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Assessing Visual Analysis Skills with Board-Certified Behavior Analysts

Marina Forsythe
Rollins College, mforsythe1@rollins.edu

Assessing Visual Analysis Skills with Board-Certified Behavior Analysts

A Thesis by

Marina N. Forsythe

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Table of Contents

Abstract

Visual analysis is the technology used in behavior analysis by researchers and practitioners to interpret their data to make clinical-based decisions. Due to recent studies uncovering varied results of visual analysis reliability, we sought to assess decision-making skills based on graph inspection. Twelve behavior analysts participated in this study by taking an online survey that assessed their ability to visually analyze a series of graphs. One subset of graphs resembled graphs commonly seen in published articles whereas the second subset resembled graphs from software programs more commonly seen in practice (e.g., in practice software) to assess their ability to generalize. This study also evaluated using a decision-making algorithm as an effective aid. Eight out of twelve participants did not meet the mastery criterion in the initial assessment phase, and only one participant then met the mastery criterion with the decision-making algorithm. The four participants that originally met mastery in baseline did not show any significant differences in responses between the graphs seen in the publication versus graphs populated in practice software programs.

Keywords: visual analysis, visual inspection, graphs, behavior analyst

Assessing Visual Analysis Skills with Board-Certified Behavior Analysts

Practicing behavior analysts spend a large portion of the day measuring different behaviors through data collection. Raw data are limited on how it can be interpreted as it does not provide all the details a practitioner is looking for and important behavior changes can be missed. The most effective way to communicate these data are through the use of graphs. Graphs are visuals used to display data and communicate important attributes such as how long data were taken, relationships between conditions, or behavior change across time. Graphs also serve as judgmental aids that assist the audience in interpreting data (Cooper et al., 2020).

Behavior analysts largely rely on three features to make data-based decisions: level, variability, and trend, all of which are visually inspected on a graph. Utilizing graphs as a visual aid acts as an effective way to communicate all of these features. They also display behavior change in an uncomplicated way that most individuals can consume (i.e., parents, caregivers, insurance companies, and other professionals; Parsonson & Baer, 1992). "The function of the graph is to communicate, in a readily assimilable and attractive manner, descriptions and summaries of data that enable rapid and accurate analysis of the facts," (Parsonson & Baer, 1992, p. 134).

Visual analysis holds importance to behavior analysts in a multitude of ways and serves as the most common form of data analysis in applied behavior analysis. This technology is widely used because one can interpret the data almost immediately, it allows one to judge the data instead of relying on others, and it is an easy skill for persons of all levels to acquire (Sanetti et al., 2014). Practitioners also favor visual analysis due to showing condition effects large enough to use as a primary method as well as the necessity to ensure interventions are producing socially significant change (Kipfmiller et al., 2019). This technology also serves convenience due to graphs being cost-effective, easy to access, and requiring a small number of resources to produce. Having immediate access to graphs allows behavior analysts to continuously visually inspect one's performance to keep their services individualized and monitor progress. It also allows data-based decisions to be made which then leads to better success instead. (Cooper et al., 2020).

Visual inspection may be easier than evaluating raw data because one's history with lines is greater than numerals, which naturally generalizes to interpreting graphs (i.e., driving a car, walking, climbing; Parsonson & Baer, 1992). Experts also say this method has low error rates making statistical analysis not needed (Brossart et al., 2006). Statistical methods, as stated by Baron (1990), "lead a researcher away from an experimental analysis…the researcher must settle for procedures that test the reliability of experimental effects against chance" (p. 168). Although visually inspecting graphs is a simple and reliable technology widely used this does not mean this skill should not be acquired by practicing applied practitioners.

Visual analysis serves as an easier alternative to interpreting data compared to other technologies such as statistics, but learning how to perform visual analysis still needs to be acquired. There has been a vast amount of research on improving the reliability of visual analysis through systematic instruction on computer-based modules or recorded lectures (Wolfe & Slocum, 2015) or equivalence-based instruction (Kipfmiller et al., 2019). Wolfe & Slocum (2015) evaluated and compared two visual analysis skill acquisition interventions which consisted of delivering systematic instruction on computer-based intervention and a recorded lecture in which participants identified the slope and level changes in AB graphs. Researchers found that these training methods were both effective for visually inspecting graphs when compared to no training and that one treatment was not more successful than the other. Blair et al. (2019) also found that improving the reliability of practicing behavior analysts' visual analysis skills was warranted due to previous research showing low agreement when inspecting graphs. Researchers in this study were able to find that equivalence-based instruction was successful in teaching visual analysis and skills maintained for 2 weeks following the study.

Additional support for teaching visual analysis would be incorporating visual aids for practitioners. Retzlaff et al. (2020) found that registered behavior technicians (RBTs) could successfully visually inspect functional analysis data by using a quick-reference guide on an e-learning module. In Brodhead & Truckenmiller (2021) the researchers found that a clinical decision-making algorithm can work as an effective visual aid for professionals to make treatment decisions (i.e., treatment is complete, continue treatment, modify treatment, or discontinue treatment). The graphs utilized in this study were computer-based, produced on other controlled studies with clear features, and extraneous variables that could affect data were controlled for (i.e., client calling out routinely, less controlled environment, etc.). As a result of, the researchers did not assess if this decision-making algorithm could serve as an effective intervention for different software graphs that practicing behavior analysts contact often.

Despite all the current training and literature on visual analysis, there is doubt that some active behavior analysts working in applied settings (i.e., an autism clinic, schools, community, in-home services, hospitals, etc.) may use visual analysis correctly to interpret graphs. In Lanovaz & Hranchuk (2021), researchers focused on the reliability and validity of visual inspection and found that the participants, who all had a BCBA-D certification, had only moderate agreement with each other. Ninci et al. (2015) evaluated recent peer-reviewed literature and found low to moderate levels of interrater agreement between visual analysts. All of this warrants further research on uncovering the reasoning behind low to moderate agreement in visual analysis.

A few hypothesized complications can be performance issues due to but are limited to, potential burnout, lack of time, and a lack of reinforcement for proper BCBA etiquette. BCBAs typically have less contact with treatment data compared to an RBT, which results in less exposure to graphs compared to a front-line employee. This can be due to having limited time outside of their billable hours, treatment settings that require additional time to transition to (i.e., in-home, in-school), or a caseload that is too large to manage. The field of applied behavior analysis is growing at increasingly high rates that exceed the supply of practitioners which will inevitably decline the quality of services (Kipfmiller et al., 2019). Investors in ABA companies also lean toward setting up contingencies that reinforce more billing such as increasing one's caseload which then leads to a decrease in the quality of supervision (Bailey & Sasson, 2022). In addition, Plantiveau et al. (2018) conducted a study that found two in every three practitioners were experiencing burnout which can produce a multitude of negative effects such as low standards of service (Plantiveau et al., 2018).

An additional complication behind this doubt also lay behind a potential skill deficit in performing visual analysis. Variables that could affect one's skill could be due to the experience and training the individual received, the type of design in the graph, or how the details of the graph were presented (Lanovaz & Hranchuk, 2021). Although a practicing BCBA has been exposed to visual analysis, generalizing this skill to other software programs graphs more commonly seen in practice (i.e., in practice software) is another potential barrier to skill acquisition.

As BACB (Behavior Analyst Certification Board) Ethical Code 1.06 states it is an ethical requirement for behavior analysts to maintain competency by participating in continued training, coaching, conferences, etc. (Behavior Analyst Certification Board, 2014). Therefore, making it one's ethical obligation to maintain competency when using technologies in practice. BACB Ethical Codes 2.17 and 2.18 both refer to a BCBA's responsibility to ensure data are being collected with fidelity, displayed in a graph, and is being used to make decisions such as continuing, modifying, or terminating the intervention. These codes also go into detail about the ethical obligation to continuously monitor data to evaluate if an intervention has the desired outcome and investigate alternative options if it's undesirable (Behavior Analyst Certification Board, 2014).

The purpose of this study is to assess behavior analysts' visual analysis skills. This study also will assess performance on graphs more common in visual analysis studies compared to graphs that are typical in practice as well as evaluate the use of a visual aid decision-making algorithm for behavior analysts who would benefit from additional support.

Method

Participants and Setting

Twelve BCBAs were recruited to participate in this study. Participants were asked to complete this study via an online platform, Qualtrics, in the form of a survey. Prior to the start of the study, each participant was prompted to complete a consent form and a demographic survey, including questions on age, gender, race, length of time practicing as a behavior analyst, primary area of practice, and educational background.

Materials

Graphs

Four sets of graphs were used in this study, and each set contained 12 graphs. All four sets originated from Kipfmiller et al. (2019) and are hypothetical graphs that generated from hypothetical completed datasets. The hypothetical graphs in Kipfmiller et al. (2019) were developed in Microsoft Excel with an autoregressive model that resembles Wolfe and Slocum's (2015) model. To create the initial pool of graphs, Kipfmiller et al. (2019) generated 240 graphs in Microsoft Excel that consisted of 10 data points each. The autoregressive equation was manipulated to recognize set criteria that will then populate graphs to fit into four categories (continue, modify, terminate, or discontinue intervention). "A continue graph" (i.e., a graph for which the correct clinical decision would be to continue conducting sessions with the intervention consisting of data with an upward trend in data but three consecutive data points at 80% or above have yet to occur.) "A complete graph" (i.e., a graph for which the correct clinical decision would be to master the intervention due to having at least three data points at 80% or above.) "A discontinue graph" (i.e., a graph for which the correct clinical decision would be to discontinuing the intervention due to flat data of at least 10 data points at 50% or below.) Lastly, "a modify graph" (i.e., a graph for which the correct clinical decision would be to modify the given intervention due to variable data or a decreasing trend.) Twelve graphs from each of the four categories were then randomly selected from the original Kipfmiller et al. (2019) pool for use in this study.

Graphs were then divided into four sets of twelve, with each set containing 3 graphs from each category. For Graph Sets 1 and 2, grid lines were removed from the original Kipfmiller et al. (2019) images, but otherwise remained identical. For Graph Sets 3 and 4, in order to evaluate graphs more similar to those seen in clinical practice, a representative sample from three commonly used practice software programs was compared. A group of behavior analysts and behavior technicians then identified common features among these figures (e.g., gridlines present, marker shape, colors, etc). Graphs Set 3 and 4 were then re-created in a graphic design program (Adobe Photoshop®). The data values were not altered, but the other graph characteristics contained the features identified as common among practice software.

A mastery criterion for each phase was set at 83% correct responses (at least 10 correct responses). Each participant's performance in each phase determined which phase they proceeded to next.

Clinical Decision-Making Algorithm

In the Evaluating DMA Phase and the Evaluating the DMA with Graphs Seen in Practice phase, the decision-making algorithm (DMA), identical to the one used by Kipfmiller et al. (2019), was displayed above every graph. The DMA, as shown in Figure 2, moved the reader through a flow chart of different yes/no questions that ultimately led them to one of four clinical decisions presented in the order: (a) intervention is complete, (b) continue intervention, (c) modify intervention, or (d) discontinue intervention.

Procedure

Phase 1: Visual Inspection Assessment

The survey began by instructing participants to answer 12 questions with response options that consisted of (a) intervention is complete, (b) continue intervention, (c) modify intervention, or (d) discontinue intervention, in this order. Each question was presented with its corresponding graph from Graph Set 1 on a different screen. No feedback was given on this phase. If mastery was not met in this phase, participants were immediately routed to the Evaluating DMA Phase whereas if mastery was met, they were immediately routed to Evaluating Graphs Seen in Practice phase, as shown in Figure 3. The following instructions were provided in this phase: For each figure, select from one of the options below indicating which data-based decision is correct. The mastery criterion is set at 80% or higher correct responses for 3 consecutive sessions. Participants were provided with the following instructions: "For each figure, select from one of the options below indicating which data-based decision is correct. The mastery criterion is set at 80% or higher correct responding for 3 consecutive sessions."

Phase 2: Evaluating DMA

Participants that did not meet the mastery criterion in the baseline condition continued to the treatment phase. This phase consisted of responding to figures from Graph Set 2. Graphs were presented in random order and were preceded by an image of the DMA, with response options the same as the baseline. The participants who did not meet mastery were done with the study. The participants who meet mastery immediately began the Evaluating the DMA with Graphs Seen in Practice phase. Participants were provided with the following instructions: "For this set of questions, we have provided you with a visual aid. Please use the visual aid to answer each question to the best of your ability. For each figure, select from one of the options below indicating which data-based decision is correct. The mastery criterion is set at 80% or higher correct responding for 3 consecutive sessions."

Phase 3: Evaluating Graphs Seen in Practice

This phase was identical to the Visual Inspection Assessment phase, except graphs from Graph Set 3 were presented. Participants who did not meet the mastery criterion in this phase immediately began the Evaluating the DMA with Graphs Seen in Practice phase. Participants that did not meet the mastery criterion were finished with the study. Instructions provided in this phase were the same as in the Visual Inspection Assessment phase.

Phase 4: Evaluating the DMA with Graphs Seen in Practice

This phase was identical to the Evaluating DMA Phase, except graphs from Graph Set 4 were presented. Participants who met the mastery criterion in the Evaluating DMA Phase or did not meet the mastery criterion in the Evaluating Graphs Seen in Practice phase immediately began the Evaluating the DMA with Graphs Seen in Practice phase. The instructions provided were the same as in the Evaluating DMA Phase.

Results

Table 1 depicts the results for each participant's score in the form of percent correct for each applicable phase. Eight out of the twelve participants did not meet the mastery criterion (83% correct) in Visual Inspection Assessment Phase. With the introduction of the DMA in the Evaluating DMA Phase, only Participant #9 met the mastery criterion of eight participants. Following the Evaluating DMA Phase, Participant #9 met the mastery criterion in the Evaluating the DMA with Graphs Seen in Practice phase. The four participants that originally met mastery in the Visual Inspection Assessment phase then proceeded to Evaluating Graphs Seen in Practice phase where they all met mastery as well.

Error Analysis

The results of the error analysis are shown in Figure 3. The researcher documented each individuals' incorrect responses based on all four response type (i.e., intervention complete, continue intervention, discontinue intervention, and modify intervention). The percentage of errors was individually calculated by dividing the total amount of errors per response by the participants' total amount of errors.

Discussion

This study assessed and evaluated the visual inspection skills of twelve behavior analysts with a decision-making algorithm (DMA) and with graphs created to resemble the visual appearance you would see in software used in practice. In contrast to previous studies, the use of a DMA did not improve behavior analysts' responses to making clinical decisions based on hypothetical data. The results also did not show any significant differences in responses between the graphs seen in publication versus graphs populated in software programs you see in practice.

Kipfmiller et al. (2019) and Brodhead & Truckenmiller (2021) both showed large differences in the accuracy of responding once the DMA was introduced to their participants. In Kipfmiller et al. (2019), the participants were front-line employees such as Registered Behavioral Technicians, whereas in Brodhead & Truckenmiller (2021) the participants were special education, teacher trainees. Both population of participants had not gone through the extensive requirements to become certified behavior analysts (i.e., fieldwork hours, masters level training in behavior analysis) or had a reinforcement history of using visual analysis in practice on a daily basis. The DMA may not have been an effective intervention for eight out of the nine participants in the Evaluating DMA Phase due to their extensive history of using visual analysis. It could also be due to their training as well. For example, if their supervisor was performing visual analysis incorrectly, this may have taught them an inaccurate way to properly use visual analysis. Another possibility is a Behavior Analyst could have a different criterion on their own for each response type (i.e., continue, complete, modify or discontinue). This study used predetermined criterion for each response type that was considered universally known. To interpret a graph correctly is to make the most appropriate clinical decision on an interventions' next step which can subjectively differ between behavior analysts. Although stated in the survey, a mastery criterion can differ depending on the behavior analyst and they could have responded based on a different mastery criterion.

Further analysis of the data, there was a correspondence between incorrect responses and the "discontinue" graphs. Of the 40 errors that occurred in the Visual Inspection Assessment Phase across all twelve participants, over half (n = 23) of the errors were on graphs for which the correct response was "discontinue". Participants in the Visual Inspection Assessment phase responded incorrectly to 64% of "discontinue" graph presentations. In many of these errors, the answer choice "modify" was selected. It is a possibility that the participants did not know what a "discontinue" response entailed and had a different interpretation. It is also possible that this could be reflective of the culture in practice; behavior analysts may not discontinue an intervention but rather continue to modify it until mastery. This potentially uncovers bad practicing habits. In addition, another common error pattern for eight participants was to select “continue intervention” instead of the correct response of “mastered”. This may be due to the removal of gridlines as visual support that practicing behavior analysts are accustomed to seeing in more software graphs seen in practice.

One limitation of this study is the difference between the data used in Evaluating Graphs Seen in Practice phase and 4 graphs versus data often analyzed in clinical practice. For example, clinical practice graphs often include many more data points than 10. Also, because of the inherent confounds often present in clinical practice, data may be more variable and have more event changes (e.g., medication changes, therapist changes, absences, decreased treatment integrity) that affect patterns in responding. Responses between the graphs seen in publication versus graphs seen in practice did not show any significant differences. For example, Participant 4 score was 92.7% in the Visual Inspection Assessment phase and 100% in Evaluating Graphs Seen in Practice Phase and Participant 10 scored 83.3% which stayed the same in both phases. Although the practitioners in this study generalized from graphs you would typically see in publications to graphs you would commonly see in practice, this does not guarantee this learned skill is being executed in practice. Future research should formulate graphs with a better resemblance of data paths commonly seen or assess with graphs from practice.

A second limitation is the primary execution of the assessment and intervention. The platform Qualtrics XM® is completely virtual which in itself has imperfections. For example, each participant agreed on the consent form that they are a BCBA or BCBA-D which relies on an honor code of their credentialing. While taking the survey there were a few noticeable visual blemishes. For example, the DMA was above each graph instead of side by side because Qualtrics was unable to fit them together with a decent format that was clear and easy to understand. Due to this formatting, the participant was required to scroll between the two visuals which increased response effort to use the DMA. The participants also may have no prior history with Qualtrics and its mechanics of it despite its user-friendly features. Also, given that their response was completely virtual, proctoring did not occur. This leads to different environmental variables such as if their surroundings were conducive for them to attend appropriately or could have falsified their answers.

Another limitation is there were no incentives given for participating in this study or for correct responding. Without reinforcement provided, the participants could guess each response or not attend as effectively. There were no establishing operations arranged to increase the effectiveness of their response (i.e., cash incentives, gift card raffle, etc.) Participation was completely on their own time as well and participants were not paid for their time which could potentially encourage the participants to engage with the survey for a shorter period of time. Incentives contingent on correct responses could potentially increase their responses and could benefit future research.

Future research should evaluate providing feedback after phases to clarify definitions as needed. In Kipfmiller et al. (2019), the researchers provided corrective feedback if their responding did not meet their satisfaction. During these feedback sessions, the researcher would vocally explain things such as defining variability and providing examples of variability. These feedback sessions then increased the two participants responding. Providing feedback may clarify issues with definitions and/or understanding of the modify and discontinue categories. This then may lead to a better assessment of true visual analysis skills without the confounds of typical practice.

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Table 1

Percent Correct on Visual Analysis in Each Phase for Each Participant

Participants	Baseline (Percent correct)	Phase 2 (Percent correct)	Phase 3 (Percent correct)	Phase 4 (Percent correct)
1	66.7%	58.3%		
2	66.7%	75%		
3	66.7%	75%		
4	92.7%		100%	
5	58.3%	75%		
6	50%	42.7%		
7	75%	66.7%		
8	100%		83.3%	
9	41.7%	91.7%		91.7%
10	83.3%		83.3%	
11	75%	75%		
12	83.3%		91.6%	
Average:	71.55%	69.92%	89.55%	91.7%

Note. This table represents the results of percent correct from each category from 12 behavior analysts

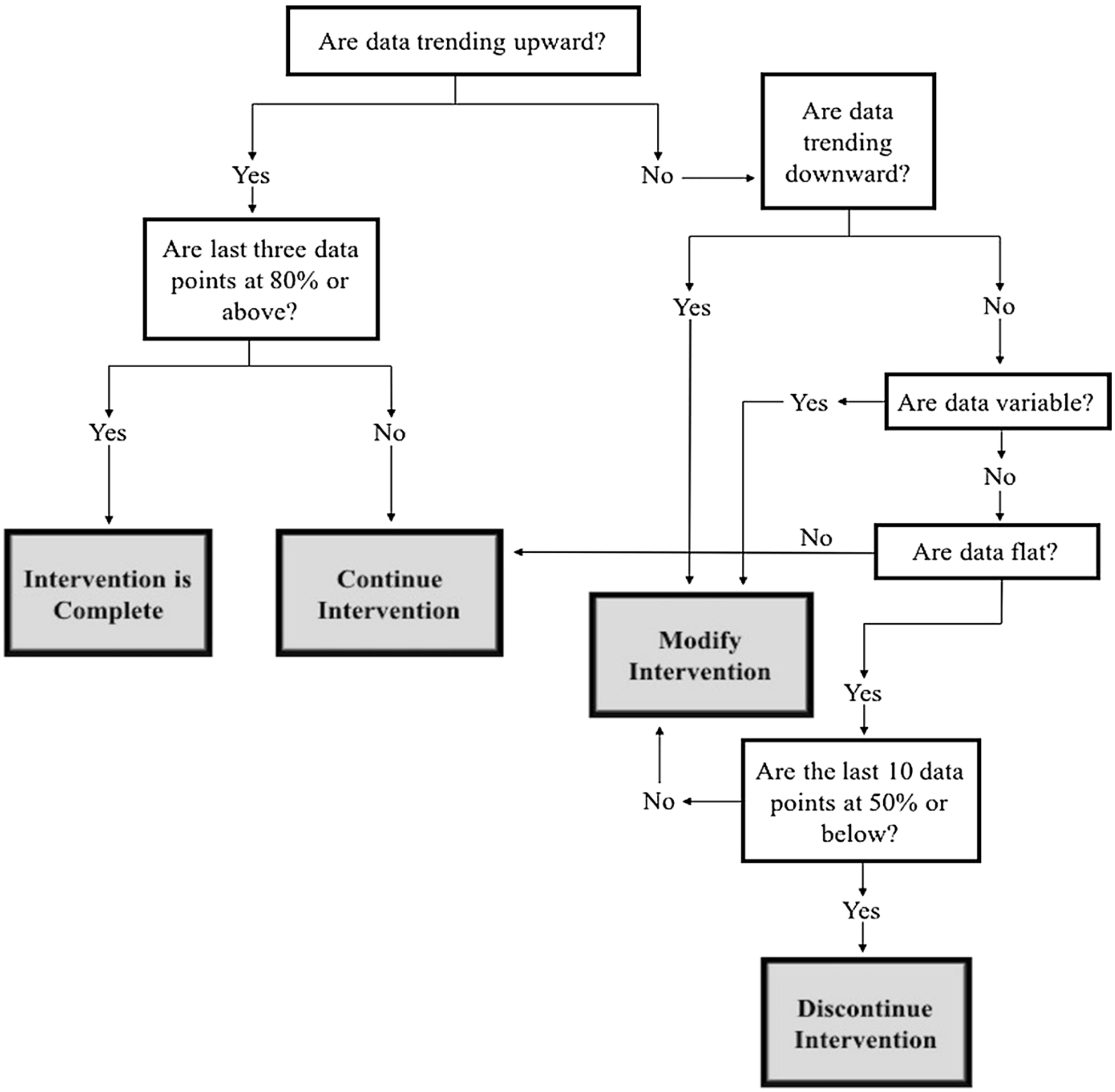
Table 2

Demographic Data for Each Participant

Participants	Gender	Age	Ethnicity	Years in practice	Area of Practice	Experience
1	Female	18-30	White/Caucasian	4-9	Clinical practice with primary children	Master's degree in ABA or related field
2	Female	31-40	Latino/Hispanic	1-3	Clinical practice with primarily children	Master's degree in ABA or related field
3	Female	31-40	Latino/Hispanic	4-9	Clinical practice with primarily children	
4	Non-binary	18-30	Black or African/African descent	1-3	Clinical practice with primarily children	Master's degree in ABA or related field
5	Female	31-40	White/Caucasian	4-9	Clinical practice with primarily children	Master's degree in ABA or related field
6	Female	18-30	White/Caucasian	Less than 1	Clinical practice with primarily children	Master's degree in ABA or related field
7	Female	31-40	White/Caucasian	4-9	Clinical practice with primarily children	Master's degree in ABA or related field
8	Female	18-30	White/Caucasian	4-9	Clinical practice with primarily children	Master's degree in ABA or related field
9	Female	18-30	Black or African/African descent	Less than 1	Clinical practice with primarily children	Master's degree in ABA or related field
10	Female	18-30	White/Caucasian	Less than 1	Clinical practice with primarily children	Master's degree in ABA or related field
11	Female	18-30	Latino/Hispanic	1-3	Education (classroom-based services)	Master's degree in ABA or related field
12	Female	18-30	White/Caucasian	1-3	Clinical practice with primarily children	Master's degree in ABA or related field

Figure 1

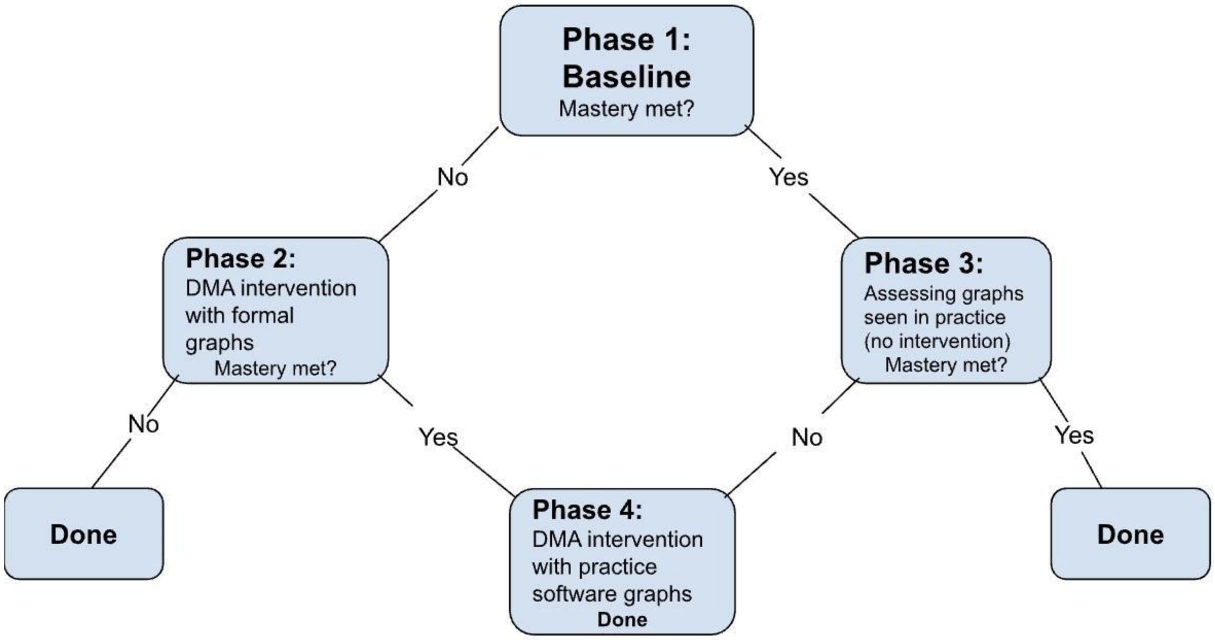
Clinical Decision-Making Algorithm (Kipfmiller et al., 2019)



Note. The decision-making algorithm (DMA) given to participants during treatment phases as seen in (Kipfmiller et al., 2019)

Figure 2

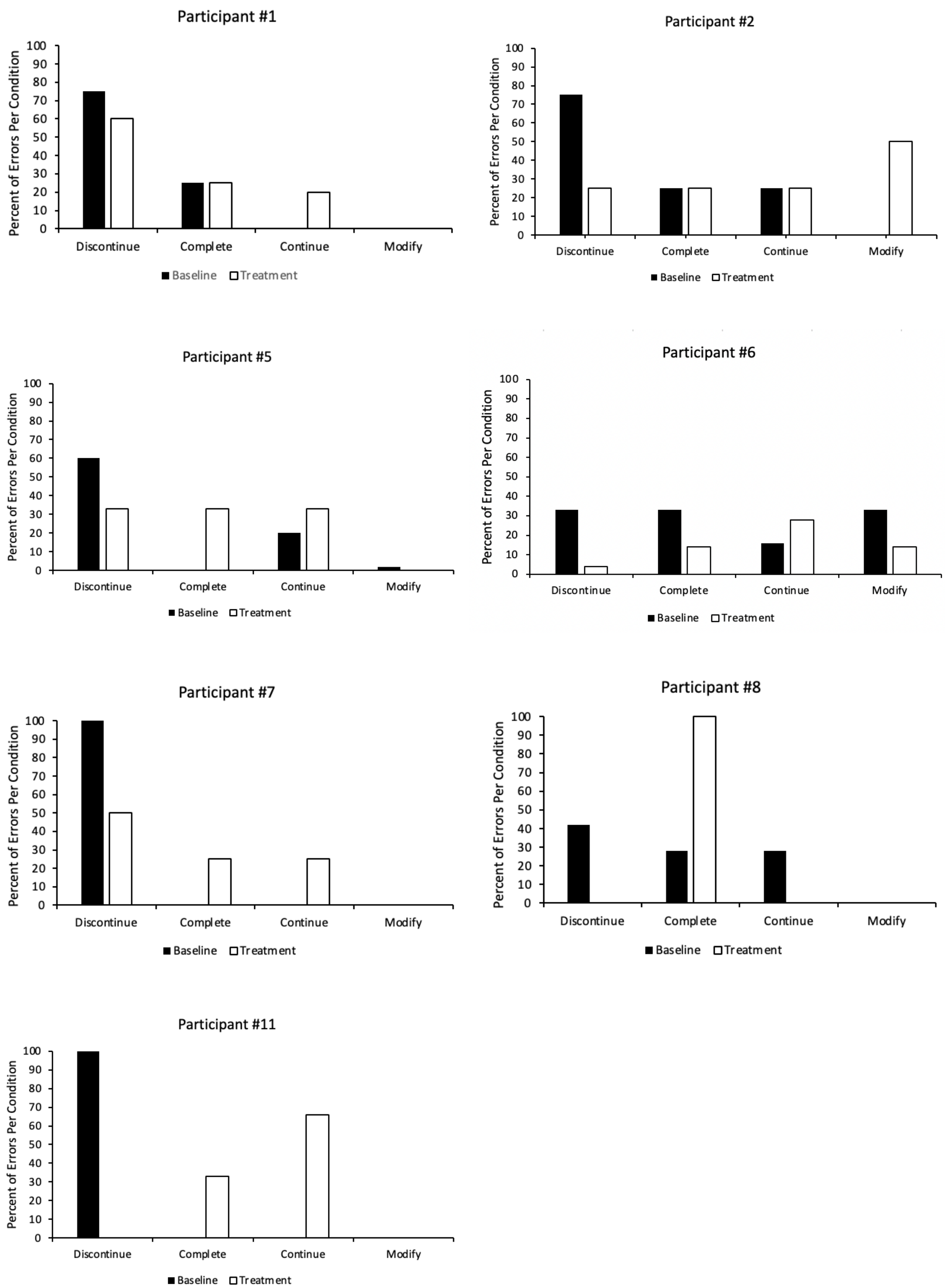
Flow Chart Visual



Note. A flow chart that visualizes the steps the participants went through in the survey

Figure 3

Percentage of Errors Bar Graphs

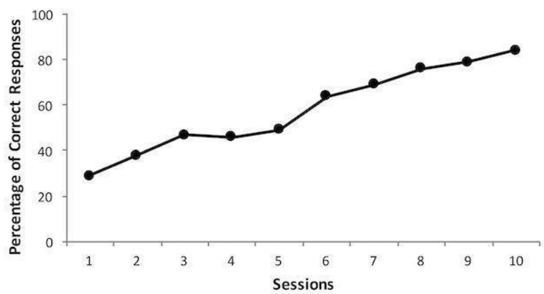


Note. Results of the error analysis for individual participants who did not meet mastery for baseline. Each question that was answered incorrectly was recorded per individual based on each response (i.e., intervention complete, continue intervention, discontinue intervention, and modify intervention). The percentage of errors was individually calculated by dividing the total amount of errors per response by the participants' total amount of errors.

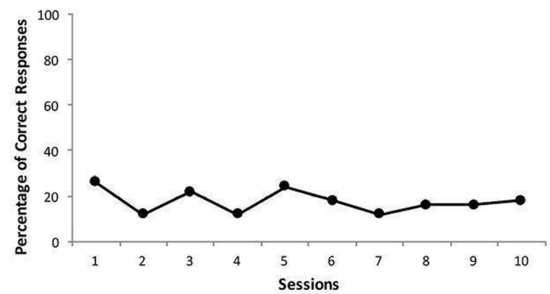
Appendices

Appendix A

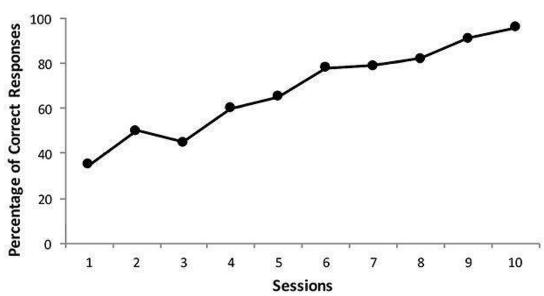
Sample Graphs



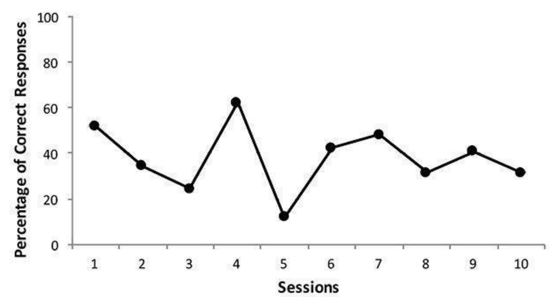
Continue Graph



Discontinue Graph

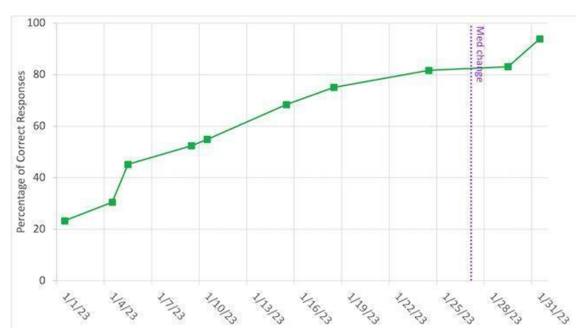


Complete Graph

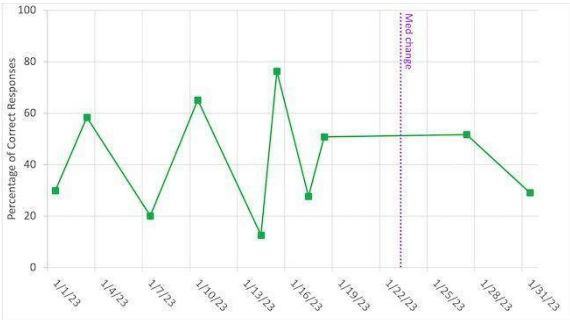


Modify Graph

Continue Graph



Complete Graph



Modify Graph

Discontinue Graph