concurrently be given the same assessment as another. During baseline a minimum of six sessions were required for the first participant, before the introduction of the intervention. A predetermined minimum of five data points was required during intervention, or until data would stabilize and upon the participant meeting the mastery criterion of three consecutive sessions with 100% accuracy in instructional decision identification. Upon the first participant's data stabilizing during intervention the following participant would be presented with the intervention. The remaining participants' introduction to the intervention would be contingent on the preceding participant's data stabilizing during intervention and upon meeting the mastery criterion. A functional relation could be inferred if the intervention results in higher levels of accurate responding from participants in the accurate identification of data patterns and instructional decisions. The absence of a functional relation could be inferred if upon contacting intervention the participants' performance level or trend has not improved from baseline.

Procedures

Baseline

During baseline, participants were provided conditional access to each online assessment via their university-based e-learning platform; they received access at the start of each session. During each assessment, the participant was required to complete one assessment with 10 graphs, with equal opportunity to respond to the identification of data pattern and instructional decision. During this condition, participants did not receive feedback or access to the intervention materials (i.e. DMM, definitions table, and interactive online training).

Intervention

During intervention sessions, participants were provided with one-time access to the interactive computer-based training developed by (Wolfe et al. 2023). The training consisted of interactive lessons that cover content on how imperative the practice of DBDM is, the process of data collection and graphing performance, fundamental components of visual analysis of graphs, the characteristics of a line graph (e.g. data points, phase change lines, x-axis, etc.) and instruction on using the DMM to make data-based instructional decisions. Participants were allotted 60 minutes to complete the training. The training was interactive and self-paced, demanding more response effort from the participants receiving the training compared to a traditional didactic format.

The participants were required to engage in various forms including clicking on images to reveal responses, hovering over labels to reveal definitions or characteristics of graphs, listening to audio instruction, reading written instruction, and watching video models. Furthermore, knowledge checks were included throughout the training, where participants could contact immediate feedback on their responses and a practice quiz at the end of the training which provided additional corrective feedback (e.g. if a participant provided an incorrect data pattern response for a graph depicting a “no progress” data pattern, an example of feedback would be “ The level and trend of the intervention data is the same as the baseline data. This learner has made NO PROGRESS.”). Upon completing the training, the participants completed one assessment (i.e. the first data point during intervention) a laminated handout of the DMM and data pattern definitions (Wolfe et al., 2023), a translucent ruler, a writing utensil and a printed copy of the assessment graphs, to measure the immediate effect of the intervention. For post-intervention sessions, feedback was delivered upon completion of assessments, providing the correct answer and explanation per the DMM (e.g. “No Progress: Based on the graphed data, the learner has not met the mastery criterion; more specifically, when drawing the level and trend lines for the baseline data and comparing that to the level and trend lines from the intervention (i.e., no progress has been made). The appropriate instructional decision is to check treatment fidelity. If the program is being implemented with fidelity, break the skill down into smaller components. If the program is not being implemented with fidelity, provide coaching and feedback to the implementer.”). Participants remained in the intervention phase until they met the mastery criterion of one hundred percent accuracy in identification of instructional decisions, across three consecutive sessions and sessions, and until data was stable (i.e. determined by three stable data points).

Maintenance and Generalization

Maintenance sessions were conducted 1-month post intervention (i.e. 1-month following the last intervention session) to measure if the gains from intervention were maintained over one-month post intervention, in the absence of materials and the DMM. The assessment format, similar to other conditions was composed of twenty questions where participants were asked to identify the data pattern and the corresponding instructional decision for 10 AB graphs. Five of the 10 graphs represented real student data, from which participants case managed in their practicum setting. The intent of including student data was to provide a generalization measure.

Social Validity

This study employed an adapted version of the social validity questionnaire used by Wolfe et al. (2023), including 11 questions that prompted participants to rate the acceptability of the intervention, how meaningful they find the dependent variables to be, and the efficacy of the intervention on increasing their levels of accuracy in the dependent variables (i.e. the accuracy of data pattern and instructional decision identification), employing a five-point Likert rating scale. The questionnaire was provided to participants through Microsoft Forms™, where participants could anonymously answer. Participants were asked to complete the questionnaire following intervention. An additional questionnaire was provided to the experts that contributed to providing agreement on the graphs used in participant assessments. This questionnaire aimed to measure how significant the experts found the competency of DBDM as it relates to BCBAs, how relevant the DMM is as a tool for BCBAs, and how prepared they felt by their university programs to conduct DBDM.

CHAPTER 3

RESULTS

Figure 2 depicts the participants' percentage of accurate responding in the identification of data patterns and instructional decisions. For the assessment during baseline where only student data was used During baseline, Antoinette scored an average of 50% accuracy instructional decisions identification (i.e. primary dependent variable), with an average of 80% accuracy in data pattern identification (i.e. secondary dependent variable). Overall, during baseline Antoinette's data had low variability, no apparent trend, having mid-levels of accuracy in instructional decision, and high levels of accuracy in data pattern identification. During intervention, Antoinette had an immediate increase of 20% in instructional decision identification, upon contacting the interactive online training. As a result of contacting the post assessment feedback in the first intervention feedback, Antoinette had an increase of an additional 30% accuracy in instructional decision identification, stabilizing with four consecutive sessions at 100%. During intervention, Antoinette did not immediately increase in data pattern identification, however after contacting the feedback from the first post-assessment, Antoinette had an additional 30% increase, and their performance stabilized with 100% accuracy for four consecutive sessions. Antoinette maintained high levels of accuracy in instructional decision and data pattern identification during the 1-month post-intervention maintenance sessions. Antoinette had an average of 90% in instructional decision and data pattern identification during maintenance.

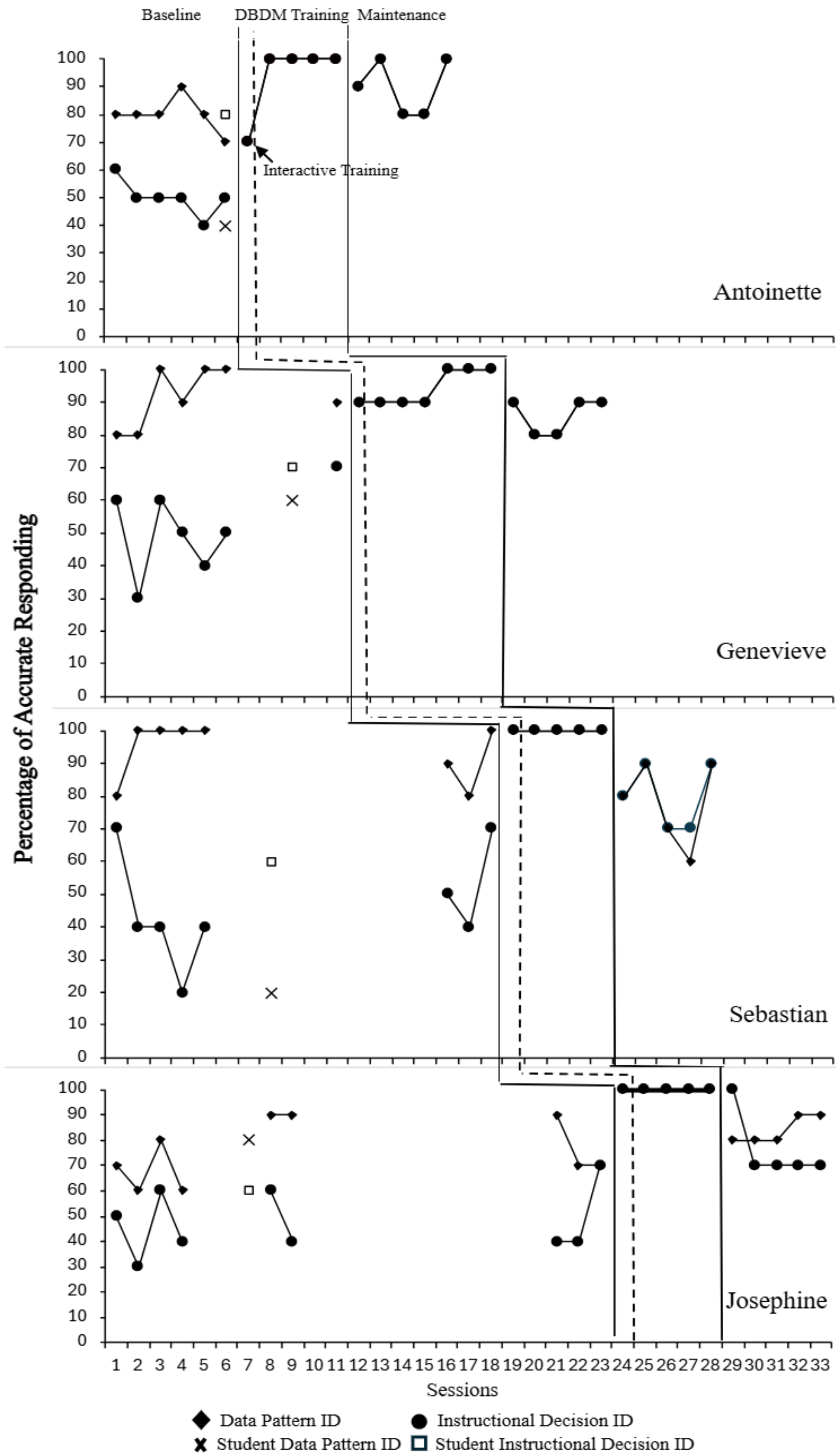
During baseline Genevieve maintained mid-levels of accuracy in instructional decisions, with an average of 48%, and scored high levels of accuracy in data pattern identification, with an average of 91%. Although Genevieve demonstrated an increasing trend in data pattern identification with low variability, there was no detectable trend in instructional decision identification (i.e. the primary dependent variable) - as there was variability in responding during baseline sessions. During intervention Genevieve had high levels of accuracy with low variability and an increasing trend. She maintained an average of 94% accuracy in both data pattern and instructional decision identification. During intervention, Genevieve had an immediate 20% increase in accurate instructional decision identification and a 10% decrease in accuracy in data pattern identification. Genevieve increased her accuracy an additional 10% in both dependent variables, with three consecutive sessions following at 100%. During maintenance Genevieve maintained low levels of variability, no detectable trend, and high levels of accuracy, with an average of 86% in both data pattern and instructional decision identification.

Sebastian scored higher levels of accuracy in data pattern identification during baseline, with low variability and an increasing trend with an average of 90% accuracy.
Sebastian had no detectable trend, with variability and mid-level performance, with an average of 43% accuracy in instructional decision identification during baseline. Upon contacting the intervention (i.e. the DBDM training package) an immediate effect was demonstrated as Sebastian scored 100% on instructional decision identification and had four consecutive sessions at 100%. Sebastian also scored five consecutive sessions at 100% accuracy in data pattern identification during intervention. During maintenance Sebastian scored moderately high levels of accuracy in both data pattern and instructional decision identification. Sebastian had low variability and no detectable trend in both dependent variables during maintenance.

During baseline, Josephine scored moderately high levels in accurate identification of data patterns, with low variability, no detectable trend, and with an average of 74% accuracy. Josephine scored mid-level in identification of accurate instructional decisions with low variability, no detectable trend, and with an average of 51% accuracy. During intervention Josephine had an immediate increase, upon being exposed to intervention, scoring 100% in accuracy across both dependent variables for five consecutive sessions, similar to Sebastian. During maintenance, Josephine had high levels of accuracy across both dependent variables, with low variability, an increasing trend in data pattern identification, and no detectable trend in instructional decision identification. Josephine had an average of 84% in accuracy in data pattern identification and 76% in accuracy in instructional decision identification.

The implications that can be drawn from the performance of the participants is that the DBDM training package was effective in increasing the participants accuracy in instructional decisions, as all participants increased to high levels of accuracy, meeting the mastery criterion of three consecutive sessions at 100% in both dependent variables. Although it is arguable that there was a functional relation between the intervention and an increase in accuracy in data pattern identification for Sebastian (i.e. he scored 100% for 63% of his sessions in data pattern identification, during baseline), due to his higher levels of responding, a functional relation is clearly depicted for the remaining participants. The efficacy of the intervention is further supported by the participants' performance during maintenance, where all materials were not provided by the researcher. Moreover, participants were able to demonstrate generalization of the gained competency during maintenance sessions, through identifying data patterns and the corresponding instructional decisions with high levels in student graphed data (i.e. the students case managed by participants in their practicum site).

Fig. 3 Participants' graphed performance



A social validity survey was provided to the participants to measure how meaningful and acceptable they found the intervention and the outcomes as a result of the intervention (see Table 4). Overall, the participants strongly agreed that being competent in conducting DBDM is relevant to clinicians and teachers. Moreover, the participants found the training package (i.e. the interactive online training and decision-making model) to be easy to navigate and that it helped them increase their confidence in conducting visual analysis and data-based instructional decisions.

Table 4 Participants' social validity findings

Statement	**Mean**	**Range**
It is critical for teachers and clinicians to know how to conduct visual analysis on student/client data.	5	5
It is critical for teachers and clinicians to know how to make data-based instructional decisions based on student/client data.	5	5
The online interactive training was easy to navigate.	5	5
The online training was effective in teaching me how to conduct visual analysis on student/client data.	5	5
The online training was effective in teaching me how to use the decision-making model to analyze student data.	5	5
The decision-making model was effective in aiding me in analyzing student/client data.	5	5
The decision-making model was effective in aiding me with making data-based instructional decisions.	4.75	4-5
The decision-making model was easy to navigate.	5	5
I would consider using the decision-making model to make instructional decisions for my future students/clients.	5	5
The decision-making model increased my confidence in visual analysis.	5	5
The decision-making model increased my confidence in making instructional decisions.	4.75	4-5

An additional Likert-scale formatted survey was provided to the expert reviewers, where they could rate how imperative being competent in conducting visual analysis and DBDM is for teachers and clinicians. The consensus across all experts was a strong agreement in that it is critical for teachers, clinicians, and BCBAs to be competent in conducting visual analysis and DBDM. Experts were also asked to rate how relevant the DMM is for BCBAs and if it would lend itself as a valid source to reference in DBDM by BCBAs, which resulted in a mean of 4.6 agreeing that the tool would be relevant and serve as a valid source to conduct DBDM. Lastly, in regard to feeling prepared by their educational programs on their abilities to conduct DBDM, resulted in a high mean of 4.6 across experts.

Table 5 Expert reviewers' social validity findings

Statement	Mean	Range
It is critical for teachers and clinicians to know how to conduct visual analysis on student/client data.	5	5
It is critical for teachers and clinicians to know how to make data-based instructional decisions based on student/client data.	5	5
It is critical that BCBAs are competent in their abilities to make data-based instructional decisions.	5	5
The decision-making model is a relevant and valid tool for BCBAs to reference or guide them in making data-based instructional decisions for their clients.	4.6	4-5
I feel my educational program(s) prepared me to make data-based instructional decisions upon becoming a new BCBA.	4.6	4-5

CHAPTER 4

DISCUSSION

This study aimed to build upon the foundational work of Wolfe et al. (2023). The same interactive online training and decision-making model developed by Wolfe et al. (2023) was employed in this study with the objective of increasing preservice BCBAs accuracy in instructional decision identification. The conclusion that can be drawn on the intervention efficacy, is that the intervention was effective in increasing accuracy in instructional decision identification across preservice BCBA graduate students. These results are similar to the findings of Wolfe et al. (2023), where the participants also increased in their accuracy in identifying instructional decisions. Although Sebastian had higher levels of data pattern identification (i.e. secondary dependent variable), with consecutive sessions scoring 100% during baseline, for the remaining participants intervention was effective in increasing their accuracy in identifying data patterns with consecutive sessions at 100% during intervention. Furthermore, participants misidentified inadequate and variable progress data patterns similar to the Wolfe et al. (2023) study, where following contacting intervention Antoinette and Genevieve inaccurately identified graphs depicting “variable progress” data patterns and identified them as inadequate progress.

This study adds to previous research through the inclusion of real student data being presented in assessments, providing a generalization measure where participants can be probed on whether the competency in conducting DBDM could translate to data from an applied setting (i.e. their practicum site). This study used a multiple probe design to control a potential testing threat that might have inadvertently caused participants to learn the answers, as addressed by Wolfe et al. (2023). This study also included an additional social validity measure, where experts agreed that the DMM is a valid and relevant tool for BCBAs to use when conducting DBDM. This study also contributed by providing maintenance data, as previous studies on DBDM have not assessed for maintenance (Wolfe et al., 2023). Additionally, during maintenance sessions, participants did not have access to materials – to include the DMM. Despite not having access to the materials, the participants overall maintained high levels of accuracy in instructional decision and data pattern identification. The high level of performance of the participants during maintenance in the absence of the DMM, suggests that the intervention is effective enough to have lasting effects.

Limitations

There are several limitations in this study that should be considered. First, although experts were given access to the DMM to provide agreement on graph data patterns and instructional decisions, they did not take the DBDM training. This could have limited the agreement and thus inadvertently caused the removal of graphs with data patterns that might have been more aligned with the training. Second, the assessments had a multiple-choice format. Having the multiple-choice format, could have prompted participants to respond with a higher accuracy in baseline because they could simply go through a “process of elimination”.

Participants were probed during baseline, after having taken an introductory applied behavior analysis course, where they had been exposed to visual analysis concepts, this could have also contributed to higher levels of responding during baseline for participants, especially in the secondary dependent variable (i.e. data pattern identification) where levels of responding were higher across all participants.

Implications for Future Research

Future researchers can address the limitations of this study by providing expert reviewers with the full intervention package, to increase consistency and accuracy in data pattern and instructional decision identification. Researchers could also develop a grading system that would allow participants to openly respond, by having a rubric which would include acceptable responses and a partial point system for responding. This would allow for a more accurate probe of participant knowledge. Future researchers could also probe participants at the beginning of their program and before they are exposed to visual analysis concepts, to eliminate the extraneous variables that come with being a student, that might have contributed to higher levels of accuracy during baseline. Furthermore, it would be ideal to include participants that perform with lower levels of accuracy in both dependent variables.

It's imperative that we continue working towards finding effective and feasible methods of training preservice BCBAs on how to conduct DBDM, as they are ethically obligated to practice DBDM – which is mandated by the BACB ethics code. Moreover, erroneous implementation of DBDM can result in detrimental outcomes for clients, including limiting their progress. Considering there is limited research addressing preservice BCBAs professional development in DBDM competency, it is relevant to continue discovering methods of instruction that can enhance their performance, to ultimately foster client progress.

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