DELAY DISCOUNTING AND TEACHER DECISION-MAKING

By

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ABSTRACT

The purpose of this dissertation was to use delay discounting to understand how teachers of students who engage in challenging behavior discount delays in behavioral treatment outcomes. Delay discounting is relevant to teacher decision-making because the length of time required to reduce challenging behavior through effective behavior interventions may deter teachers from adhering to recommended behavioral interventions. Further, discount rates may serve as an indicator of future treatment adherence (or non-adherence). The goal of the dissertation is to inform the behavioral consultation practices of behavior specialists working with teachers of students who engage in challenging behavior in order to improve the outcomes of students receiving behavioral support through the behavioral consultation model.

Chapter 2 addressed limitations to a previous delay discounting (White et al., 2023). Using the monetary choice questionnaire (MCQ; Kirby et al., 1999), the researchers reduced the length of the delay discounting task, assessed monetary and treatment discounting, and recruited 317 participants to increase statistical power to run additional inferential statistics. In the study, the authors administered the MCQ to assess discounting of monetary rewards and a treatment choice questionnaire (TCQ) modeled from the MCQ to assess discount rates of treatment outcomes. Results of the study indicate that teachers discounted monetary rewards similar to discounting of treatment outcomes. A significant difference between location groups in the low discounting group indicated that respondents that teach in the southern region of the U.S. had higher discount rates compared to remaining U.S. regions. Additionally, the authors created a 10-step fraudulent response detection process to remove any fraudulent reposes from the data set.

Chapter 3 extended the findings of Chapter 2 by determining if a specific variable – severity of behavior – impacted teachers’ rate of discounting. The authors administered two TCQs to assess

behavior severity as a state influence. One TCQ evaluated discounting of treatment outcomes for hypothetical severe challenging behavior, and the other TCQ evaluated discounting of treatment outcomes for hypothetical mild challenging behavior. Further, the authors replicated and extended the fraudulent response detection process described in Chapter 2. Results of the study indicate that teachers did discount delays to both monetary outcomes and treatment outcomes, and teachers did have higher discount rates in the severe TCQ compared to the mild TCQ. Additionally, extending the fraudulent response detection process guarded against fraudulent responses, and the inclusion of attention check questions aided in identifying fraudulent responses.

Chapter 4 presents readers with a delay discounting tutorial. The authors (1) described translational research, delay discounting, and teacher decision-making, (2) provided researchers with a step-by-step description on how to collect delay discounting data using survey research methodology and fraud protections, and (3) described areas for future research using delay discounting to examine teacher decision-making.

This dissertation is dedicated to Mom and Dad.
Thank you for always supporting me.

TABLE OF CONTENTS

CHAPTER 1 INTRODUCTION 1
REFERENCES 13
APPENDIX 20

CHAPTER 2 USING THE MONETARY CHOICE QUESTIONNAIRE TO ANALYZE THE EFFECTS OF DELAY TO TREATMENT OUTCOMES ON TEACHER DECISION-MAKING 22
REFERENCES 47
APPENDIX 52

CHAPTER 3 DOES SEVERITY OF BEHAVIOR IMPACT TEACHERS' DISCOUNT RATES? 75
REFERENCES 102
APPENDIX 107

CHAPTER 4 A TUTORIAL ON CREATING, DISSEMINATING, AND PREVENTING FRAUD IN DELAY DISCOUNTING SURVEY RESEARCH 122
REFERENCES 147
APPENDIX 151

CHAPTER 5 CONCLUSION 153
REFERENCES 162

CHAPTER 1

INTRODUCTION

Challenging Behavior in School Settings

Individuals with disabilities often engage in challenging behavior in school settings (David et al., 2022; Lee et al., 2022; Rivera et al., 2019). *Challenging behavior* can be defined as behavior that impedes the learning of the individual or others and/or threatens the physical or health safety of the individual or others (David et al., 2022). Common topographies (forms) of challenging behavior in school settings include, but are not limited to, noncompliance, physical aggression, self-injury, property destruction, and stereotypies (Alter et al., 2013; Matson & Nebel-Schwalm, 2007). Unfortunately, challenging behavior often limits students' educational opportunities because students who exhibit challenging behaviors are less likely to receive the same quality and quantity of educational opportunities as their peers (Adamson & Lewis, 2017).

Challenging behavior can also lead to social isolation from peers and can negatively impact a student's educational and social development (Lee et al., 2022; Rivera et al., 2019). For example, students who engage in challenging behavior are at higher risk of experiencing exclusionary practices (i.e., suspension and/or expulsion; Clayback & Hemmeter, 2021) and restrictive procedures (e.g., restraint and/or seclusion; LaVigna et al., 2022) resulting in time away from the classroom (McGuire & Meadan, 2022), and in worst cases, lasting psychological trauma (Freeman et al., 2023). Further, when challenging behavior is left untreated in school, students who engage in challenging behavior are at a higher risk for injury, grade retention, school suspension, and incarceration (Clayback & Hemmeter, 2021; David et al., 2022; Lee et al., 2022; McGuire & Meadan, 2022).

While challenging behavior can be difficult for teachers to manage in the classroom (Adamson & Lewis, 2017; McGuire & Meadan, 2022; Rispoli et al., 2017), challenging behavior can be reduced via effective delivery of behavioral interventions (David et al., 2022; Horner et al., 2002; Kasari & Smith, 2013; Stahmer et al., 2015; Rivera et al., 2019). For example, many school systems use positive behavior interventions and supports (PBIS) to systematically implement evidence-based behavioral interventions to all students based on their behavioral support needs (James et al., 2019). For students requiring intensive or individualized behavioral support plans, teachers can implement function-based treatments that are specifically designed to address the reasons why the student is engaging in challenging behavior (Kasari & Smith, 2013). Examples of function-based treatments that are evidence-based practices include antecedent manipulations (e.g., increasing choice-making opportunities; White et al., 2022), functional communication training (David et al., 2022), and differential reinforcement (David et al., 2022). Teachers' correct implementation of PBIS and function-based treatments yield reductions in students' engagement in challenging behavior (James et al., 2019; Lee & Gage, 2019).

Behavioral Consultation

Once children enter public school, teachers become a primary provider of behavior interventions to decrease challenging behavior (Collier-Meek et al., 2018; DiGennaro Reed & Codding, 2014; Kasari & Smith, 2013; McGuire & Meadan, 2022). In fact, the Individuals with Disabilities Act (IDEA) requires teachers to conduct functional behavior assessments (FBA) and develop behavioral intervention plans (BIP) for students with disabilities who engage in challenging behavior that impedes their learning and/or the learning of others (Drasgow & Yell, 2001; Machalicek et al., 2007; IDEA Improvement Act, 2004). To this end, IDEA mandates that teachers are responsible for (1) assessing student challenging behavior, (2) choosing and developing an intervention to address challenging behavior, and (3) implementing the intervention (West et al., 2013; White et al., 2023). Despite the aforementioned requirements, teachers consistently report that they are insufficiently prepared to make decisions regarding behavioral interventions for their students who engage in challenging behavior (McGuire & Meadan, 2022; Regan & Michaud, 2011). When additional support is needed to manage or address challenging behavior, educational experts and researchers recommend that teachers collaborate with a consultant to decrease student engagement in challenging behavior (Andersen & Daley, 2013; McGuire & Meadan, 2022; Wilkinson, 1997).

School-based consultation can be defined as a collaboration between two professionals (i.e., consultant and consultee) whereby the consultant provides recommendations to the consultee (Briere et al., 2015). *Behavioral consultation* is a subset of school-based consultation, broadly defined, where a behavior specialist (consultant) works with a teacher (consultee) to modify student challenging behavior (Butler et al., 2002). The behavioral consultation model emerged from the strategies and interventions grounded in behavior analysis such as data collection, identifying antecedents to and consequences of challenging behavior, and implementation of evidence-based treatment plans (Wilkinson, 1997). Behavioral consultation in school settings has been shown to (a) improve teachers' behavior management strategies, (b) improve teachers' implementation of behavior interventions, and (c) improve student outcomes (Briere et al., 2015; Goldenthal et al., 2021; Owens et al., 2017; Wilkinson, 1997).

The behavioral consultation process includes four stages: 1) problem identification, 2) problem analysis, 3) intervention implementation, and 4) intervention evaluation (Luiselli, 2002; Brinkman et al., 2007). The first stage focuses on the consultant and consultee identifying the problem often through interviews and baseline data collection. The second stage involves identifying the reasons why the problem is happening through functional behavior assessment. The third stage involves the teacher adhering to and implementing a recommended intervention as was designed by the consultant. The final stage includes a formal evaluation of the teachers' adherence and implementation of the intervention as well as student progress.

The goal of behavioral consultation is the change the behavior of the teacher (i.e., adherence to a recommended intervention), which, in turn, changes the behavior of the student (i.e., decreased engagement in challenging behavior) (Noell et al., 2022; Owens et al., 2017). A behavioral consultant does not implement behavior intervention plans (aside from training). Instead, consultants provide recommendations to teachers, and teachers have the choice of whether to adhere to the consultant's recommendations upon future instances of challenging behavior (Butler et al., 2002).

Treatment Adherence

Assuming the behavioral consultant makes an appropriate recommendation (i.e., an evidenced-based intervention that targets the students' behavioral function), the teacher must adhere to the behavioral consultant's recommendations for the treatment to yield a positive outcome (Brinkman et al., 2007; Falletta-Cowden & Lewon, 2022). *Treatment adherence* is considered a subset of treatment fidelity (i.e., a continuous measurement of the extent to which core elements of a treatment plan are implemented as designed; Johnson et al., 2018; Kim et al., 2018) and refers to the accurate and continued implementation of a treatment as it was designed (Allen & Warzak, 2000; Falletta-Cowden & Lewon, 2022). As a binary measure, treatment adherence indicates if the entire plan was (a) implemented as was designed or (b) was not implemented as was designed (Collier-Meek et al., 2018; Erdy et al., 2020; Garbacz et al., 2022).

Teachers certainly can adhere to recommended behavioral interventions (Noell et al., 2005); however, research suggests teachers often do not adhere to recommended behavioral interventions in the classroom (Collier-Meek et al., 2018). For example, a study by Biggs et al. (2008) examined teachers' adherence to a violence prevention program and found intervention adherence varied considerably – some teachers adhered to the intervention entirely (i.e., implemented the intervention as was prescribed), some teachers adhered to the intervention moderately (i.e., implemented some of the intervention part of the time), and some teachers did not adhere to the intervention at all (i.e., abandoned the intervention; Biggs et al., 2008). Results of the study indicate that teachers' adherence to the recommended intervention was linked to teachers' attitudes regarding the intervention, teachers' educational philosophies, and student behavior (Biggs et al., 2008). Unsurprisingly, positive student outcomes were significantly associated with their teachers' adherence to the intervention (Biggs et al., 2008). Knowing that teachers' adherence to recommended behavior interventions directly influences student outcomes (Long et al., 2018), a question then becomes: How can researchers evaluate variables that influence teachers' decisions to adhere, or not, to recommended behavior interventions?

Translational Research

Translational research presents an innovative framework for evaluating variables that affect teacher decision-making, including treatment adherence. Translational research unites fundamental scientific principles with a concern for everyday problems and outcomes (Mace & Critchfield, 2010). Translational research uses scientific knowledge, often discovered in 'pure basic' research, to address applied problems and to understand the underlying determinants of societal problems (e.g., obesity, risky behavior; Julian et al., 2022). The goal of translational research is to draw resources, capacities, procedures, and outcomes from varying scientific disciplines to enhance the overall well-being of persons (Edwards, 2017). To enhance societal well-being, translational researchers attempt to disseminate research outcomes to field-based settings so that effective and efficient practices can be implemented in applied settings such as schools, hospitals, and community centers (Edwards, 2017).

Translational research has yet to be fully explored as a means for understanding how teachers make decisions and is an emerging research method in the field of education (Jones et al., 2022). In fact, academic journals (e.g., *Journal of the Experimental Analysis of Behavior*) have recently called for an increase in translational research to understand real world problems, such as challenges in educational settings (Mace & Critchfield, 2010). Research in behavioral economics is one area of study that commonly uses translational research to understand human behavior and is often discussed in behavior-analytic journals. Behavioral economics attempts to understand the underlying determinants of behavior by analyzing the relationship between the price of a commodity (i.e., reward) and the demand for the commodity (Bickel et al., 1993). By combining the fields of behavioral science and economics, behavioral economics interprets human choices through classic economic principles (Bickel et al., 1993; Gilroy et al., 2018). The behavioral economic framework provides researchers with the capacity to examine, measure, and interpret behavior in complex, real-world scenarios (Gilroy et al., 2018). Behavioral economic approaches can also be applied to evaluate response allocation among various types of rewards and magnitudes to determine variables that may impact choice (Borrero et al., 2007; Gilroy et al., 2018).

Delay Discounting

Delay discounting is one way to understand teachers' decision-making of behavioral interventions. Delay discounting is a behavioral economic approach for understanding human decision-making and refers to the process whereby the value of a reward decreases as the delay to receive the reward increases (Odum et al., 2002). That is, the longer a person must wait for a reward, the less valuable the reward becomes (Koffarnus & Bickel, 2014). Delay discounting is commonly used to describe human patterns of decision making and provides a framework for evaluating decisions in a choice context (Critchfield & Kollins, 2001; Gilroy & Kaplan, 2020).

Decades of research indicates that delay discounting can be used as a method to better understand why individuals engage in patterns of decision-making as a reward or outcome becomes delayed (Bickel et al., 1999; Call et al., 2015; Dixon et al., 2003; Gilroy & Kaplan, 2020; Odum et al., 2002). For example, researchers have used delay discounting to analyze at-risk drinking of college students (Naudé et al., 2022), internet addiction (Cheng et al., 2021), opioid misuse (Tompkins et al., 2016), risky sexual behavior (Sweeney et al., 2020), overeating eating habits (Felton et al., 2020), gambling addiction (Dixon et al., 2016), cigarette smoking (Bickel et al., 1999), dangerous driving (Romanowich et al., 2020), cannabis misuse (McIntyre-Wood et al., 2021), and engagement in on-task behavior by students (Reed & Martens, 2011).

Discounting of delayed rewards is often analyzed by providing a person with the choice between two types of rewards: one that is available immediately and one that is available after some delay. When the rewards only differ in immediacy (e.g., receiving a $100 reward today vs a $100 reward in 7 days), most people choose the immediate reward (Call et al., 2015; Meyerson & Green, 1995). The decrease in value of the delayed reward is called *temporal discounting* (Meyerson & Green, 1995). When the amount of the immediate reward decreases and the delay between both rewards stays constant (e.g., receiving a $50 reward today vs a $100 reward in 7 days), most people will eventually select the delayed reward (Call et al. 2015). The point where a person selects the delayed reward instead of the immediate reward is called the *indifference point*

(Bickel et al., 1999; Call et al., 2015). When multiple indifference points are obtained across various delays (e.g., 1 day, 1 week, 3 months, 2 years), discount rates (*k* values) are calculated using quantitative models. Using discount rates, researchers can then determine if a persons' selections of rewards are influenced by delays to access the reward, and if so, to what extent.

Delay Discounting and Teacher Decision-Making

Delay discounting is relevant to teacher decision-making because the length of time required to reduce challenging behavior through effective behavior interventions may deter teachers from adhering to recommended behavioral interventions (and therefore reduce the value of the treatment outcome; White et al., 2023). Further, discount rates may serve as an indicator of future treatment adherence (or non-adherence). In fact, delay discounting researchers commonly evaluate the extent to which medical patients adhere to recommended medical treatments and define treatment adherence as: the extent to which a patient follows a medical treatment plan (e.g., medication regimen, stretching plan) over time as was recommended by the medical provider (LeBeau et al., 2016).

A recent study by White et al. (2023) used the delay discounting framework to understand how current special education teachers of students who engage in challenging behavior make decisions regarding behavioral interventions. In the study, 22 special education teachers completed an online delay discounting task that asked participants to make hypothetical treatment decisions for a hypothetical student that engaged in challenging behavior. The task consisted of 378 trials and took an average of 39 minutes to complete. For each trial, participants were asked to choose between two options - a larger delayed reward (LDR) (i.e., behavior reduction after some delay) and a smaller immediate reward (SIR) (i.e., immediate behavior reduction) (see Figure 1 below for an example trial). The immediate reward varied from 0.01

years to 10 years, the delayed reward remained constant at 10 years, and there were 7 delays (i.e., 1 week, 2 weeks, 1 month, 6 months, 1 year, 3 years, and 10 years) (Call et al., 2015; Odum et al., 2002). Using the Johnson and Bickel (2008) criteria for identifying nonsystematic delay-discounting data, the researchers determined that 21 of the 22 participants made selections consistent with delay discounting (see Figure 2 below, which represents group responding observed by White et al.). Further, results from the Bayesian model selection (Franck et al., 2015) indicated the Rachlin (2006) model best described the 21 remaining datasets. For 18 of these participants, the median R^2 was high at .90 (IQR .47—.96).

Like previous research findings (Call et al., 2015; Gilroy & Kaplan, 2020), results obtained by White et al. (2023) provide initial support that delay discounting may be used as a framework for evaluating practice-related decisions. However, there are several limitations to White et al. that must be addressed. First, the authors replicated the original procedure for discounting of delayed rewards (Odum et al., 2002) that included 378 repetitive choice trials. Within the traditional delay discounting procedure, each trial is presented twice (i.e., in an ascending and descending order) which increases the effort and time required to complete the survey. The large number of trials resulted in task completion averaging 39 min, which likely resulted in participants not completing the survey thus explaining the small sample size. The recruited sample was also underpowered and prevented the authors from assessing variables that may be associated with discounting. Efforts to decrease the number of trials and time to complete the survey may allow for researchers to study delay discounting in larger samples of teachers. Further, the delays presented (i.e., up to a 10-year delay) do not reflect the period in which teachers provide services to students and may have resulted in participant attrition or biased responding (e.g., side-bias selections) (Vanderveldt et al., 2016). Finally, because White et al.

did not assess participant discounting of a commonly evaluated commodity (i.e., money), the researchers were unable to determine if discounting of treatment outcomes is due to the commodity (i.e., behavior reduction) or an individual trait variable (often referred to as impulsivity; see Odum et al., 2011 for a discussion of trait variables).

Purpose of the Dissertation

The purpose of this dissertation is to use build upon my previous research in teacher decision-making by using the delay discounting framework to understand how teachers of students who engage in challenging behavior discount delays in behavioral treatment outcomes. The goal of the dissertation is to inform the behavioral consultation practices of specialists working with teachers of students who engage in challenging behavior in order to improve the outcomes of students receiving behavioral support through the behavioral consultation model.

Chapter 2. The purpose of Chapter 2 was to extend the work completed by White et al. (2023). Specifically, the aim of the first study was to determine if the monetary choice questionnaire (MCQ; Kirby et al., 1999) captured delay discounting of hypothetical rewards by teachers of students who engage in challenging behavior consistent with previous delay discounting literature (White et al., 2023). To do so, the authors administered the MCQ to assess discount rates of monetary rewards and a treatment choice questionnaire (TCQ) modeled from the MCQ to assess discount rates of real-world outcomes (i.e., treatment effects). By using the MCQ, I address limitations to my previous delay discounting study (i.e., length of delay discounting task, use of non-real-world delays, no comparison between real and hypothetical outcomes, underpowered sample size). Further, a sample of 317 teachers were recruited in order to determine what, if any, demographic characteristics correlate to discounting of delays to treatment effects. I asked the following research questions:

1. Using the monetary choice questionnaire as a tool to measure delay discounting, do teachers of students who engage in challenging behavior discount hypothetical treatments as a function of delays to the treatment outcomes?
2. What, if any, demographic variables are associated with teachers' discount rate in treatment outcomes?

Chapter 3. The purpose of Chapter 3 was to extend the findings of study one by (a) determining if a specific variable – severity of behavior – impacts teachers' rate of discounting, (b) adding additional fraudulent protections to the survey, and (c) adding an additional step to the fraudulent response detection process. Two treatment choice questionnaires were administered to evaluate discounting of treatment effects as a function of severity of problem behavior. One treatment choice questionnaire evaluated discounting of treatment outcomes for a hypothetical student that engaged in severe challenging behavior, and the other treatment choice questionnaire evaluated discounting of treatment outcomes for a hypothetical student that engaged in mild challenging behavior. Assessing specific variables that may impact rates of discounting expands on previous delay discounting research attempting to evaluate how environmental variables or context impact discounting. Further, we extended the fraudulent prevention and detection process by (1) password protecting the survey, (2) removing the incentive amount on the recruitment flier, (3) embedding additional Qualtrics fraud protections into the survey, (4) including three attention check questions, and (5) avoiding survey dissemination on public social media feeds. I asked the follow research questions:

1. How does severity of behavior impact the discount rate of teachers of students who engage in challenging behavior?

2. Does the proportion of fraudulent survey responses decrease with additional fraudulent response protections?

Chapter 4. The purpose of Chapter 4 is to translate the methodology and findings from studies one and two into a tutorial for researchers interested in using delay discounting to analyze variables that impact teacher decision-making. Specifically, the tutorial (a) describes translational research and delay discounting as they relate to teachers' decision-making, (b) provides researchers with a tutorial on how to collect delay discounting data using survey research methodology and fraudulent response protections, and (c) describes how researchers can use delay discounting data to inform future research.

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APPENDIX

Figure 1.
Example of a choice trial in White et al., (2023)

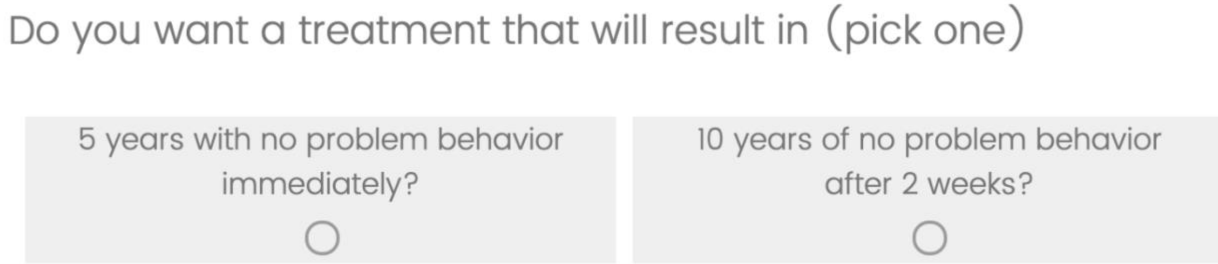
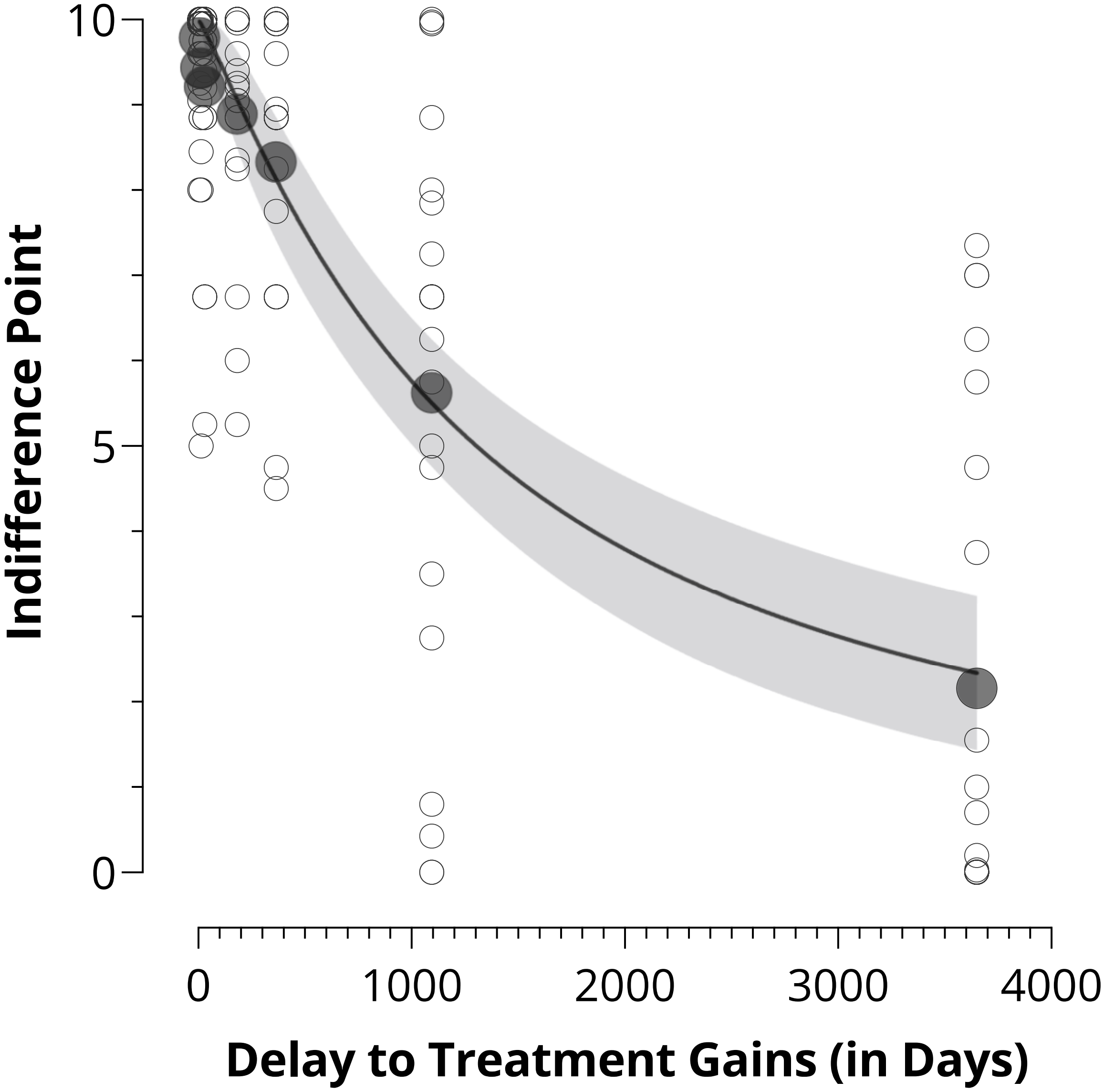


Figure 2.

Delay discounting graph from White et al. (2023). The graph depicts indifferent point as a function of delay to treatment gains (in days)—the open circles depict individual participant indifferent points at each delay, with larger shaded circles depicting the mean indifference point across all 22 participants.



Note. The curve depicts that participant preferences for treatment outcomes decreased as the delay to behavior reduction increased.

CHAPTER 2

USING THE MONETARY CHOICE QUESTIONNAIRE TO ANALYZE THE EFFECTS OF DELAY TO TREATMENT OUTCOMES ON TEACHER DECISION-MAKING

One of the biggest challenges facing teachers and administrators today is the management of challenging behavior in the classroom (Charlton et al., 2021). When additional behavior support is needed in school settings, both general and special educators are encouraged to collaborate with behavioral consultants to functionally assess student engagement in challenging behavior and develop a treatment plan to decrease the challenging behavior (Owens et a., 2020; Watson & Robinson, 1996). Within the behavioral consultation model, consultants work indirectly to modify student challenging behavior by providing teachers with the skills to directly address future instances of challenging behavior (Falletta-Cowden & Lewon, 2022). Therefore, teachers are responsible for delivering consultant-recommended behavior interventions to their students who engage in challenging behavior in the classroom (Falletta-Cowden & Lewon, 2022; Collier-Meek et al., 2018).

The success of consultant-recommended behavioral interventions relies on the correct implementation of the intervention as was prescribed, often referred to as treatment adherence (Rispoli et al., 2017). However, teachers commonly do not implement recommended behavior interventions as they were prescribed or abandon the intervention entirely (Rispoli et al., 2017). The choice to not implement a recommended behavior intervention as designed may be due to a lack of training or support that teachers need to implement behavior interventions (Briere et al., 2015). Further, in a study by Collier-Meek et al. (2018), teachers report that the greatest barriers to implementing behavior interventions are (1) physically managing the challenging behavior, (2) remembering to implement the intervention, and (3) competing classroom and instructional responsibilities. Teachers in the study also reported temporal-related barriers such as the length of time it takes to implement an intervention and rate of behavior reduction as additional barriers to treatment implementation (Collier-Meek et al., 2018). Regardless of the variables that may impact teacher decision-making of recommended behavioral interventions, teacher choice to implement interventions differently than prescribed, or not at all, is problematic, because the teacher may implement an intervention contraindicated to behavioral function, may utilize restrictive procedures (e.g., restraint), or reinforce the challenging behavior causing it to persist over time (Allen & Warzak, 2000).

Even if teachers implement an intervention as prescribed, reduction to challenging behavior may not be immediate (Allen & Warzak, 2000). In fact, interventionists often encounter some sort of a delay before they see reductions in challenging behavior (Allen & Warzak, 2000; Call et al., 2015; Hagermoser Sanetti et al., 2014). For example, a study by Romaniuk et al. (2002) implemented a choice-making intervention to decrease participants engagement in challenging behavior in a school setting. Even though the trained therapist adhered to the intervention across all participants, challenging behavior did not decrease to a rate of zero immediately for any participant. The Romaniuk et al. study demonstrates that even when a highly trained professional implements a behavioral intervention, challenging behavior may not decrease immediately or may not decrease to zero levels. Delays to reductions in challenging behavior are concerning, because when immediate changes in behavior are not contacted by teachers, teachers may stop implementing the intervention all together or may choose to implement a different intervention (Allen & Warzak, 2000; Kasari & Smith, 2013).

Teacher decision-making of recommended behavioral interventions can be understood in a choice context. Consider an example where a teacher has been recommended to implement a behavior intervention to decrease a student's engagement in challenging behavior. In this scenario, as it relates to adherence, the teacher has two options. Option 1 is to implement the recommended behavior intervention as was prescribed, and option 2 is to not implement the recommended intervention as prescribed. A rational decision may be for the teacher to choose option 1 – adhere to the recommended intervention. However, there may be barriers (e.g., lack of resources, instructional limitations, personal philosophies) that prevent the teacher from adhering to the recommended intervention. When teachers encounter barriers to treatment adherence, they may be inclined to choose option 2 and not adhere to the recommended treatment.

Keeping with the example, consider a scenario where the teacher implements the behavior intervention as recommended by a behavior consultant, but the student continues to engage in challenging behavior. In this scenario, it would be reasonable to assume that the teacher's future adherence to the intervention could decrease because the intervention did not immediately reduce the challenging behavior. In fact, when there are concurrent schedules of reinforcement available (i.e., multiple response options to choose from), most people do prefer the schedule that results in (a) more frequent reinforcement, (b) a greater magnitude of reinforcement, and (c) less response effort (Allen & Warzak, 2000). In the above example, reinforcement is assumed to be reductions in challenging behavior. When the teacher selected option 1 (i.e., adhered to the recommended intervention), they did not immediately access reinforcement (i.e., behavior did not decrease). Not surprisingly, the teacher may choose to not adhere to the recommended intervention in the future and instead provide a consequence contraindicated to behavioral function (e.g., reinforce the behavior) the next instance of challenging behavior. Here, the teacher may instead reinforce the challenging behavior, because reinforcing the behavior will likely result in immediate behavior reduction (Iwata et al., 1982).

However, the extent to which and under what conditions teachers decide to select option 2 (i.e., not adhering to the recommended intervention) are not well understood.

Delay Discounting

One way to evaluate teacher decision-making in a choice context is through delay discounting. Delay discounting is a behavioral economic measurement of the reduction in the value of a reward as the delay to access the reward increases (Grey et al., 2016). That is, rewards become devalued as a function of their delayed receipt (Kaplan et al., 2016). Delay discounting is commonly used to describe human patterns of decision making (Critchfield & Kollins, 2001; Gilroy & Kaplan, 2020) and to estimate impulsive decisions such as cigarette smoking (Bickel et al., 1999), gambling (Dixon et al., 2003), and, more recently, treatment non-adherence (White et al., 2023). Studies by Call et al. (2015) and Gilroy and Kaplan (2020) use the delay discounting framework to better understand caregivers' long-term treatment adherence. Both studies demonstrated that caregivers' decision-making was indeed influenced by delays to treatment effects and suggests that delays to treatment effects are a factor in how caregivers make decisions of whether to implement recommended behavioral treatments. Further, by validating that caregivers discount the value of delayed treatment outcomes, Call et al. and Gilroy and Kaplan suggested delayed discounting could be an appropriate method to analyze decision-making in the treatment of problem behavior.

A recent study by White et al. (2023) extended Call et al. (2015) and Gilroy and Kaplan (2020) by using the delay discounting framework to analyze how special education teachers of students with disabilities discount delays in behavioral treatment effects. Twenty-two special education teachers completed a delay discounting task containing 7 delays (i.e., 1 week, 2 weeks, 1 month, 6 months, 1 year, 3 years, and 10 years) and 27 immediate rewards for a total of 378 choice trials. Results of the study suggest that teachers of students with disabilities may discount delays in behavioral treatments consistent with the delayed discounting hyperboloid model. However, the researchers were only able to recruit 22 participants minimizing the statistical power needed to further analyze associations between variables and discount rates and generalizability of their results.

Another limitation of White et al. (2023) was the use of the traditional delay discounting task (i.e., 378 trial task) to evaluate participant choices. The length of time it takes to complete the task (average 39 min/participant) and the repetitive nature of the task (i.e., presentation of 378 similar trials) may have influenced participant dropout thereby decreasing the sample size (Call et al., 2015). Efforts to decrease the length of time required to assess delay discounting (e.g., decreasing the number of trials) may make it possible to study delay discounting in larger samples (Call et al., 2015). Additionally, the delays used previous research (i.e., 1 week, 2 weeks, 1 month, 6 months, 1 year, 3 years, and 10 years) likely do not represent the duration a teacher works with a student; teachers typically do not serve students for up to 10 years. Administering a discounting task with delays that reflect real-world scenarios may yield more generalizable results.

Given the above-mentioned limitations to White et al. (2023), modifications to the discounting task are necessary to make task completion more feasible for teachers of students who engage in challenging behavior. One way to address the multiple limitations to White et al. is to administer an abbreviated delay discounting assessment commonly used in the behavioral economic literature, the Monetary Choice Questionnaire (MCQ; Kirby et al., 1999). The 27-item MCQ (Kirby et al., 1999) is a widely used and validated measure of delay discounting of hypothetical rewards (Gray et al., 2016; Kaplan et al., 2016). The MCQ has a test-retest reliability score of .71 across 1-year (Hamilton et al., 2015; Towe et al., 2015), mitigates floor and ceiling effects (Myerson et al., 2014), and the difference in discounting scores between test and control groups further attests to the tools' construct validity (Myerson et al., 2014). The MCQ is a self -report task where individuals are asked to choose between two monetary rewards: a smaller immediate reward (SIR) and a larger delayed reward (LDR). Within the MCQ, three magnitudes of rewards are assessed to provide discount rates (*k* values) for small, medium, and large rewards as well as an overall discount rate (Gray et al., 2016). Estimating discount rates across multiple reward sizes allows researchers to assess a *magnitude effect* – the tendency for discount rates to decrease as the magnitudes of the delayed rewards increase (Kirby et al., 2009). The MCQ's ease of administration has resulted in the MCQ being a core procedure in survey and clinical research on delay discounting in applied settings (Kaplan et al., 2016).

The Current Study

Administering the MCQ to teachers of students who engage in challenging behavior will address limitations in White et al. (2023) in the following ways. First, the MCQ includes 27 choice trials. Because researchers encourage assessing discounting in a common commodity (e.g., money) as well as a real-world outcome (e.g., treatment outcomes), participants were only provided with two delay discounting questionnaires each containing 27 choice trials (e.g., total of 54 choice trials) as opposed to 378. Further, responding to 54 choice trials requires much less time and effort to complete as compared to the traditional delay discounting task (Kaplan et al., 2016). Second, the MCQ includes delays that range from 7 days to 186 days. These delays are well within the typical period of time in which a teacher serves a student. Finally, the decrease in choice trials, decrease in time and effort to complete the task, and framing of delays to represent real-world scenarios may result in a larger participant sample increasing the statistical power required for additional analyses.

The purpose of the study was to make procedural adjustments to previous research (White et al., 2023) by using the monetary choice questionnaire (MCQ; Kirby et al., 1999) to assess discounting of delay rewards by teachers of students who engage in challenging behavior. The MCQ addresses limitations to White et al. because it allows the researchers to (a) reduce the length of the task, (b) assess monetary and treatment discounting, and (c) recruit more participants to increase statistical power to run additional inferential statistics. In the study, the authors administered the MCQ to assess discount rates of monetary rewards and a treatment choice questionnaire (TCQ) modeled from the MCQ to assess discount rates of real-world outcomes (i.e., treatment effects). Further, a large sample of 317 teachers were recruited to determine what, if any, demographic characteristics are associated with discounting of delays to treatment effects. I asked the following research questions:

1. Using the monetary choice questionnaire as a tool to measure delay discounting, do teachers of students who engage in challenging behavior discount hypothetical treatments as a function of delays to the treatment outcomes?
2. What, if any, demographic variables are associated with teachers' rate of discounting treatment outcomes?

Method

Recruitment

The delay discounting survey was disseminated on February 22, 2023, and closed on February 27, 2023. We recruited respondents by distributing a recruitment flier (Figure 3) to personal contacts (e.g., emailing professional colleagues) and social media (i.e., Facebook and Twitter). To participate, respondents needed to be (1) a current teacher (2) who currently serves students who engage in challenging behavior. During the six days in which the survey was opened, 5,240 responses were recorded. After filtering out fraudulent responses (discussed in detail below), 317 responses remained.

Fraudulent Response Detection

Internet-based survey research presents opportunities to recruit a diverse participant pool across a large geographic area (Griffin et al., 2021). Further, anonymity and confidentiality of internet-based research provides a space for participants to disclose honest information, especially for those who may be apprehensive to express their opinions (Ballard et al., 2019). Unfortunately, the confidentiality and anonymity in internet-based research also allows for the collection of fraudulent, bot, and/or smart software responses that resemble human-like data (Ballard et al., 2019; Griffin et al., 2021; Teitcher et al., 2015). After receiving over 5000 responses in six days, the researchers examined the data and hypothesized that the survey had fallen victim to fraudulent survey responses. Upon reviewing responses in the survey program Qualtrics (Qualtrics, Provo, UT), the authors immediately identified many responses flagged by Qualtrics as fraudulent. The authors ended data collection (Storozuk et al., 2020) and employed an in-depth fraud detection process.

The total number of recorded responses (N=5,240) was filtered to 317 using a 10-step fraud detection process (Figure 4). First, the survey program Qualtrics (Qualtrics, Provo, UT) identified duplicate responses and potential bots (Ballard et al., 2019; Griffin et al., 2021). Qualtrics fraud protections utilized for the current study included reCAPTCHA (Completely Automated Public Turing Test to tell Computers and Humans Apart) to identify potential bots and prevent ballot box stuffing (a tool that places a cookie on respondent’s browser) to identify duplicate respondents (Griffin et al., 2021; Lawlor et al., 2021; Pratt-Chapman et al., 2021).

Next, the researchers filtered out responses that were not 100% complete (Buchanan & Scofield, 2018). Third, we filtered responses based on a Qualtrics-generated fraud score (i.e., variable labeled Q_RelevantIDFraudScore). The minimum fraud value is 0, and the maximum fraud value is 130. Based on RelevantID and Qualtrics recommendations, a score greater than or equal to 30 indicates fraudulent responding; therefore, we removed responses with a fraud score greater than 29. Next, we filtered out any response that provided the same email address in more than one response as this indicated a duplicate response (Ballard et al., 2019; Lawlor et al., 2021). Next, we removed any response with a location, determined by latitude and longitude coordinates collected through Qualtrics, outside of the United States (Ballard et al., 2019; Griffin et al., 2021; Pratt-Chapman et al., 2021; Storozuk et al., 2020). We then filtered out responses where the response duration was under 300s or over 3600s (Ballard et al., 2019; Buchanan & Scofield, 2018; Griffin et al., 2021). Based on pilot data collected with graduate students in a university special education master's program, the survey was anticipated to take an average of 16 min to complete.

Then, we removed any response with the same IP address as another response, and we also removed any response with the same latitude and longitude coordinates as another response (Griffin et al., 2021; Lawlor et al., 2021). Finally, two independent researchers visually inspected the remaining 417 responses for email addresses provided by respondents (Ballard et al., 2019; Griffin et al., 2021; Storozuk et al., 2020). There were five phases included in the email filtration process. We removed any email address that (a) ended in more than four numbers (Griffin et al., 2021), (b) were missing (e.g., entering a name instead of an email address; Pratt-Chapman et al., 2021), (c) contained more than one "@," ".com," or email system (e.g., "gmail"), (d) contained the word "bot," "poll," or "survey," and (e) comprised of a random string of characters (e.g., svzajpdhnpbe8367; Griffin et al., 2021; Pratt-Chapman et al., 2021). Interobserver agreement for the email analysis was 89%. At the completion of the filtration process, we were left with 317 responses. We sent emails to all respondents that were identified as fraudulent to alert them that they would not be receiving compensation (Pratt-Chapman et al., 2021).

Participants

The final sample was comprised of 317 participants. The majority (58.4%) of participants were between 30 and 39 years old, identified as white non-Hispanic (72.6%), and held a special education license (84.2%). 52.4% of participants identified as male and 45.4% of participants identified as female. About half of the participants held a bachelor's degree (49.8%) and had six to 10 years of experience as a teacher (46.4%). The majority of participants reported receiving professional development in developing interventions to reduce challenging behavior (93.4%), professional development in implementing interventions to reduce challenging behavior (89%), and previous experience collaborating with a related service provider to decrease student engagement in challenging behavior (90.9%). Please see Table 1 for all participant reported demographics.

Procedure

Participants completed the study[1] in the survey program Qualtrics. The study included a total of 72 questions; there was one reCAPTCHA question, one question regarding informed consent, two questions clarifying inclusion criteria, 54 delay discounting questions (the MCQ and TCQ each consisted of 27 choice trials), and 14 questions related to teacher and school demographics (see Table 2 for demographic questions). The study took an average of 17 minutes and 24 sec (range, 5 min 1.8 sec – 59 min 46.8 sec) to complete. Upon completion of the task,

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[1]Please click the following link to access the survey.
https://msu.co1.qualtrics.com/jfe/form/SV_6xPNlmYfjB5uW5E

participants were given an opportunity to provide their e-mail address to receive compensation in the form of a $10 Amazon.com gift card.

To begin the survey, participants read an institutional review board (IRB) informed consent document and indicated if they consented or did not consent to participate. Upon consent, participants then answered screening questions to determine if they were a current teacher serving students who engage in challenging behavior. If participants passed the screening (i.e., answered "yes" to all screening questions), they were then presented with the MCQ or the TCQ. The order of the MCQ and TCQ were randomized across participants (Lemley et al., 2017).

Monetary Choice Questionnaire

When presented with the MCQ, participants were provided the following statement:

> For the first part of this experiment, you will be asked to make choices about hypothetical amounts of money. You will not receive any money; however, we ask that you make choices as if you were to receive the money. For each trial, you will see two options. One option will offer money today. The other option will offer money after some delay. Pick the option that you would rather have. You will continue to see two options presented to you after each choice that you make. Please continue to pick the option that you would rather have.

After reading the statement, the MCQ began. The first MCQ trial (see Figure 5) appeared on participants' screens and each subsequent trial was presented individually on separate pages.

Treatment Choice Questionnaire

When presented with the TCQ, participants were provided the following statement:

> For the second part of this experiment, you will be asked to make choices about treatment

> options for a hypothetical student that engages in challenging behavior. The treatment outcomes are hypothetical, but we ask that you make choices as they were real. You will see two options. One option will offer you a treatment that will stop your student's engagement in challenging behavior immediately. The other option will offer you a treatment that will stop your student's engagement in challenging behavior after some delay. Pick the option that you would rather have. You will continue to see two options presented to you after each choice that you make. Please continue to pick the option that you would rather have.

The first treatment choice trial (see Figure 6) appeared on participants' screens. The treatment choice questionnaire was modeled after the MCQ (Dassen et al., 2015; Mezzio et al., 2018; Schultz van Endert & Mohr, 2022; Tompkins et al., 2016) whereby monetary rewards were changed to days without challenging behavior.

Demographic Questions

Following completion of the MCQ and the TCQ, participants answered 14 demographic questions. Please see Table 2 for demographic questions.

Data Analysis

Data analysis entailed three steps: (1) fraudulent response detection (discussed above in recruitment), (2) calculation of discount rates, and (3) statistical analysis. In the next section, we will describe steps two and three of our data analysis.

Discount Rates

A freely available Excel-based spreadsheet tool was used to calculate *k* values (Kaplan et al., 2014). To calculate discount rates (*k* values), participant selections in the MCQ and TCQ were entered into the Excel[2] spreadsheet. For each of the 27 items in both questionnaires, a "0" was entered if the participant selected the SIR, and a "1" was entered if the participant selected the LDR (Kaplan et al., 2016). A participant with many 0s and few 1s indicates steep discounting (i.e., high *k* value), and a participant with few 0s and many 1s indicates shallow delay discounting (i.e., low *k* value) (Kaplan et al., 2016). Overall *k* values are estimated based on the entire 27-item response pattern across trials (Kaplan et al., 2016; Nighbor et al., 2018). The tool computed standard hyperbolic-based *k*, transformed log and natural log *k*, and supplementary measures (proportion of LDR choices, summary statistics). Because the distribution of raw *k* values tends to be skewed, we used the log transformation of *k* values (Kaplan et al., 2016; Nieto et al., 2022; Peng et al., 2019). As a second method to evaluate group discounting (Myerson et al., 2014), we analyzed the proportion of participants choosing the SIR across trials. The tool also provided consistency scores to identify participants showing lack of comprehension or effort (Kaplan et al., 2016). Consistency scores below 75% were excluded from the analysis (Kaplan et al., 2016). We excluded 173 participants due to their overall consistency scores being less than 75% in either the MCQ or the TCQ leaving a total of 144 participants included for analysis (Dassen et al., 2015).

Decision-Making Across Contexts. Because the same participants completed a questionnaire for both rewards (i.e., money and treatment outcomes), a dependent samples *t* test was conducted to determine if participants' mean log geomean *k* values were significantly different between the two rewards (Bickel et al., 1999; Dassen et al., 2015; Madden et al., 2010). Liner regression was run to determine if discount rate in the MCQ predicted discount rate in the TCQ.

[2] The scoring tool can be downloaded through the following link: https://kuscholarworks.ku.edu/handle/1808/15424.

Statistical Analysis

One way ANOVA was conducted to determine if discount rates in the TCQ were different for groups of participants within demographic variable groups (i.e., age, ethnicity, highest level of education, number of years of experience, location, percent of students receiving FRL, and percent of students that engage in challenging behavior). Post hoc tests determined if there were any statistically significant differences in discount rates in the TCQ between the groups. Independent samples t-tests were conducted to determine if discount rates in the TCQ were different for groups within dichotomous demographic variable groups (i.e., gender, holding a special education license, previous experience with professional development in developing interventions and implementing interventions, previous experience collaborating with a related service provider).

Participants were then split into two groups, low and high discounting, via a median split of log geomean *k* values in the TCQ (Nighbor et al., 2019; Romanowich et al., 2020). We used nonparametric tests due to outliers and the smaller samples sizes from to the median split. Mann-Whitney U tests were run to determine differences in discount rate between dichotomous demographic variable groups (i.e., gender, holding a special education license, previous experience with professional development in developing interventions and implementing interventions, previous experience collaborating with a related service provider). Kruskal-Wallis H tests were run to determine differences in discount rate between groups within categorical demographic variable groups (i.e., age, ethnicity, highest level of education, number of years of experience, location, percent of students receiving FRL, and percent of students that engage in challenging behavior). When outliers were present, we included all outliers in the analysis. Statistical analyses were conducted in SPSS (Version 27) with assistance from Laerd Statistics

(2017).

Results

Discount Rates

Table 3 summarizes the primary variables used to analyze discounting of delayed rewards. These variables include raw overall *k* values and log transformed geomean *k* values for both the MCQ and the TCQ. For participants included in statistical analysis, the mean log geomean *k* value in the TCQ was .023 (95 CI, -.086 to .132) lower than the mean log geomean *k* value in the MCQ. There was no statistically significant decrease in the mean log geomean *k* value for the TCQ compared to the mean log geomean *k* value in the MCQ, $t(143) = .420$, $p = .675$, suggesting that participants discounted hypothetical monetary rewards similar to hypothetical treatment outcomes. Additionally, there was a statistically significant correlation between the mean log geomean *k* value in the MCQ and TCQ, $r(142) = .724$, $p < .001$. Results of the linear regression indicate log geomean *k* values in the MCQ accounted for 52.4% of the variation in log geomean *k* values in the TCQ with adjusted R^2 = 52.1% and was statistically significant, $F(1,142) = 156.295$, $p < .001$. The regression equation was: predicted log *k* values in the TCQ = -.508 + .701 x (log geomean *k* values in the MCQ).

Monetary Discounting

For monetary discounting, the mean(SD) overall *k* value for participants included in analysis was 0.0856(0.0964) and the mean(SD) log geomean *k* value was -1.6239(0.9026). Raw *k* values are ranked from 1 to 9 with 1 being the lowest rank ($k = 0.00016$) and 9 being the highest rank ($k = 0.25$). Using the *k* value ranks (see Table 4), the raw overall *k* value falls between rank 7 (0.041) and rank 8 (0.1) suggesting that, as a group, participants did discount delayed monetary rewards (Towe et al., 2015). We then graphed the group proportion choices of the SIR at each *k* value (Figure 7) and found that the proportion of SIR selections decreased systematically as a function of delays. That is, at the largest delays, a large proportion of participants (.88) chose the SIR, and at the smallest delays, a small proportion of participants (.25) chose the SIR.

Treatment Outcome Discounting

For discounting of treatment outcomes, the mean(SD) overall *k* value for participants included in the analysis was 0.0887(0.1063) and the mean(SD) log geomean *k* value was -1.647(0.8743). The mean overall *k* value falls between rank 7 and rank 8 indicating steep discounting of hypothetical treatment outcomes at the group level. We graphed the group proportion choices of the SIR at each *k* value (Figure 8). At the largest delays, a large proportion of participants (.88) chose the SIR, and at the smallest delays, a smaller proportion of participants (.31) chose the SIR.

Statistical Analysis

For the one-way ANOVAs, there were not significant outliers in any group, as assessed by boxplots, and skewness and kurtosis statistics as well as inspection of Q-Q plots confirmed that the discount rates were approximately normal across all groups. We used the Bonferroni correction to adjust the p value to .00714. Homogeneity of variances, as assessed by Levine's test for equality of variances, was met for age (p = .099), ethnicity (p = .194), and highest level of education (p = .497). Homogeneity of variances was not met for number of years of experience as a teacher (p = .036), location (p = .021), percentage of students receiving FRL (p = .001), and percentage of students who engage in challenging behavior (p = .017). We used Welch's ANOVA for variables that did not meet homogeneity of variances. There were no statistically significant differences in discount rates between any groups (Table 5).

For the independent samples t-tests, inspection of Q-Q plots confirmed that the discount rates were approximately normal across variables. We used the Bonferroni correction to adjust the p value to .01. Homogeneity of variances was not assumed for gender ($p = .002$); therefore, we used a Welch t-test. Homogeneity of variances was assumed for obtaining a special education license ($p = .250$), previous experience receiving professional development in developing behavioral interventions ($p = .832$), previous experience receiving professional development in implementing behavioral interventions ($p = .766$), and previous experience collaborating with a related service provider ($p = .481$). Male mean discount rate in the TCQ was 0.133 (95% CI, -.175 to .442) higher than female mean discount rate. For participants obtaining a special education license, the mean discount rate was 0.336 (95% CI, 0.741 to 0.07) higher than the mean discount rate of those not obtaining a special education license. For participants with experience receiving professional development in developing behavioral interventions, the mean discount rate was 0.395 (95% CI, -1.022 to .233) higher than the mean discount rate of those with no experience receiving professional development in developing behavioral interventions. For participants with experience receiving professional development in implementing behavioral interventions, the mean discount rate was 0.424 (95% CI, -.99 to .14) higher than the mean discount rate of those with no experience receiving professional development in implementing behavioral interventions. For participants with experience collaborating with a related service provider, the mean discount rate was 0.059 (95% CI, -.546 to .43) higher than the mean discount rate of those with no experience collaborating with a related service provider. There were no statistically significant differences in mean discount rate between groups (Table 6).

Low and High Discounting Groups

Participants were then split into a low and high discounting group via a median split of log geomean *k* values in the TCQ (Mdn = -1.5981). 62 participants (43.1%) were assigned to the low discounting group. 82 participants (56.9%) were assigned to the high discounting group. For the Mann-Whitney U tests, we used the Bonferroni correction to adjust the *p* value to .01. There were no statistically significant differences between groups for either the low or high discount rates (Table 8). For the Kruskal-Wallis H tests, we used the Bonferroni correction to adjust the *p* value to .00714. There were statistically significant differences in discount rates between location groups in the low discounting group: “Northeast” (*n* = 10), “Midwest” (*n* = 36), “South” (*n* = 18), and “West” (*n* = 11). Pairwise comparisons were performed with a Bonferroni correction, and values presented are mean ranks with adjusted *p* values. The post hoc analysis revealed statistically significant differences in discount rate between the Northeast (23.8) and South (56.61) (*p* = .001), and Midwest (33.81) and South (*p* = .002). There were no other statistically significant differences between groups for either the low or high discount rates (Table 8).

Discussion

Teachers often collaborate with behavioral consultants when designing and implementing behavioral interventions intended to decrease students’ engagement in challenging behavior (McGuire & Meadan, 2022). The success of consultant recommended behavioral interventions relies on teachers’ adherence to the intervention as was prescribed; however, teachers commonly do not adhere to recommended behavioral treatments (Allen & Warzak, 2000; Gilroy & Kaplan, 2020). There are many reasons why a teacher may not adhere to a recommended behavioral intervention including lack of training (Brock & Beaman-Diglia, 2018), rate of behavioral incidents (Collier-Meek et al., 2018), and progress monitoring for all students (Kasari et al., 2013). The current study used delay discounting to analyze how delays to treatment outcomes impact teacher decision-making. Understanding how delays to reductions in challenging behavior influence teachers' decision to adhere to recommended interventions may aid in understanding why teachers may or may not adhere to interventions so that future research can develop strategies to support teachers adherence to interventions.

This study explored the relationship between monetary discounting and treatment outcome discounting and analyzed associations between demographic variables and discount rates obtained in the TCQ. Results of our study indicate that teachers discounted monetary rewards similar to discounting of treatment outcomes. Additionally, we did not find any significant associations between demographic variables and un-dichotomized discount rate (i.e., prior to the median split). However, we did find one significant difference between location groups in the low discounting group, indicating that respondents that teach in the southern region of the U.S. had higher discount rates compared to remaining U.S. regions. Furthermore, we created a 10-step fraudulent response detection process to remove any fraudulent reposes from our data set.

Delay Discounting

As evidenced by the group discount rates (i.e., raw and log transformed) and proportion of SIR choices across delays, respondents discounted delays in both monetary rewards and delayed treatment outcomes. The group mean raw discount rate was higher in the TCQ, but the log transformed discount rate was higher in the MCQ. Based on the statistical analysis, the difference in discount rates were not significant. As proposed by Meyerson et al. (2014), visually analyzing proportions of SIR or LDR is atheoretical (i.e., it does not relay on theoretical mathematical assumptions) and may be an alternative approach to analyzing delay discounting. As such, we analyzed, at the group level, the proportion of participants that selected the SIR over the LDR as the delays decreased. In both the MCQ and the TCQ, participant selections of the SIR were higher when delays were longer and selections of the LDR were higher when delays were shorter. Of note, a greater proportion of participants selected the SIR over the LDR at the shortest delays in the TCQ. This may suggest that even small delays (e.g., 7 days) to reductions in challenging behavior may motivate teachers to select a treatment option that yields immediate behavior reduction. An avenue for future research may be in replicating the proportion method (Meyerson et al., 2014) to analyze discounting across different rewards. We make this suggestion because (a) the Excel scoring tool (Kaplan et al., 2016) was created to analyze discount rates of monetary rewards, (b) Meyerson et al. suggests that the proportion method may be a better analytic procedure when analyzing discounting of non-monetary rewards, and (c) the scoring of proportions is much simpler than the calculation of discount rates (Meyerson et al., 2014). Using the proportion method may be advantageous for researchers new to delay discounting, and we encourage future researchers to continue to analyze discounting using the proportion method.

The previous research on rates of delay discounting across rewards is mixed. Some studies (Call et al., 2015; Gilroy & Kaplan, 2020; Madden et al., 2003; Odum et al., 2011) indicate that discounting of hypothetical monetary rewards resembles discounting of hypothetical real- world rewards. On the other hand, some studies (Bickel et al., 1999; Dassen et al.., 2015; Jarmolowicz et al., 2020; Lemley et al., 2017; Odum, 2011; Odum et al., 2020) indicate that discounting of real-world rewards is greater than discounting of hypothetical monetary rewards. Results of the current study suggest that discounting of hypothetical monetary rewards is similar to discounting of treatment effects. These results are consistent with previous research examining delay discounting as it relates to treatment adherence (Call et al., 2015; Gilroy & Kaplan, 2020). Similar levels of discounting across rewards may indicate a trait effect – our participants may be likely to discount a variety of rewards similarly (Call et al., 2015; Odum et al., 2011). Continued research on teacher decision-making of behavioral treatment outcomes will provide more evidence to a trait effect, if one is present.

Based on our analysis, respondents in the low discounting group that teach in the South had higher discount rates compared to those that teach in the Northeast and Midwest. Put another way, teachers in the Northeast and Midwest regions of the U.S. had the lowest discount rates. We present a possible explanation for this finding. Teachers who perceive themselves as being culturally responsive are linked to decreased student behavioral challenges in the classroom (Fallon et al., 2021). And, teachers who incorporate student customs, spoken languages, and traditions into the classroom are more likely to have less disruptions to learning in their classroom (Fallon et al., 2021; Fallon et al., 2023). Further, a recent study by Childs & Wooten (2023) indicated that schools that include curriculum to increase cultural responsiveness (e.g., Diversity Equity and Inclusion; DEI), may decrease teachers' bias towards students of different cultural or racial backgrounds which may, in turn, decrease negative attitudes of these students when they engage in challenging behavior. It is possible that teachers who are less culturally responsive or teaching in less culturally responsive regions (e.g., Florida), as evidenced by state laws, may be more included to discount delays to behavior reduction. However, we did not test this hypothesis, and future researchers may continue to explore how differences between regions and cultural backgrounds impact rates of discounting.

There are limitations to this study that can be addressed in future research. First, we removed any participant from data analysis if their consistency scores were below 75% in either the MCQ or the TQC. This decision assumes that discounting should be similar across the rewards and may bias our findings in our favor. However, we made this decision because consistency scores are used to filter out respondents that may not be attending to the questionnaire (Kaplan et al., 2016). Including participants with consistency scores less than 75% in one questionnaire may cause problems to the validity of their data; if a participant did not attend to one questionnaire (as indicated by their consistency score), we cannot be certain that they attended to the other questionnaire even if that consistency score was greater than 75%. Future research may consider examining patterns of responding for participants that did not pass the consistency check with one reward but did pass the consistency check with a different reward and providing recommendations on how to proceed in data analysis.

Second, the TCQ did not specify the target challenging behavior to be decreased nor was the intervention specified. Because delay discounting can be influenced by context (Odum et al., 2011), participants may have made choices between the SIR and LDR based on their previous experience with challenging behavior or with implementing behavioral interventions. An avenue for future research may be in analyzing discounting between tasks that provide a specific target behavior definition verses tasks that leave the behavior open for respondent interpretation (like the current study did). Continued research evaluating task directions may lead to improvements in creating delay discounting tasks.

Third, the TCQ was modeled directly from the MCQ whereby monetary rewards were replaced by decreases in challenging behavior. We did not control for difficulty between the two tasks despite the fact that trials in the TCQ did contain 36 more words compared to the TCQ. Of note, previous research (Gilroy & Kaplan, 2020; Jarmolowicz et al., 2020; Lemley et al., 2017) also did not control for difficulty between two different delay discounting tasks. An avenue for future research may be in determining if controlling for task difficulty is a necessary step in data analysis. Additionally, future researchers may consider attempting to equate the number of words per trial across delay discounting tasks with different rewards.

Fraudulent Response Detection

This study suggests that researchers utilizing internet-based survey methodology may inadvertently recruit fraudulent or bot responses (Griffin et al., 2021). Additionally, the promise of compensation upon completion of the survey seems to have prompted a large collection of bot responses; our previous research using survey methodology that did not promise compensation resulted in a small proportion of bot responses (White et al., 2023). This study expands previous studies exploring fraudulent response detection in survey research by outlining a 10-step fraud detection process. Our 10-step process to eliminated 4,923 (93.3%) fraudulent responses leaving us with a total of 317 valid responses.

We did include a Captcha verification question at the beginning of our survey. To our surprise, the Captcha verification did not prevent fraudulent responses. In fact, a study by Liu and Wronski (2018) found that fraudulent responders can bypass Captcha-type questions or launch an automated form-filler after completing the Captcha question (Dupuis et al., 2018). Based on our data and previous findings (Pratt-Chapman et al., 2021), Captcha questions alone are insufficient at detecting survey fraud. Future researchers should continue to include Captcha-type questions in their survey, but need to understand that additional fraud protections are needed to identify fraudulent responders that can bypass the security question.

As previously reported, duplicate IP addresses may not indicate fraudulent responses as people may access the survey from a communal space (e.g., same household, place of work, or shared spaces with public wi-fi; Ballard et al., 2019). However, we decided to take a conservate approach to removing responses based on duplicate IP address because smartphones, VPNs, and smart software have the ability to produce their own unique IP address (Ballard et al., 2019;

Lawlor et al., 2021). Of note, many of the responses with shared IP addresses did not share the same latitude and longitude coordinates, suggesting that the IP address were not valid. A limitation to the study is that we may have excluded a legitimate participant during our fraud detection process. We recognize that excluding legitimate participants removes important data and minimizes our sample size; however, the inclusion of fraudulent responses could lead to inaccurate results (Lawlor et al., 2021). Future research should continue to evaluate participant IP addresses to identify potential fraudulent responders. Online survey research needs more clarity regarding filtering out responses based on IP address.

The increased use of sophisticated software to create bots that search for incentive surveys certainly warrants additional research for identifying these fraudulent responses (Ballard et al., 2019). Even a small percentage of fraudulent or bot responses can invalidate a data set or analysis (Dupuis et al., 2018). An avenue for future research may be in analyzing the proportion of bot responses to incentive surveys from specific platforms. As an example, researchers can disseminate surveys across platforms (e.g., Amazon Mechanical Turk (MTurk), Facebook, Twitter, professional websites), analyze the proportion of bot responses from each platform, and provide practical recommendations for avoiding platforms that can easily infiltrated by survey bots. The current study determined that posting a recruitment flier on public Twitter or Facebook feeds elicits a large number of fraudulent responders. Future researchers may consider exploring other social media platforms (e.g., Instagram, Tik Tok).

In addition to the concerns about the validity of data, researchers now face an ethical dilemma about the (1) use of research funds to pay participants (Griffin et al., 2021; Storozuk et al., 2020) and (2) dissemination of survey results to a broader audience (Dupuis et al., 2018). This study initially received 5,240 survey responses; if the research team was to distribute compensation to all respondents, the total cost to pay respondents would have been $52,400. This dollar amount is concerning as (a) the research team did not receive near that amount of money to compensate participants, and (b) we can assume our university, which provided hard cost funding to compensate participants, and institutional review board would have major concerns with providing our team with a large sum of additional money. Bot creation is now a lucrative form of income – if data are not closely monitored and filtered, bots may submit hundreds of responses that can potentially deplete funds allocated to compensate research participants (Griffin et al., 2021; Storozuk et al., 2020). This is a growing area of concern for individuals and agencies (e.g., universities, federal funds) that provide funding to support research (Griffin et al., 2021).

Conclusion

Understanding the relationship between discounting of delayed treatment outcomes (i.e., decreases in challenging behavior) and teachers' adherence to recommended behavioral interventions is still a ripe area for research. As research consistently finds that teachers seldom implement behavioral interventions as recommended by the consultant (Anderson & Daly, 2013), treatment non-adherence becomes a major concern because the success of behavioral treatments relies on correct implementation of recommended treatments (Rispoli et al., 2017). Using delay discounting, future researchers may aid in (a) understanding why treatment non-adherence occurs and (b) developing supports or strategies that encourage teachers' adherence to recommended behavioral interventions.

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APPENDIX

Figure 3

Recruitment Flier

MICHIGAN STATE
UNIVERSITY

Recruiting Teachers to Take a Survey About Challenging Behavior

Doctoral Candidate Allison Cascarilla and Dr. Matthew Brodhead are recruiting teachers to participate in a survey about educators' perceptions of challenging behavior.

Description of survey: We are recruiting teachers of students who engage in challenging behavior to take an online survey evaluating how teachers make decisions regarding treatments for challenging behavior. The survey should take 10 - 20 minutes to complete.

General requirements: In order to participate, you must be (1) a current teacher who (2) currently serves a student who engages in challenging behavior.

Compensation: Participants will receive a $10 Amazon.com gift card.

To participate, please scan the QR code or visit the link:

https://msu.co1.qualtrics.com/jfe/form/SV_ac7UUSjdKYJTLEO

For additional information or any questions please contact Dr. Matthew Brodhead at mtb@msu.edu.

Figure 4
Fraudulent Response Detection Process

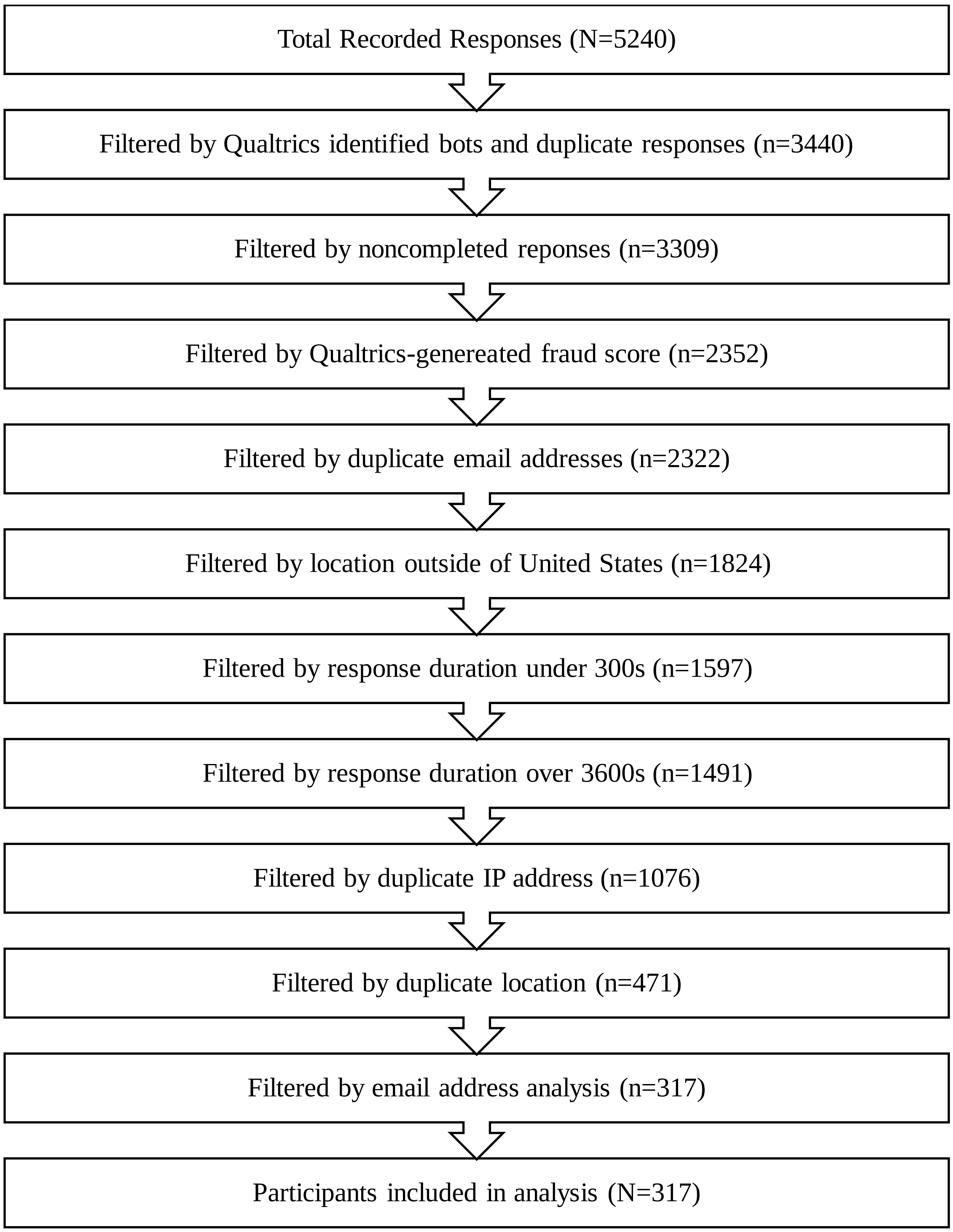

Table 1
Participant Demographic Information

Participants (N=317)			
Age (years)		**Special Education License**	
< 20	6 (1.9%)	Yes	267 (84.2%)
20 - 29	45 (14.2%)	No	50 (15.8%)
30 - 39	185 (58.4%)		
40 - 49	65 (20.5%)	**Teaching Area**	
50 - 59	14 (4.4%)	Early Childhood	24 (7.6%)
> 60	2 (.6%)	Elementary	117 (36.9%)
		Middle	143 (45.1)
Ethnicity		High	75 (23.7)
White - Non-Hispanic	230 (72.6%)	Post-Secondary	30 (9.5)
Latino/Hispanic	17 (5.4%)	Other	1 (.3%)
Black	44 (13.9%)		
Asian/Pacific Islander	18 (5.7%)	**Teaching Environment**	
Native Hawaiian	6 (1.9%)	General Education	144 (45.4%)
Multiethnic	2 (.6%)	Early Intervention	88 (27.8%)
		Resource Setting	74 (23.3%)
Gender		Specialized Day Program	70 (22.1%)
Male	166 (52.4%)	Self-Contained Classroom	91 (28.7%)
Female	144 (45.4%)	Residential Facility	38 (12%)
Transgender Male	3 (.9%)	Home Program	19 (6%)
Transgender Female	2 (.6%)	Hospital	7 (2.2%)
Not Listed	1 (.3%)	Other	3 (.9%)
Prefer not to say	1 (.3%)		
		Students Receiving Free/Reduced Lunch (%)	
Highest Level of Education		0	27 (8.5%)
High School/GED	6 (1.9%)	1 - 25	78 (24.6%)
Some College	19 (6%)	26 - 50	125 (39.4%)
Associate Degree	39 (12.3%)	51 - 75	69 (21.8%)
Bachelor Degree	158 (49.8%)	76 - 100	18 (5.7%)
Master's Degree	88 (27.8%)		
Doctoral Degree	7 (2.2%)	**Students Engage in Challenging Behavior (%)**	
		1 - 25	86 (27.1%)
Teaching Experience (years)		26 - 50	132 (41.6%)
< 1	6 (1.9%)	51 - 75	65 (20.5%)
1 - 5	66 (20.8)	76 - 100	34 (10.7%)

Table 1 (cont'd)

6 - 10	147 (46.4%)		
11 - 15	63 (19.9%)	**Professional Development (Developing)**	
16 - 20	25 (7.9%)	Yes	296 (93.4%)
> 20	10 (3.2%)	No	21 (6.6%)
Teaching Region (USA)		**Professional Development (Implementing)**	
Northeast	47 (14.8%)	Yes	282 (89%)
Midwest	140 (44.2%)	No	35 (11%)
South	83 (26.2%)		
West	47 (14.8%)	**Collaboration with Related Service**	
		Yes	288 (90.9)
		No	29 (9.1%)

Table 2
Demographic Questions

Demographic Questions
1. What is your age?
2. What is your ethnicity?
3. To which gender to you most identify with?
4. What is the highest level of education you have obtained?
5. How many years of experience do you have teaching in a classroom?
6. In which region of the United States do you currently live?
7. Do you currently hold a special education teaching certificate or license?
8. In what area do you currently teach?
9. In what environment do you currently teach?
10. What percentage of students at your school receive free or reduced school meals?
11. What percentage of students that you serve engage in challenging behavior?
12. Have you received any professional development and/or training in developing behavioral interventions for students who engage in problem behavior?
13. Have you received any professional development and/or training in implementing behavioral interventions for students who engage in problem behavior?
14. During your time as an educator, have you ever collaborated or consulted with a related service provider (e.g., behavior consultant) for designing and implementing behavioral interventions for your students who engage in problem behavior?

Figure 5

First Trial of the MCQ

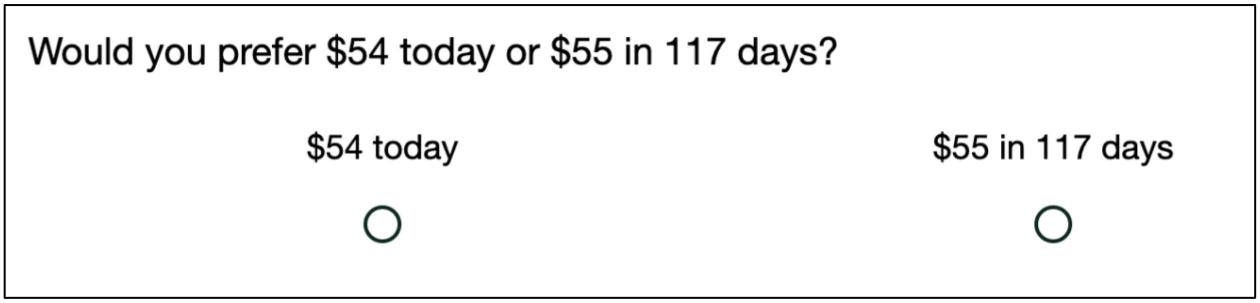

Figure 6
First Trial of the TCQ

Would you prefer a treatment that will result in 54 days without problem behavior immediately or a treatment that will result in 55 days without problem behavior after 117 days of treatment implementation.

54 days without problem behavior immediately	55 days without problem behavior after 117 days of treatment implementation

Table 3
Delay Discounting Variables Included in Data Analysis

Participant ID	MCQ		TCQ	
	Overall *k* value	Log geomean *k* value	Overall *k* value	Log geomean *k* value
1*	0.249423298	-0.60462103	0.198791677	-0.732911969
2	0.001586399	-1.964436804	0.003896509	-2.525478706
3	0.000398112	-2.800772034	0.000398989	-3.064206127
4	0.000215343	-3.034837123	0.198791677	-1.249026843
5	0.009706451	-1.72997282	0.003986971	-2.55772772
6	0.000158203	-3.733803196	0.049724154	-1.633438773
7	0.004837067	-2.071824248	0.249423298	-0.701039306
8	0.000158203	-3.376684571	0.000158203	-2.770100971
9*	0.249423298	-0.932745139	0.249423298	-0.703598967
10*	0.101273937	-1.060579336	0.249423298	-1.069678965
11*	0.040956979	-1.457617597	0.249423298	-0.60462103
12*	0.000158128	-3.800717035	0.000158128	-3.599932289
13	0.248371318	-1.550592679	0.249423298	-1.766543856
14*	0.249423298	-0.668165612	0.249423298	-0.701849955
15	0.000398512	-2.966232869	0.001001837	-1.67079424
16	0.000158203	-3.317470103	0.249423298	-1.766268201
17	0.000158128	-3.083628722	0.013639184	-1.634130724
18	0.007832739	-1.988202481	0.249423298	-0.997572597
19*	0.009706451	-2.011356597	0.040956979	-1.595368463
20*	0.040956979	-1.457617597	0.248896752	-0.670944365
21*	0.249423298	-0.669367387	0.025492269	-1.468713558
22	0.248896752	-0.670944365	0.249423298	-0.799078881
23	0.000158203	-3.733803196	0.000158128	-3.36556068
24*	0.249423298	-0.703598967	0.249423298	-0.60462103
25*	0.002511154	-2.669499896	0.002535234	-2.6733238
26*	0.249423298	-0.669367387	0.249423298	-1.303111613
27	0.249423298	-0.60462103	0.000398512	-2.567436967
28*	0.249423298	-0.60462103	0.249423298	-0.60462103
29*	0.249423298	-0.60462103	0.249423298	-0.669367387
30*	0.006004661	-2.144561402	0.002535234	-2.539299052
31*	0.248371318	-0.867379598	0.009706451	-2.144830503
32	0.025762303	-1.461297377	0.113187835	-1.098672653
33	0.248371318	-1.733107168	0.15843801	-0.86681926
34*	0.101273937	-1.060579336	0.025762303	-1.592986253
35	0.15843801	-0.799235304	0.100862085	-2.136821608

Table 3 (cont'd)

36*	0.249423298	-0.839514416	0.249423298	-0.60462103
37	0.009706451	-1.542919842	0.248896752	-1.504108818
38	0.001593704	-2.71630614	0.000398089	-2.964286679
39	0.248371318	-1.635786658	0.249423298	-1.469690941
40*	0.15843801	-0.799235304	0.248896752	-0.670944365
41*	0.000158128	-3.700508937	0.001586399	-2.803874752
42	0.101273937	-1.194659367	0.000158203	-3.23417351
43	0.015745325	-1.738794738	0.000251165	-2.817919361
44*	0.025762303	-1.459319995	0.01586679	-1.733374186
45	0.198791677	-1.810526308	0.000158203	-3.399815177
46	0.248896752	-1.807367838	0.002511154	-2.501791211
47	0.249423298	-2.668210687	0.249423298	-0.60462103
48*	0.15843801	-1.334387616	0.025492269	-1.598005529
49*	0.005286315	-2.274733639	0.025762303	-1.733217798
50	0.249423298	-2.27203624	0.249423298	-1.069535336
51*	0.002511154	-2.669499896	0.040956979	-1.457617597
52*	0.041011431	-1.364947561	0.025492269	-1.598005529
53	0.000398246	-3.238001352	0.081101537	-1.491545119
54	0.000251316	-2.699189825	0.249423298	-1.032350969
55	0.003920869	-1.669724578	0.198791677	-1.84970111
56	0.01847676	-2.734703477	0.000158203	-2.443336404
57	0.00089246	-2.728700704	0.000858317	-2.200245179
58	0.249423298	-2.367105968	0.248371318	-2.225792918
59	0.000341704	-2.569167631	0.001002193	-2.932868438
60	0.117462824	-1.128986687	0.248896752	-0.670944365
61*	0.249423298	-0.60462103	0.249423298	-0.60462103
62*	0.249423298	-0.800017243	0.249423298	-0.60462103
63	0.002452386	-2.095706853	0.000251316	-2.601296847
64	0.249423298	-1.702343518	0.000398512	-1.736448914
65	0.000158203	-3.733715236	0.000158128	-3.700508937
66	0.032504598	-1.6667373	0.000158128	-3.198169239
67*	0.249423298	-0.932826239	0.249423298	-0.60462103
68	0.101273937	-2.13036665	0.000631858	-2.599427176
69	0.158275864	-1.40163942	0.198791677	-1.136677653
70	0.000158203	-2.929135342	0.025762303	-2.466934869
71*	0.009706451	-2.406644368	0.040956979	-1.595417697
72	0.000158203	-3.398905741	0.00025118	-2.203977352
73*	0.248896752	-0.670944365	0.025762303	-1.592986253
74*	0.086980252	-1.062556718	0.009706451	-2.004442571

Table 3 (cont'd)

75*	0.249423298	-0.60462103	0.248371318	-1.004175967
76*	0.009706451	-2.011356597	0.009706451	-2.011356597
77	0.249423298	-0.800017243	0.248896752	-0.80380065
78*	0.064446792	-1.194245594	0.006004661	-2.006761302
79*	0.041011431	-1.227119289	0.01586679	-1.599294154
80*	0.101273937	-0.864372474	0.040956979	-1.727653999
81*	0.001001837	-3.199854658	0.00063138	-3.067350364
82*	0.051680781	-1.227533062	0.015745325	-1.735756396
83*	0.002511154	-2.669509854	0.015745325	-1.871125052
84	0.003896509	-2.904621032	0.249423298	-1.163594159
85*	0.249423298	-0.60462103	0.249423298	-0.60462103
86	0.006280187	-1.863497126	0.051680781	-2.628916527
87	0.012410085	-1.872999605	0.249423298	-1.669039276
88*	0.015745325	-1.871125052	0.004837067	-2.278035309
89	0.000158128	-3.022286669	0.009759664	-2.968822814
90	0.000397589	-3.004328594	0.249423298	-1.56990826
91*	0.12667139	-0.930867842	0.064446792	-1.334633526
92	0.117941069	-1.665121325	0.000398512	-2.418232108
93*	0.064446792	-1.334633526	0.009706451	-2.011356597
94	0.002862234	-2.804056699	0.001583814	-3.031660622
95	0.040956979	-1.264056801	0.248371318	-1.535133648
96*	0.025492269	-1.598005529	0.025492269	-1.598005529
97*	0.15843801	-0.863780918	0.249423298	-0.936105976
98*	0.040956979	-1.328325626	0.01586679	-1.733374186
99	0.249423298	-1.669039276	0.249423298	-0.701039306
100*	0.101273937	-1.194659367	0.249423298	-0.60462103
101	0.249423298	-0.60462103	0.15843801	-1.269455504
102	0.198791677	-0.86220394	0.000251316	-2.734107162
103*	0.249423298	-0.60462103	0.000158128	-3.800717035
104	0.000158203	-3.211504013	0.127536243	-1.108401545
105	0.000158203	-3.512307789	0.00063331	-2.401489295
106	0.000158128	-3.733957037	0.249423298	-0.902421632
107	0.01586679	-1.157646899	0.249423298	-0.800495926
108	0.002535234	-2.536471075	0.013316663	-1.670125783
109*	0.249423298	-0.60462103	0.249423298	-0.701849955
110	0.001001837	-2.670498061	0.000158128	-3.237586989
111*	0.051680781	-1.226722413	0.000251316	-3.667043198
112*	0.198791677	-0.732911969	0.249423298	-0.60462103
113	0.249423298	-1.602037476	0.015745325	-2.46811756

Table 3 (cont'd)

114	0.198791677	-0.864600845	0.006004661	-2.2732384
115*	0.249423298	-0.60462103	0.249423298	-0.60462103
116	0.15843801	-0.928527275	0.15843801	-1.699776176
117*	0.009706451	-2.144830503	0.248896752	-1.272855025
118*	0.248896752	-0.670944365	0.249423298	-0.60462103
119	0.010019134	-2.251524018	0.249423298	-0.60462103
120	0.000158128	-3.465907541	0.000158203	-3.233790298
121	0.249423298	-1.735540597	0.101002229	-1.26547276
122	0.000158278	-3.001019208	0.000215343	-2.66938495
123*	0.040956979	-1.328325626	0.015745325	-1.871125052
124	0.000158128	-2.632282427	0.002535234	-2.735126483
125	0.00508122	-2.515921185	0.015745325	-2.46811756
126	0.000158128	-2.736298789	0.000158128	-3.700499716
127*	0.064446792	-1.095267657	0.249423298	-0.60462103
128	0.249423298	-0.83887705	0.249423298	-0.89747454
129	0.009706451	-2.187085416	0.001583814	-1.868950804
130	0.249423298	-1.073057784	0.249423298	-2.668298646
131*	0.009723443	-2.004329858	0.020140403	-1.597070862
132	0.249423298	-1.791010578	0.015745325	-2.223900562
133	0.248896752	-0.999149574	0.248896752	-0.999149574
134*	0.025762303	-1.592986253	0.015745325	-1.735756396
135*	0.009706451	-2.011356597	0.015745325	-1.871125052
136*	0.032504598	-1.458906222	0.025762303	-1.592986253
137	0.000316469	-3.03310401	0.065212406	-0.961181877
138	0.003896509	-1.800445854	0.007832739	-1.793135474
139*	0.025492269	-1.598005529	0.012410085	-2.007079636
140	0.004001777	-2.126002581	0.000631858	-2.629614598
141*	0.009706451	-2.011356597	0.015745325	-1.871125052
142*	0.000158128	-3.700499716	0.000158203	-3.60030084
143	0.062667782	-1.403140485	0.025762303	-2.268752388
144*	0.041011431	-1.463925498	0.025492269	-1.598005529
145*	0.034864417	-1.129493488	0.032166933	-1.633521023
146	0.248371318	-1.75668817	0.001584352	-2.714840398
147*	0.025762303	-1.733025446	0.025762303	-1.460655939
148	0.100862085	-0.862623463	0.025762303	-2.356779924
149	0.001001837	-3.266768497	0.000354803	-2.602665829
150*	0.100862085	-0.928946797	0.015745325	-1.871125052
151	0.249423298	-0.997572597	0.006004661	-1.85665603
152	0.15843801	-1.799755296	0.249423298	-1.866000475

Table 3 (cont'd)

153*	0.002535234	-2.539299052	0.009706451	-2.273691294
154	0.249423298	-0.60462103	0.000974887	-3.004319349
155	0.015745325	-2.097886814	0.000398989	-1.799085179
156	0.249423298	-1.16690789	0.000631786	-2.66987443
157	0.249423298	-1.336894181	0.100862085	-1.267515635
158	0.065212406	-1.366493572	0.040956979	-2.516098146
159*	0.009706451	-2.142590393	0.01847676	-1.73580563
160*	0.000158128	-3.800717035	0.249423298	-0.60462103
161*	0.249423298	-0.60462103	0.248896752	-0.670944365
162*	0.015745325	-1.871125052	0.064446792	-1.194245594
163*	0.065212406	-0.961181877	0.15843801	-0.799235304
164	0.000158128	-3.800717035	0.000158128	-2.972685092
165	0.249423298	-0.765785664	0.000502072	-3.268681744
166*	0.000158128	-3.800717035	0.000158128	-3.800717035
167*	0.158275864	-0.865402215	0.117462824	-0.993892816
168	0.249423298	-0.669367387	0.248371318	-1.676124648
169	0.117941069	-1.528152638	0.000215343	-3.633456335
170	0.249423298	-1.796495327	0.002932389	-2.666723931
171	0.000398246	-3.238001352	0.000398246	-3.238001352
172	0.000158128	-2.731770235	0.000158278	-3.145274562
173*	0.007633445	-2.143642132	0.025762303	-1.592986253
174	0.00025118	-3.050294236	0.249423298	-1.204224578
175*	0.041011431	-1.463925498	0.249423298	-0.60462103
176	0.000502072	-1.768023165	0.024812579	-2.139306281
177	0.051680781	-1.562257631	0.000158203	-2.464361742
178	0.009706451	-1.633635448	0.100862085	-2.067867982
179	0.003887578	-1.904790577	0.184185513	-1.66501829
180	0.249423298	-2.068064691	0.015745325	-1.998091092
181	0.249423298	-1.167795297	0.000158203	-2.366422708
182*	0.100862085	-0.928946797	0.041011431	-1.191848689
183*	0.040956979	-1.457617597	0.009706451	-1.606464424
184*	0.000158203	-3.733715236	0.000158128	-3.335573786
185*	0.015745325	-1.871125052	0.015745325	-1.871125052
186	0.040956979	-1.457617597	0.249423298	-1.00137203
187*	0.025762303	-1.733217798	0.009723443	-2.004329858
188*	0.025492269	-1.598005529	0.025492269	-1.598005529
189	0.117941069	-1.301520506	0.002140425	-2.937549393
190	0.000398512	-2.256399406	0.15843801	-1.406534966
191	0.041011431	-2.766761764	0.249423298	-1.650235292

Table 3 (cont'd)

192*	0.000158128	-3.800717035	0.000158128	-3.800717035
193	0.249423298	-1.035128071	0.249423298	-0.701849955
194*	0.158610699	-0.765394537	0.249423298	-0.935841181
195	0.000158128	-3.432610517	0.000158128	-3.068415147
196	0.249423298	-1.832763569	0.000251316	-2.666043205
197	0.248371318	-0.735690722	0.005399593	-1.878768757
198*	0.015745325	-1.871125052	0.006004661	-2.144561402
199	0.000158278	-2.310847668	0.006004661	-2.249141557
200*	0.025492269	-1.598005529	0.249423298	-0.936656935
201	0.003128056	-2.772054539	0.01586679	-2.023512868
202*	0.002511154	-2.669499896	0.001002193	-2.801634642
203	0.006003171	-2.972841692	0.003896509	-2.49646335
204	0.248896752	-1.303725587	0.001001837	-3.199854658
205*	0.041011431	-1.092870753	0.040956979	-1.36119932
206*	0.025762303	-1.866635348	0.006004661	-2.006810536
207*	0.025492269	-1.729097036	0.041011431	-1.463925498
208*	0.025492269	-1.598005529	0.025492269	-1.598005529
209	0.000158203	-3.467203135	0.002216792	-2.597690204
210*	0.249423298	-0.60462103	0.249423298	-0.60462103
211*	0.025492269	-1.468713558	0.041011431	-1.597253115
212	0.249423298	-0.935257684	0.039592402	-1.969332574
213	0.000158128	-3.733957037	0.03117499	-1.601509777
214*	0.002511154	-2.669499896	0.015745325	-1.871125052
215*	0.101273937	-1.331686463	0.040956979	-1.457617597
216*	0.065212406	-1.325239964	0.025762303	-1.729838979
217	0.000158128	-3.63374894	0.056304337	-1.597515434
218*	0.000158128	-3.800717035	0.000158128	-3.800717035
219	0.000631786	-2.42143921	0.15843801	-1.668360811
220	0.249423298	-1.000201517	0.065212406	-1.885820159
221	0.058018638	-1.995018488	0.249423298	-1.335525376
222	0.198791677	-1.733785633	0.249423298	-1.136421493
223	0.000631786	-2.467794492	0.000158203	-2.667542026
224*	0.249423298	-0.60462103	0.065212406	-1.377724649
225*	0.025492269	-1.598005529	0.041011431	-1.463925498
226*	0.249423298	-0.767143548	0.249423298	-0.801056263
227	0.006003171	-2.040304035	0.009723443	-1.93232381
228	0.248896752	-0.670944365	0.000158203	-2.867637587
229	0.000703468	-2.729263387	0.000158203	-3.154774296
230*	0.009706451	-2.011356597	0.006004661	-2.144561402

Table 3 (cont'd)

231	0.003896509	-1.303760616	0.000199396	-3.271449452
232*	0.065212406	-1.189871307	0.249423298	-0.669367387
233	0.006192098	-2.264551256	0.040956979	-2.132746201
234	0.158610699	-1.016581849	0.015742217	-1.901486791
235*	0.040956979	-1.328325626	0.01847676	-1.73580563
236*	0.002511154	-2.53602599	0.009706451	-2.004648003
237*	0.000158128	-3.800717035	0.000158128	-3.800717035
238*	0.015745325	-1.735756396	0.009723443	-2.004329858
239*	0.025492269	-1.598005529	0.009723443	-2.004329858
240*	0.001583814	-3.132393641	0.032166933	-1.096550533
241*	0.00716867	-2.141182583	0.025762303	-1.729838979
242*	0.000158203	-3.733803196	0.000158128	-3.700508937
243*	0.01586679	-1.866578991	0.009723443	-2.004329858
244*	0.002511154	-2.669499896	0.01586679	-1.733374186
245*	0.015745325	-1.871125052	0.025492269	-1.598005529
246	0.000158203	-3.499805995	0.000158128	-3.800717035
247*	0.051680781	-1.323951339	0.009706451	-1.873556496
248*	0.002511154	-2.53602599	0.002511154	-3.003399955
249	0.249423298	-1.667670352	0.002511154	-1.976038174
250	0.000631786	-3.165144486	0.249423298	-1.271439694
251	0.000631786	-1.763422696	0.000158128	-3.063336595
252	0.015745325	-1.871125052	0.000158203	-2.196286662
253	0.006004661	-1.737794775	0.249423298	-0.839514416
254*	0.00063082	-3.165441594	0.001586399	-2.800515137
255	0.249423298	-1.356845929	0.001001837	-1.898113469
256*	0.009706451	-2.011356597	0.006004661	-2.144561402
257*	0.040956979	-1.457617597	0.025492269	-1.468713558
258	0.15876863	-1.432016527	0.127536243	-1.129033102
259	0.249423298	-1.484745595	0.040160881	-1.93200451
260	0.002511154	-2.531709754	0.249423298	-1.662527494
261	0.000158128	-3.569463242	0.000158128	-3.733957037
262*	0.051680781	-1.194239845	0.025492269	-1.598005529
263	0.007917323	-2.101667162	0.000199396	-2.668210687
264	0.025762303	-1.867229473	0.000631858	-2.534463691
265*	0.032166933	-1.633521023	0.249423298	-0.668165612
266	0.000158128	-3.221688135	0.000398512	-2.43861392
267	0.158610699	-1.565574481	0.081101537	-1.603297865
268	0.000316224	-3.433081722	0.000398989	-3.201417797
269*	0.000158128	-3.467203135	0.000158128	-3.800717035

Table 3 (cont'd)

270	0.249423298	-1.921847283	0.249423298	-1.06790131
271	0.142077124	-1.370083951	0.249423298	-0.932826239
272	0.000398246	-3.238001352	0.000158128	-3.238001352
273*	0.065212406	-1.189871307	0.002535234	-2.408207545
274	0.249423298	-0.825610994	0.021449241	-1.668459141
275*	0.249423298	-0.60462103	0.249423298	-0.60462103
276*	0.009706451	-2.011356597	0.009706451	-2.011356597
277	0.038695356	-2.181644733	0.000158128	-2.707727895
278	0.01586679	-2.048054118	0.01586679	-2.268018276
279	0.002511154	-2.802993006	0.000158128	-2.799958843
280*	0.248896752	-0.802576903	0.249423298	-0.669367387
281	0.065212406	-1.76406509	0.249423298	-2.001614535
282	0.249423298	-1.932634059	0.249423298	-1.834128954
283*	0.249423298	-0.703598967	0.249423298	-0.825045466
284*	0.15843801	-0.799235304	0.249423298	-0.60462103
285*	0.003896509	-2.410320844	0.002511154	-2.669499896
286*	0.065212406	-1.189871307	0.041011431	-1.323537565
287*	0.15843801	-0.799235304	0.065212406	-1.189871307
288	0.025411381	-2.018783016	0.000631786	-2.632748946
289*	0.025527821	-1.594821671	0.01847676	-1.73580563
290	0.025762303	-1.592986253	0.000631858	-2.864087804
291	0.040956979	-1.469481488	0.000158128	-2.432760641
292	0.065212406	-1.189871307	0.249423298	-1.073057784
293*	0.005515022	-2.272425773	0.009706451	-2.011356597
294*	0.025492269	-1.598005529	0.002511154	-2.669499896
295	0.000158128	-3.600152855	0.000158128	-2.699626052
296	0.000158128	-2.534109186	0.248371318	-2.003314555
297*	0.000158128	-3.800717035	0.000158128	-3.800717035
298	0.127536243	-1.787786286	0.249423298	-0.60462103
299*	0.025492269	-1.598005529	0.025492269	-1.598005529
300*	0.248371318	-0.868547007	0.249423298	-0.60462103
301	0.012410085	-1.990811352	0.248371318	-1.997894126
302	0.040956979	-2.135220957	0.002003831	-2.434369867
303*	0.025762303	-1.733217798	0.015745325	-1.735756396
304*	0.002535234	-2.673673908	0.065212406	-1.189871307
305*	0.249423298	-0.701039306	0.249423298	-0.60462103
306	0.15843801	-1.197561172	0.015577582	-2.268940876
307*	0.064446792	-1.194245594	0.004837067	-2.278035309
308	0.248371318	-1.135407562	0.00063082	-3.165441594

Table 3 (cont'd)

309	0.249423298	-0.60462103	0.249423298	-1.269037937
310	0.000398989	-3.271449452	0.000158278	-3.223209364
311	0.000158128	-2.700520299	0.000158128	-3.200358748
312	0.000398989	-2.733083373	0.000158128	-3.800717035
313	0.002535234	-2.602408107	0.000199396	-3.434904786
314*	0.249423298	-0.60462103	0.249423298	-1.03388586
315*	0.249423298	-0.668165612	0.249423298	-0.60462103
316	0.249423298	-0.60462103	0.000158128	-3.433648382
317*	0.248896752	-0.670944365	0.249423298	-0.60462103
All Mean (SD)	0.0874(0.1019)	-1.8683(0.9095)	0.0855(0.1063)	-1.9168(0.8771)
Included Mean (SD)	0.0856(0.0964)	-1.6239(0.9026)	0.0887(0.1063)	-1.6470(0.9224)

Note. The asterisk indicates that the participant was included in the statistical analysis due to consistency score being greater than or equal to 75% in both the MCQ and TCQ.

Table 4

Choice Trial Values and Their Associated k Ranks

Trial Order	SIR	LDR	Delay (days)	*k* at indifference	*k rank*
13	34	35	186	0.00016	1
1	54	55	117	0.00016	1
9	78	80	162	0.00016	1
20	28	30	179	0.0004	2
6	47	50	160	0.0004	2
17	80	85	157	0.0004	2
26	22	25	136	0.001	3
24	54	60	111	0.001	3
12	67	75	119	0.001	3
22	25	30	80	0.0025	4
16	49	60	89	0.0025	4
15	69	85	91	0.0025	4
3	19	25	53	0.006	5
10	40	55	62	0.006	5
2	55	75	61	0.006	5
18	24	35	29	0.016	6
21	34	50	30	0.016	6
25	54	80	30	0.016	6
5	14	25	19	0.041	7
14	27	50	21	0.041	7
23	41	75	20	0.041	7
7	15	35	13	0.1	8
8	25	60	14	0.1	8
19	33	80	14	0.1	8
11	11	30	7	0.25	9
27	20	55	7	0.25	9
4	31	85	7	0.25	9

Note. This table was edited from Kirby et al. (1999).

Figure 7

Proportion of SIR choices at each k rank in the MCQ at the group level

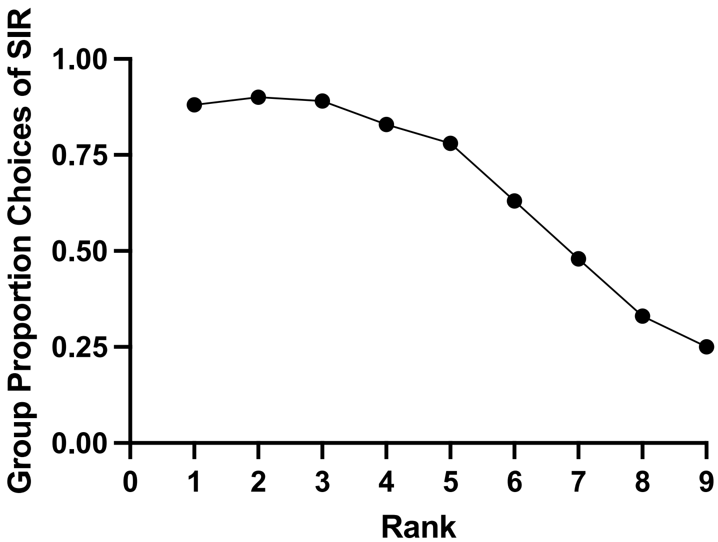

Figure 8
Proportion of SIR choices at each k rank in the TCQ at the group level

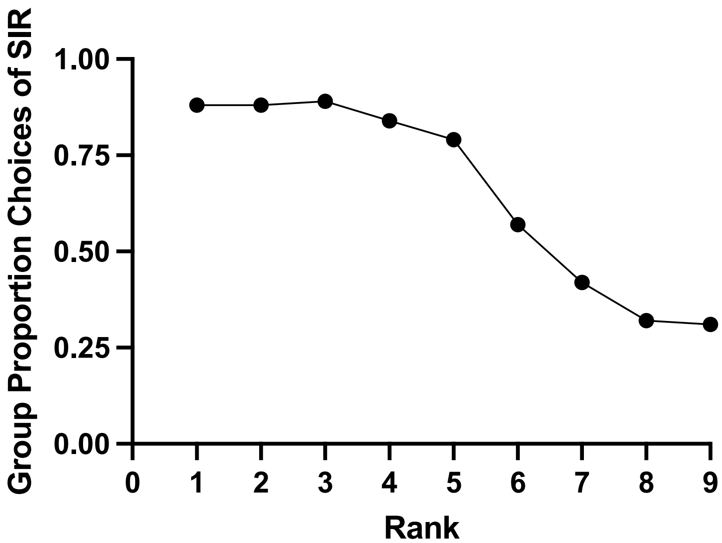

Table 5

ANOVA Results

Variable	Results
Age	$F(4, 139) = .321, p = .864$
Ethnicity	$F(4, 139) = .693, p = .598$
Education	$F(4, 139) = .146, p = .964$
Experience	$F(5, 19.092) = 1.141, p = .373$
Location	$F(3, 51.031) = 2.220, p = .097$
FRL	$F(4, 31.611) = .296, p = .878$
Challenging Behavior	$F(3, 48.567) = .683, p = .567$

Table 6
T-test results

Variable	Results
Gender	$t(102.176) = .857, p = .393$
License	$t(142) = -1.636, p = .104$
PD Developing	$t(142) = -1.242, p = .216$
PD Implementing	$t(142) = -1.487, p = .139$
Collaboration	$t(142) = -.238, p = .812$

Table 7
Mann-Whitney U results

Variable	Low Discounting Group	High Discounting Group
Gender	U = 611.5, z = -.284, p = .776	U = 511, z = -1.012, p = .312
License	U = 502, z = 1.021, p = .307	U = 345, z = 2.553, p = .011
PD Developing	U = 224.5, z = .342, p = .732	U = 80, z = .467, p = .668
PD Implementing	U = 258.5, z = .374, p = .709	U = 126, z = .797, p = .455
Collaboration	U = 292, z = .985, p = .325	U = 315, z = 1.955, p = .051

Table 8

Kruskal-Wallis H results

Variable	Low	High
Age	$\chi^2(4) = 3.561$, $p = .469$	$\chi^2(4) = 7.18$, $p = .127$
Ethnicity	$\chi^2(3) = 3.078$, $p = .38$	$\chi^2(4) = 4.4$, $p = .355$
Education	$\chi^2(3) = 9.842$, $p = .02$	$\chi^2(4) = 4.608$, $p = .33$
Experience	$\chi^2(5) = 4.069$, $p = .54$	$\chi^2(5) = 5.343$, $p = .375$
Location	$\chi^2(3) = 19.083$, $p < .001$	$\chi^2(3) = 2.445$, $p = .485$
FRL	$\chi^2(4) = 2.474$, $p = .649$	$\chi^2(4) = 2.95$, $p = .566$
Challenging Behavior	$\chi^2(3) = 5.545$, $p = .136$	$\chi^2(3) = 6.875$, $p = .076$

CHAPTER 3

DOES SEVERITY OF BEHAVIOR IMPACT TEACHERS' DISCOUNT RATES?

Human-subjects researchers commonly use delay discounting to understand human patterns of decision-making (Bailey et al., 2021; Odum, 2011). As defined by Kaplan et al. (2016), delay discounting is a behavioral phenomenon whereby the value of a reward decreases as a function of its delayed receipt. This means that as the longer someone must wait for a reward, the less that individual values the reward; therefore, the reward loses value. So, when rewards only differ in immediacy (e.g., receiving $100 today vs $100 in 7 days), most people choose the immediate reward (Call et al., 2015; Meyerson & Green, 1995; White et al., 2023). When the amount of the immediate reward decreases and the delay between reward stays constant (e.g., receiving $50 today vs $100 in 7 days), most people eventually choose the delayed reward (Call et al. 2015; White et al., 2023). Reliably, humans (and nonhuman animals) often prefer smaller more immediate rewards to larger delayed reward (Kaplan et al., 2016; Schulz van Endert & Mohr, 2022).

The degree to which a person discounts delays may be impacted by trait or state influences (Odum et al., 2020). *Trait influences* are stable variables inherent in an individual such as disability status, repeated patterns of behavior, and genetic predispositions that impact discounting over time (Odum et al., 2011; Odum et al., 2020; Shultz van Endert & Mohr, 2022). For example, research indicates that individuals with attention-deficit/hyperactivity disorder (Burns et al., 2019) and individuals who have been characterized as impulsive (Shultz van Endert & Mohr, 2022) demonstrate steeper discounting compared to control groups. *State influences* are situational variables that temporality impact how a person discounts delayed rewards such as environmental arrangements, deprivation, or severity of maladaptive behavior (e.g., drug use with a clean or dirty needle; Odum et al., 2000) (Odum et al., 2020). State influences that have shown to impact discounting include the type of commodity (Odum et al., 2011), reward magnitude (Dixon et al., 2016), and context in with the decisions are made (Dixon et al., 2006).

To date, few studies have analyzed specific state influences on delay discounting (Odum et al., 2020). That is, many state influences are hypothesized but have not been directly tested for. An exception is a study by Dixon et al. (2006) demonstrating how degrees of discounting are influenced by context (i.e., state influence). In the study, the researchers compared discount rates of people with a gambling addiction in two contexts: a gambling context (i.e., betting facility) and nongambling context (i.e., coffee shop). Results of the study indicate that delay discounting was higher in the gambling context as compared to the nongambling context suggesting that the context or environment in which a person is making decisions impacts how they discount delayed rewards (Dixon et al., 2016; Odum et al., 2020).

From a therapeutic perspective, identifying state influences may be critical in creating interventions to address maladaptive behavior (e.g., drug dependance; Dixon et al., 2006; Dixon et al., 2016). For example, a person who missuses drugs previously adhered to a home-based intervention designed to eliminate their drug use. However, when the individual leaves their home and attends a gathering a friend’s home, the motivation to abstain from drug use might diminish. Here, the degree to which the person discounted the delayed outcomes of partaking in drug use is likely contextual: the individual likely discounts the outcomes of drug use to a higher degree in the friend-gathering context as opposed to their home context. Because context (e.g., attending a friend’s gathering) likely contributes to not adhering to the intervention, the practitioner prescribing the intervention to eliminate drug use will hopefully create an intervention that includes a plan for at home as well at a friend’s gathering. Further, validation of state influences from previous research (Dixon et al., 2016) indicate that even people who engage in risky behavior can alter their choice to not engage in the risky behavior based on environmental variables.

Teacher Decision-Making

Based on previous research (White et al., 2023), teachers of students who engage in challenging behavior may discount delays in behavioral treatment outcomes. Further, based on outcomes from White et al., teachers may prefer behavioral interventions that result in immediate reductions to challenging behavior. While the effects of delays to treatment outcomes have been shown to impact teacher decision-making (White et al., 2023), the extent to which environmental variables impact teacher decision-making are not well understood. Identifying variables that may impact rates of discounting is critical for understanding engagement of risky behavior (e.g., treatment non-adherence) and creating interventions designed to decrease risky behavior (Xu et al., 2022).

A state influence that that may impact how teachers of students who engage in challenging behavior discount treatment effects is the *severity* of the target behavior (Dixon et al., 2006). That is, the severity of challenging behavior may impact how teachers make choices regarding behavioral interventions after delays to reductions in challenging behavior. According to teachers, stereotypies (motor and vocal) and non-compliance are often perceived as the least severe challenging behaviors and physical aggression and self-injury are often viewed as the most severe of challenging behaviors in school settings (Matson & Nebel-Schwalm, 2007). Further, the physical management of challenging behavior is a frequently reported barrier to intervention implementation (Collier-Meek et al., 2018). However, to date, researchers have not pinpointed behavior severity as a variable that impacts teachers' adherence to behavioral interventions.

The Monetary Choice Questionnaire (MCQ; Kirby et al., 1999) provides an excellent foundation for evaluating if behavior severity is a state influence that impacts teachers' discount rate may serve as a proxy to future treatment adherence (White et al., 2023). Using the MCQ, researchers can manipulate a variety of variables that may impact how an individual makes choices regarding receipt of delayed rewards. For example, researchers have used the MCQ to analyze how motivating operations (Balance et al., 2022), cannabis intake (Jarmolowicz et al., 2020), and intertemporal tradeoffs (Ma et al., 2021) impact degrees of discounting as state influences.

Survey Research

The internet is becoming an extremely common environment for disseminating research surveys and collecting data (Ballard et al., 2019; Dupuis et al., 2019; Lawlor et al., 2021). Collecting survey responses via internet-based survey instruments allows researchers to reach a wide variety of participants across large geographic regions, is cost-effective, reduces the length of time needed to recruit participants, and provides participants with a confidential space to provide information (Ballard et al., 2019; Griffin et al., 2021; Storozuk et al., 2020). Online data collection can also help remove experimenter bias, observation bias, and participant reactance (Buchanan & Scofield, 2018). Furthermore, online survey research is especially useful when attempting to reach a population that is deemed "hard to reach" as it minimizes the amount of time needed to participate (e.g., travel time; Griffin et al., 2021).

Survey Fraud

Despite the many benefits of internet-based survey research, the use of internet-based survey research can create challenges to the quality and validity of collected data (Ballard et al., 2019). Because online surveys provide confidentiality and anonymity for respondents, the collection of fraudulent responses becomes almost inevitable especially for those who promise compensation or incentive upon survey completion (Griffin et al., 20121; Lawlor et al., 2021; Storozuk et al., 2020). Previous research has described fraudulent responses as: (1) respondents who misrepresent themselves to fit eligibility criteria (i.e., misrepresentation fraud; Ballard et al., 2019; Chandler et al., 2017; Lawlor et al., 2021; Teitcher et al., 2015), (2) respondents who participate more than once (i.e., duplicate fraud; Ballard et al., 2019; Lawlor et al., 2021; Teitcher et al., 2015), or (3) responses submitted by smart software (i.e., computer programmed bots; Buchanan & Scofield, 2018; Griffin et al., 2021; Lawlor et al., 2021). Bots, defined as malicious internet software designed to preform automated tasks (Griffin et al., 2021; Pratt-Chapman et al., 2021), can be quickly created or downloaded by any user with access to a computer. Further, these bots can be programmed to search the internet specifically for surveys that provide compensation or incentives; unfortunately, creating bots to complete surveys has now become a lucrative form of income (Griffin et al., 2021).

Misrepresentation and duplicate fraud are relatively easy to identify using ‘find duplicates’ in data analysis software, but as technology rapidly advances, fraudulent responses can be extremely difficult to detect (Giffin et al., 2021; Pratt-Chapman et al., 2021). For example, placing a cookie in the web browser cache (a process available in Qualtrics) was a common method for preventing duplicate responses; however, participants can complete the same survey on multiple devices, using different browsers, or add in a cookie-blocking feature on their browser (Chandler et al., 2017). Further, bots have the ability to produce human-like responses (e.g., producing logical short answer responses), create unique Internet Protocol (IP) addresses, and pass Captcha-type questions (Ballard et al., 2019; Dupuis et al., 2019; Griffin et al., 2021; Storozuk et al., 2020; Teitcher et al., 2015). Over time, bots have become more sophisticated by mimicking human behavior (Pratt-Chapman et al., 2021). For example, bots were originally thought to complete surveys rapidly; however, bots can now be programmed to complete surveys in specified durations of time (Storozuk et al., 2020). As another example, bots can also be programmed to imitate click counts or click patterns that resemble how a human would click through a survey (Buchanan & Scofield, 2018). Further, respondents can download or code automated form-fillers or ‘survey bots’ designed to complete online surveys with accuracy (Dupuis et al., 2019; Pratt-Chapman et al., 2021; Storozuk et al., 2020). Using survey bots, respondents can utilize JavaScript, virtual private networks (VPN), and virtual private servers (VPS) to bypass safeguards, such as Qualtrics ballot box stuffing, designed to protect against bots (Griffin et al., 2021; Storozuk et al., 2020).

While recruiting for a research study (Chapter 2), the authors inadvertently drafted thousands (i.e., 4,923) of fraudulent responses. Despite the use of reCAPTCHA and ballot-box stuffing, fraudulent responders were able to access and complete the survey. The authors used a 10-step fraudulent response detection process whereby 5,240 responses were filtered to a total of 317 responses. However, the authors did not password protect their survey, included the incentive amount on their recruitment flier, did not have all Qualtrics fraud protections enabled (i.e., password protection, security scan monitor, prevent indexing), did not use any attention check questions, and disseminated the survey on public social media pages.

Current Study

The first purpose of the study was to extend the findings of Chapter 2 by administering two treatment choice questionnaires (TCQ) to assess the influence of behavior severity on choice. Specifically, the two treatment choice questionnaires evaluated discounting of treatment effects as a function of severity of challenging behavior. One TCQ evaluated discounting of treatment outcomes for a hypothetical student that engages in severe challenging behavior, and the other TCQ evaluated discounting of treatment outcomes for a hypothetical student that engages in mild challenging behavior. To address the first purpose, I asked the follow research question: how does severity of behavior impact the discount rate of teachers of students who engage in challenging behavior?

The second purpose of the study was to replicate and extend the fraudulent response detection process described in Chapter 2. We extended the fraudulent detection process by (1) password protecting the survey, (2) removing the incentive amount on the recruitment flier, (3) embedding additional Qualtrics fraud protections into the survey, (4) including three attention check questions, and (5) avoiding survey dissemination on public social media feeds. To address the second purpose, I asked the following research question: does the proportion of fraudulent survey responses decrease with additional fraudulent response protections?

Method

Recruitment

The survey was disseminated on April 4, 2023, and closed on April 30, 2023. To recruit participants, we distributed a recruitment flier to personal contacts and shared the flier on closed Facebook groups designed to support teachers. To participate, respondents needed to be (1) a current teacher (2) that is currently serving students who engage in challenging behavior. We collected a total of 1,837 responses and filtered the responses, discussed in detail below, to 259 responses.

Fraudulent Response Detection

We filtered 1,837 responses to 259 responses using an 11-step fraud detection process (see Figure 9). First, Qualtrics (Qualtrics, Provo, UT) identified duplicate responses and potential bots. Second, we removed responses based on three attention-check questions embedded in the survey (Buchanan et al., 2018): (1) please type the second word in the following list: teacher, student, school; (2) please type the third word in the following list: teacher, student, behavior; and (3) please type the month in which you completed this survey. Third, we filtered out responses based on a Qualtrics-generated reCAPTCHA score; scores less than 0.5 are likely fraudulent. Next, we filtered responses based on a Qualtrics-generated fraud score; scores greater than or equal to 30 are likely fraudulent. We then filtered out responses that were not 100% complete. Next, we filtered out responses where the response duration was under 300s or over 3600s. We then analyzed latitude and longitude coordinates and removed any duplicate locations between responses. We also removed any duplicate IP address between responses. We then removed any response with a latitude and longitude coordinate outside of the United States. Next, we filtered out any response with a duplicate email address to another response. Finally, two independent researchers visually inspected the remaining 411 email addresses provided by respondents. We removed any response with an email address that (a) ended in more than four numbers (Griffin et al., 2021), (b) were missing, (c) contained more than one "@," ".com," or email system (e.g., "gmail"), (d) contained the word "bot," "poll," or "survey," and (e) comprised of a random string of characters (Griffin et al., 2021; Pratt-Chapman et al., 2021). Interobserver agreement for the email analysis was 86%. After filtering the responses, we were left with a total of 259 responses.

Participants

We recruited a sample of 259 participants. The majority of participants were white-non-Hispanic (83.4%), were female (76.8%), and held a special education license (64.5%). 39.4% of participants were between the ages of 30 and 39 years old, 48.6% held a master's degree, 32.4% had one to five years of experience as a teacher, and 42.1% reported that 1% to 25% of their students engaged in challenging behavior. 48.3% of participants taught in a middle school, 43.2% taught in a general education setting, and 32.4% of participants reported that between 26% and 50% of their schools' student body receive free or reduced lunch (FRL). Most participants had received professional development in developing behavior interventions (83%) and implementing behavior interventions (86.1%) to decrease challenging behavior, and 86.9% reported that they had previously collaborated with a related service provider to decrease a students' engagement in challenging behavior. Please see Table 9 for all collected participant demographic information.

Procedure

Participants completed the study in the survey program Qualtrics (Qualtrics, Provo, UT). The study included a total of 76 questions: one question requiring participants to enter a password, one reCAPTCHA question, one question regarding informed consent, two questions clarifying inclusion criteria, 54 delay discounting questions (i.e., the MCQ and TCQ each consisted of 27 choice trials), 14 questions related to teacher and school demographics, and three attention check questions. The study took an average of 19 minutes and 1 sec (range, 5 min 10 sec – 56 min 28 sec) to complete. Upon completion of the task, participants were given an opportunity to provide their e-mail address to receive compensation in the form of a $10 Amazon.com gift card.

To begin the study, participants entered the password found on our recruitment flier (Figure 10). Participants then read an institutional review board (IRB) informed consent document and indicated if they consented to participate in the study or did not consent to participate in the study. Upon consent, participants then answered screening questions to determine if they were a current educator serving students who engage in challenging behavior. If participants passed the screening (i.e., answered “yes” to all screening questions), they were then presented with the monetary choice questionnaire or one of the treatment choice questionnaires. Participants were randomly assigned to either the mild TCQ or the severe TCQ. The presentation of the MCQ and assigned TCQ were randomized across participants (Lemley et al., 2017).

Monetary Choice Questionnaire

For the MCQ, participants were provided with the following statement:

> For the first part of this experiment, you will be asked to make choices about hypothetical amounts of money. You will not receive any money; however, we ask that you make choices as if you were to receive the money. For each trial, you will see two options. One option will offer money today. The other option will offer money after some delay. Pick the option that you would rather have. You will continue to see two options presented to you after each choice that you make. Please continue to pick the option that you would rather have.

After reading the statement, the MCQ began. The first MCQ trial appeared on participants’ screens and each subsequent trial was presented individually on separate pages.

Treatment Choice Questionnaire

Participants were randomly assigned to one of two treatment choice questionnaires.

Version 1 asked participants to make choices between treatment outcomes for mild challenging behavior and version 2 asked participants to make choices between treatment outcomes for severe challenging behavior. Below is the statement given to participants assigned to version 1(mild):

> For the second part of this experiment, you will be asked to make choices about treatment options for a hypothetical student that engages in mild challenging behavior. For this hypothetical student, challenging behavior is defined as: **student leaving their seat without permission for their teacher (emphasis added)**. The treatment outcomes are hypothetical, but we ask that you make choices as they were real. You will see two options. One option will offer you a treatment that will stop your student's engagement in mild challenging behavior immediately. The other option will offer you a treatment that will stop your student's engagement in mild challenging behavior after some delay. Pick the option that you would rather have. You will continue to see two options presented to you after each choice that you make. Please continue to pick the option that you would rather have.

Below is the statement given to participants assigned to version 2(severe):

> For the second part of this experiment, you will be asked to make choices about treatment options for a hypothetical student that engages in severe challenging behavior. For this hypothetical student, challenging behavior is defined as: **open-handed strike to another person's face resulting in a mark (emphasis added)**. The treatment outcomes are hypothetical, but we ask that you make choices as they were real. You will see two options. One option will offer you a treatment that will stop your student's engagement in severe challenging behavior immediately. The other option will offer you a treatment that

will stop your student's engagement in severe challenging behavior after some delay. Pick the option that you would rather have. You will continue to see two options presented to you after each choice that you make. Please continue to pick the option that you would rather have.

The first TCQ trial appeared on participants' screens. The TCQ was modeled after the MCQ (Tompkins et al., 2016) and included 27 dichotomous choice trials.

Demographic Questions

Following completion of the monetary and treatment choice questionnaire, participants answered 14 demographic questions.

Data Analysis

Data analysis entailed three steps: (1) fraudulent response detection (discussed above in recruitment), (2) calculation of discount rates, and (3) statistical analysis. In this section, we will describe steps two and three of our data analysis.

Discount Rates

Participant selections in the MCQ and TCQs were entered into Kaplan et al. (2016) automated spreadsheet scoring tool in Excel. In the spreadsheet, a "0" is entered if the participant selects the smaller sooner reward, and a "1" is entered if the participant selects the larger delayed reward (Kaplan et al., 2016). For statistical analysis, we used the log transformation of k values (Kaplan et al., 2016; Nieto et al., 2022; Peng et al., 2019). The tool also calculates the proportion of participants choosing the smaller immediate reward (SIR); therefore, we also analyzed the proportion of participants choosing the SIR across trials (Myerson et al., 2014). Consistency scores below 75% were excluded from the analysis (Kaplan et al., 2016). We excluded 29 participants due to their overall consistency scores being less than 75% in either the MCQ or the

TCQ leaving a total of 230 participants included for analysis.

Decision-Making Across Contexts. A paired samples *t* test was run to determine if participants' log geomean *k* values were significantly different between the MCQ and assigned TCQ. Liner regression was run to determine if discount rate in the MCQ predicted discount rate in the TCQ.

Decision-Making Across Severity. An independent samples t-test was run to determine if participants' log geomean *k* values in the mild behavior TCQ and the severe behavior TCQ were significantly different between the two versions.

Statistical Analysis

Independent samples t-tests were conducted to determine if discount rates in the TCQ were different for groups within dichotomous demographic variable groups (i.e., holding a special education license, previous experience with professional development in developing interventions and implementing interventions, previous experience collaborating with a related service provider, ethnicity). One way ANOVA was conducted to determine if discount rates in the TCQ were different for groups within categorical demographic variable groups (i.e., gender, age, highest level of education, number of years of experience, location, percent of students receiving FRL, and percent of students that engage in challenging behavior). Post hoc tests determined if there were any statistically significant differences in discount rates in the TCQ between the groups. Analyses were conducted in SPSS (Version 27) with assistance from Laerd Statistics (2017).

Results

Fraudulent Responses

The current survey was open and available for respondents to complete for 27 days. In the 27 days we received a total of 1,837 responses. On average, about 68 responses were recorded per day. Compared to Chapter 2, 5,240 responses were recorded in six days; on average, about 873 responses were recorded per day. The additional fraudulent protections allowed for survey two to be opened for 21 days longer than survey one. Additionally, survey two recorded, on average, 805 less responses per day. See Table 10 for survey data.

Discount Rates

Table 11 includes raw overall *k* values and log transformed geomean *k* values for the MCQ and the TCQs. We identified two outliers in the MCQ and five outliers in the severe TCQ; we decided to include the outliers. Inspection of Q-Q plots confirmed data were normally distributed in the MCQ and both TCQs. Log geomean *k* values in the mild TCQ were .022 points, 95% CI [-.138, .094] lower than the log geomean *k* values in the MCQ, $t(123) = -.373$, $p = .709$. There was a statistically significant correlation between log geomean *k* values in the MCQ and the mild TCQ, $r(122) = .696$, $p < .001$. Log geomean *k* values in the severe TCQ were .0687 points, 95% CI [-.093, .230] higher than the log geomean *k* values in the MCQ, $t(105) = .843$, $p = .401$. There was a statistically significant correlation between log geomean *k* values in the MCQ and the severe TCQ, $r(104) = .351$, $p < .001$. Results suggest that participants discounted monetary rewards similar to discounting of hypothetical treatment outcomes.

Results of the linear regression indicate log geomean *k* values in the MCQ accounted for 48.5% of the variation in geomean *k* values in the mild TCQ with adjusted R^2 = 48.1% and was statistically significant, $F(1,122) = 114.8$, $p < .001$. The regression equation was: predicted log geomean *k* values in the mild TCQ = -.536 + .696 x (log geomean *k* values in the MCQ). Results of a second linear regression indicate log geomean *k* values in the MCQ accounted for 12.3% of the variation in geomean *k* values in the severe TCQ with adjusted R^2 = 11.5% and was statistically significant, $F(1,104) = 14.627$, $p < .001$. The regression equation was: predicted log geomean *k* values in the severe TCQ = -1.173 + .36 x (log geomean *k* values in the MCQ).

Log geomean *k* values in the severe TCQ ($M = 1.7264$, $SD = .7268$) were .11 (95% CI, -.316 to .096) higher than log geomean *k* values in the mild TCQ ($M = -1.8363$, $SD = .8401$); however, the difference was not statistically significant, $t(228) = -1.051$, $p = .295$. Results suggest that participants discounted treatment outcomes for mild challenging behavior similar to discounting of treatment outcomes for severe challenging behavior.

Monetary Discounting

For monetary discounting, the mean(SD) overall *k* value for participants included in the analysis was 0.0578(0.0819) and the mean(SD) log geomean *k* value was -1.8054(0.7062). Using *k* value ranks, the raw overall *k* value falls between rank 7 (.041) and rank 8 (0.1) suggesting that, as a group, participants did discount delayed monetary rewards (Towe et al., 2015). When graphing the group proportion choices of the SIR at each *k* value (Figure 11), the researchers found that the proportion of SIR decreased systematically as a function of delays. At the largest delay, a large proportion of participants (.93) chose the SIR, and at the smallest delay, a small proportion of participants (.11) chose the SIR.

Treatment Outcome Discounting: Mild

24 included participants completed the mild TCQ. The mean(SD) overall *k* value for participants included in the analysis was 0.0589(0.0868) and the mean(SD) log geomean *k* value was -1.8363(0.8401). The raw overall *k* value falls between rank 7 (.041) and rank 8 (0.1) suggesting that, as a group, participants did discount delayed monetary rewards (Towe et al., 2015). The researchers graphed the group proportion choices of the SIR at each *k* value (Figure 12) and found that the proportion of SIR decreased systematically as a function of delays. At the

largest delay, a large proportion of participants (.86) chose the SIR, and at the smallest delay, a small proportion of participants (.21) chose the SIR.

Treatment Outcome Discounting: Severe

106 included participants completed the severe TCQ. The mean(SD) overall *k* value for participants included in the analysis was 0.0634(0.0924) and the mean(SD) log geomean *k* value was -1.7265(0.7268). The raw overall *k* value falls between rank 7 (.041) and rank 8 (0.1) suggesting that, as a group, participants did discount delayed monetary rewards (Towe et al., 2015). The researchers then graphed the group proportion choices of the SIR at each *k* value (Figure 13) and found that the proportion of SIR decreased systematically as a function of delays. At the largest delay, a large proportion of participants (.88) chose the SIR, and at the smallest delay, a small proportion of participants (.22) chose the SIR.

Statistical Analysis

Because we did not detect a statistically significant state influence of severity on discount rates, we conducted an exploratory post hoc analysis. There was not a statistically significant difference between the means of the mild and severe TCQs; therefore, we combined the log geomean *k* values from both groups into a single variable for the remaining statistical analysis. For the independent samples t-tests, inspection of Q-Q plots confirmed that the discount rates were approximately normal across variables. We used the Bonferroni correction to adjust the *P* value to .01. Homogeneity of variances was not assumed for obtaining a special education license ($p < .001$). Mean log geomean *k* value for obtaining a special education license was .115, 95% CI [-.31 to .08] higher than those who did not hold a license; however, the difference was not statistically significant, $t(227.239) = -1.165$, $p = .245$. Homogeneity of variances was not assumed for receiving previous professional development in developing behavioral interventions

(p = .007). Mean log geomean k value for participants receiving previous professional development in developing behavioral interventions was .009, 95% CI [-.215 to .197] higher than participants who had not received previous professional development in developing behavioral interventions; however, the difference was not statistically significant, $t(90.375) = -.086$, $p = .932$. Homogeneity of variances was not assumed for receiving previous professional development in implementing behavioral interventions (p = .022). Mean log geomean k value for participants receiving previous professional development in implementing behavioral interventions was .007, 95% CI [-.305 to .172] higher than participants who had not received previous professional development in implementing behavioral interventions; however, the difference was not statistically significant, $t(58.057) = -.558$, $p = .579$. Homogeneity of variances was assumed for previous experience collaborating with a related service provider (p = .1). Mean log geomean k value for participants with previous experience collaborating with a related service provider was .097, 95% CI [-.404 to .208] higher than participants who did not have with previous experience collaborating with a related service provider; however, the difference was not statistically significant, $t(228) = -.625$, $p = .533$. There were not enough participants in each ethnic group, therefore, we recoded ethnicity to white non-Hispanic and people of color. Homogeneity of variances was assumed for ethnicity (p = .875). Mean log geomean k value for participants that were white non-Hispanic was .406 95% CI [.121 to .691] higher than participants who were people of color. The difference in means was statistically significant, $t(228) = 2.808$, $p = .005$, $d = .522$. Cohen's d indicates a medium effect size.

For the one-way ANOVAs, inspection of Q-Q plots confirmed that the discount rates were approximately normal across all groups. We used the Bonferroni correction to adjust the P value to .00714. Homogeneity of variances was assumed was assumed for gender (p = .057).

Mean male log geomean *k* value was higher (*M* = -1.529, *SD* = .858) than females (*M* = -1.836, *SD* = .75); transgender females (*M* = -3.7), gender nonconforming (*M* = -2.933), and individuals who prefer not to say (*M* = -.486) each had one participant. The mean difference was not statistically significant, *F*(4, 225) = 3.586, *p* = .007. Homogeneity of variances was assumed was assumed for age (*p* = .424). Mean log geomean *k* value was highest for participants ages 20-29 (*M* = -1.692, *SD* = .8323) compared to participants ages 30-39 (*M* = -1.779, *SD* = .823), participants ages 40-49 (*M* = -1.788, *SD* = .781), participants ages 50-59 (*M* = -1.821, *SD* = .624), and participants over 60 years old (*M* = -2.1, *SD* = .903); however, mean difference was not statistically significant, *F*(4, 225) = .547, *p* = .702. Homogeneity of variances was assumed was assumed for highest level of education (*p* = .123). Mean log geomean *k* value was highest for participants with a doctoral degree (*M* = -1.654, *SD* = .858) compared to some college (*M* = -2.112, *SD* = .941), associate degree (*M* = -1.725, *SD* = 1.063), bachelor degree (*M* = -1.868, *SD* = .88), and master's degree (*M* = -1.742, *SD* = .684); however, mean difference was not statistically significant, *F*(4, 225) = .606, *p* = .658. Homogeneity of variances was assumed was assumed for number of years of experience as a teacher (*p* = .433). Mean log geomean *k* value was highest for participants with less than one year experience (*M* = -1.375, *SD* = 1.089) compared to participants with one to five years of experience (*M* = -1.763, *SD* = .81), six to 10 years of experience (*M* = -1.732, *SD* = .878), 11 to 15 years of experience (*M* = -1.952, *SD* = .725), 16 to 20 years of experience (*M* = -1.645, *SD* = .67), and more than 20 years of experience (*M* = -1.902, *SD* = .726); however, mean difference was not statistically significant, *F*(4, 225) = .768, *p* = .574. Homogeneity of variances was assumed was assumed for location (*p* = .304). Mean log geomean *k* value was highest for participants teaching in the South (*M* = -1.7719, *SD* = .736) compared to participants in the Northeast (*M* = -1.814, *SD* = .826), participants in the

Midwest (*M* = -1.784, *SD* = .877), and participants in the West (*M* = -1.7728, *SD* = .671); however, mean difference was not statistically significant, $F(4, 226) = .033$, $p = .992$. Homogeneity of variances was assumed was assumed for percentage of students receiving FRL ($p = .772$). Mean log geomean *k* value was highest for participants in schools were 1-25% of students received FRL (*M* = -1.745, *SD* = .787) compared to 0% (*M* = -1.828, *SD* = .639), 26-50% (*M* = -1.757, *SD* = .801), 51-75% (*M* = -1.779, *SD* = .761), and 76-100% (*M* = -1.787, *SD* = .838); however, mean difference was not statistically significant, $F(4, 225) = .213$, $p = .931$. Homogeneity of variances was assumed was assumed for percentage of students that engage in challenging behavior ($p = .965$). Mean log geomean *k* value was highest for participants with 1-25% of students that engage in challenging behavior (*M* = -1.742, *SD* = .778) compared to 26-50% (*M* = -1.789, *SD* = .83), 51-75% (*M* = -1.878, *SD* = .781), and 76-100% (*M* = -1.871, *SD* = .155); however, mean difference was not statistically significant, $F(4, 226) = .302$, $p = .824$.

Discussion

The current study expanded upon previous delay discounting studies analyzing teacher decision-making of behavioral treatment outcomes (Chapter 2; White et al., 2023). Consistent with previous research, teachers did discount delays to both monetary outcomes and treatment outcomes, and, based on raw overall *k* values, teachers did have higher discount rates in the TCQs compared to the MCQ. Additionally, respondents discounted treatment outcomes of severe challenging behavior to a higher degree compared to discounting of mild challenging behavior. We also expanded upon previous research in fraudulent response prevention and detection by (1) adding additional fraud protections prior to disseminating the survey and (2) completing an 11-step fraudulent response detection process. The fraud protections guarded against fraudulent responses, and the inclusion of attention check questions aided in identifying fraudulent responses. Below, we discuss these findings in detail along with directions for future research.

Delay Discounting

The current study was the first to examine a specific possible state variable on discounting of delayed treatment outcomes. Despite the fact that we did not find statistically significant results for a state effect, we did find initial evidence (i.e., difference in mean scores of raw and log geomean *k* values) suggesting that there may be a state effect on the severity of challenging behavior. Respondents did have higher discount rates in the severe TCQ compared to the mild TCQ. Previous studies exploring state effects have obtained more robust differences between discounting of monetary rewards and nonmonetary rewards (Odum et al., 2020). For example, delay discounting researchers studying drug addiction consistently find a state effect between monetary and drug-related outcomes (Bickel et al., 2012; Bickel & Marsch, 2001; Odum et al., 2020). Higher degrees of discounting for drug-related outcomes are thought to be due to the Withdrawal Hypothesis (people discount rewards that are associated with drug withdrawal, because obtaining a small amount of a drug prevents the withdrawal symptoms) or Addiction Hypothesis (people susceptible to substance abuse discount that substance more steeply compared to other rewards; Dixon et al., 2003; Odum et al., 2002; Odum et al., 2020). These aforementioned theories may explain why state effects are prevalent in discounting research related to addiction.

There are no withdrawal or addiction symptoms related to students abstaining from challenging behavior in the traditional sense, and this may explain why the current study did not find a significant state effect on severity. However, stress, burnout, and exhaustion negatively impact treatment adherence (Collier-Meek et al., 2018; Kanne & Mazurek, 2011) and may be loosely related to the negative effects experienced while in withdrawal. Future research should continue to explore possible state variables (e.g., resource availability, difficulty of the intervention, burnout, levels of stress) and their impact on discounting of treatment outcomes. Continued research may identify state variables that would ultimately inform treatment adherence to improve student outcomes.

Based on our results, teachers may discount hypothetical treatment outcomes similar to hypothetical monetary rewards, and the degree of discounting in monetary rewards was positively correlated with the degree of discounting for treatment outcomes. This finding has now been replicated three times – once in Chapter 2 and twice in the current study. Additionally, a recent review (Odum et al., 2020) found that discounting of monetary outcomes was positively correlated with non-monetary outcomes across 22 studies – indicating a trait effect. The similarity in discounting across rewards begs the question whether the MCQ, used as a control, is required in future delay discounting studies analyzing teacher decision-making and may be a ripe area for future discounting research in general (i.e., not only discounting in teachers; Weatherly et al., 2010). The implications for removing the MCQ as a control would be to shorten the delay discounting task provided to teachers in future research - eliminating the MCQ removes 27 choice trials which may decrease the time and effort required to complete the task. A shorter task may decrease participant attrition and allow future researchers to continue to explore discounting in larger samples of teachers. Continued replications of a trait effect between discounting of monetary rewards and treatment outcomes will hopefully provide enough empirical support for the TCQ to be used in isolation.

The study did find a statistically significant difference between the mean log geomean k values between participants who are white non-Hispanic and participants who are of color –

mean discount rate was higher for respondents who were white non-Hispanic compared to respondents of color. This finding is preliminary and we caution against making overarching claims regarding the difference in mean discount rates based on race or ethnicity because (a) previous delay discounting research has yet to explore differences in discounting between racial groups, and (b) the sample size for each group was not equal. The statistically significant difference was unexpected, and certainly warrants future research. An area for future research may be in exploring the association between student-teacher race match. For instance, having a Black teacher is consistently associated with lower rates of challenging behavior by Black students in the classroom (Accavitti & Williford, 2022). And, a study by Mashburn et al. (2006) found that teachers' race was significantly associated with perceptions of students' engagement in challenging behavior. In the study, teachers who were white perceived behavioral problems as more severe compared to other racial groups. Future researchers may consider continuing to analyze discount rates of teachers as a function of race or ethnicity. This may give insight to how teachers' characteristics, and possibly implicit bias (Mashburn et al., 2006), impact how teachers make decisions for behavioral interventions.

An additional avenue for future research may be in using the 5-trial adjusting delay discounting task to analyzing teacher decision-making. The 5-trial adjusting delay discounting task quicky calculates (e.g., less than 1 min) discount rates by providing in individuals with five dichotomous choice trials between a SIR and a LDR (Koffarnus & Bickel, 2014). In this task, the SIR is half the amount of the LDR. Additionally, the 5-trial adjusting delay discounting task was created to be used to evaluate any reward (Koffarnus & Bickel, 2014). Because the 5-trial adjusting delay discounting task can calculate discount rates of any reward extremely quickly, this task may be applied to future research evaluating discounting of delayed treatment outcomes by teachers. If the 5-trial adjusting delay discounting task captures discounting of delay treatment outcomes, the 5-trial task may be a more efficient task option, compared to the TCQ, to use in applied research settings.

There were a few limitations related to the current analysis of discount rates. First, we defined the target behavior for both the mild and severe TCQs; however, we cannot be certain that respondents carefully read the behavior definition provided. To address this limitation, future researchers may consider including the behavior definition for a second time (i.e., outside of the task directions) on its own page in the survey. Isolating the behavior definition may increase the probability of participants reading the definition. Additionally, researchers may include a knowledge question asking participants to identify the target behavior definition they were provided. Correspondence between the provided definition and correctly answering the knowledge question may confirm that participants read and comprehended the behavioral definition. Second, because we did not find a statistically significant difference between discounting in the mild verses severe TCQ, we combined the log geomean *k* values from both questionnaires into a single TCQ variable. Creating a single TCQ variable from two questionnaires has not been cited in the research literature, but the researchers believed combining the discount rates from the two TCQs was appropriate due to the exploratory nature of the current study. Additionally, combining the discount rates from both questionnaires increased the statistical power for analysis.

Fraudulent Response Detection

This study enhanced the fraud detection process by (1) password protecting the survey, (2) removing the incentive amount on the recruitment flier, (3) embedding additional Qualtrics fraud protections into the survey, (4) including three attention check questions, and (5) avoiding survey dissemination on public social media feeds. We are unsure which of the aforementioned protections prevented an influx of fraudulent responses; however, the inclusion of attention check questions proved to be extremely helpful during the fraud detection process as filtering out incorrect answers to the attention check questions was relatively simple. Future research may consider evaluating specific fraudulent preventions (e.g., password protection, attention check questions) in a component analysis arrangement to determine which protections result in minimal recruitment of fraudulent responses. Continued research in the area of fraud prevention is especially important as fraudulent responders continue to invade online survey research in order to earn compensation (Storozuk et al., 2020).

Despite our extra precautions designed to prevent fraudulent responses, bots were still able to enter the correct password, pass the reCAPTCHA question, and correctly answer attention-check questions. And, despite previous notions that captcha-type questions prevent bots (Lawlor et al., 2021), bots have now proven to be able to pass this protection. As stated by Griffin et al. (2021), the infiltration of fraudulent responses is not a human verses bot issue; rather, humans are creating extremely sophisticated bots to complete surveys for financial gain. For example, fraudulent responders who do not qualify to complete a survey based on screening questions have been found to initiate a survey multiple times in order to pass screening questions (Chandler & Paolacci, 2017; Lawlor et al., 2021). To do so, these fraudulent responders persistently attempt to provide correct answers to screening questions until they gain access to the survey (Lui & Wronski, 2018). It is possible this same process occurred for fraudulent responders that answered attention check questions correctly. Future researcher may consider including more than three attention-check questions to filter out more fraudulent responses at the beginning of the fraudulent detection process. Additionally, researchers may consider diversifying attention check questions (e.g., including open-ended questions, knowledge questions, or multiple-choice questions), and comparing which question type accurately identifies fraudulent responses (Lui & Wronski, 2018). As an example, researchers could ask similar free response questions throughout their survey and compare response. A researcher may ask, “What is your first and last name,” “What are your initials,” and “What is your last name?” Here, researchers can compare consistency across these three responses. Furthermore, researchers may ask in-depth free response questions that require respondents to write a lengthily response (e.g., two sentences). The logic behind this type of question is that duplicate responses should not occur by chance, and the identification of a duplicate would likely indicate a fraudulent response (Griffin et al., 2021).

Step five of our email analysis (i.e., removing email addresses that contain a random string of characters) was the most difficult step in the fraudulent response detection process. Consistent with previous research (Griffin et al., 2021; Pratt-Chapman et al., 2021), we removed any respondent with an email address that comprised of a random string of characters. A limitation to the current email filtration process is that identifying random strings of characters is subjective to the researcher – there is no formal definition of a ‘random string of characters.’ For example, one researcher may consider ‘nwanatr’ to be random string while a second may interpret the string to not be random. In this study, we removed an email that was identified as a random string by either researcher – the researchers did not need to agree. A previous study (Pratt-Chapman et al., 2021) did define a random string of characters as: at least 10 random numbers or letters in a row. However, the authors did not abide by this previous definition to a random string of characters, because we felt as the definition was already outdated – bots are rapidly advancing. In the current data set, the researchers found emails that comprised of less than 10 random characters (e.g., ahn3yos) and believed these emails were likely fraudulent and needed to be removed. We believe the analysis of fraudulent email addresses is extremely important for future research as researchers have yet to agree on a standard definition for a random string of characters. Continued analysis on fraudulent email addresses will hopefully lead to a formal definition of a random string of characters to ease the fraudulent detection process.

Future research should continue to explore innovations in fraud detection (Ballard et al., 2019). Additionally, researchers need to be aware of the rapid evolutions in technology and smart software as bot responses increasingly resemble human-like responses (Griffin et al., 2021). An additional avenue for future research may be in developing an automated or semiautomated algorithm that can detect potential instances of fraud (Ballard et al., 2019). Research in automated detection may be especially important as the current fraud detection process can be time-intensive (Ballard et al., 2019) and is subject to human error (i.e., email analysis). Further, developing an automated or semiautomated algorithm can be easily disseminated to the research community to enhance validity of survey research across fields. Researchers may also consider minimizing their compensation or adopting a raffle system whereby participants are randomly selected to receive compensation (Griffin et al., 2021; White et al., 2023). As an example, Griffin et al. (2021) changed their protocol from all participants receiving a $5 gift card upon survey completion to raffling ten $100 gift cards. The change in compensation drastically reduced the number of bot responses during their recruitment period. Results of the study suggest that raffle systems may prevent infiltration of bot responses; future research may consider analyzing the proportion of recorded fraudulent responses as a function of compensation.

Conclusion

The current study provided a framework for evaluating state influences on teachers' discounting of treatment outcomes. We found preliminary evidence suggesting that there may be a state effect of severity of behavior on discount rates, and we encourage replications of the current study to further explore how severity of challenging behavior impacts how teachers make decisions. For a third time, this study has shown that teachers do discount delayed treatment outcomes. Our goals for this line of research were to (1) quantitatively evaluate how delays to treatment outcomes impact how teachers make decisions, (2) to inform the behavioral consultation process, and (3) untimely improve the outcomes of students receiving behavioral interventions in the classroom.

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APPENDIX

Figure 9

Fraudulent Response Detection Process

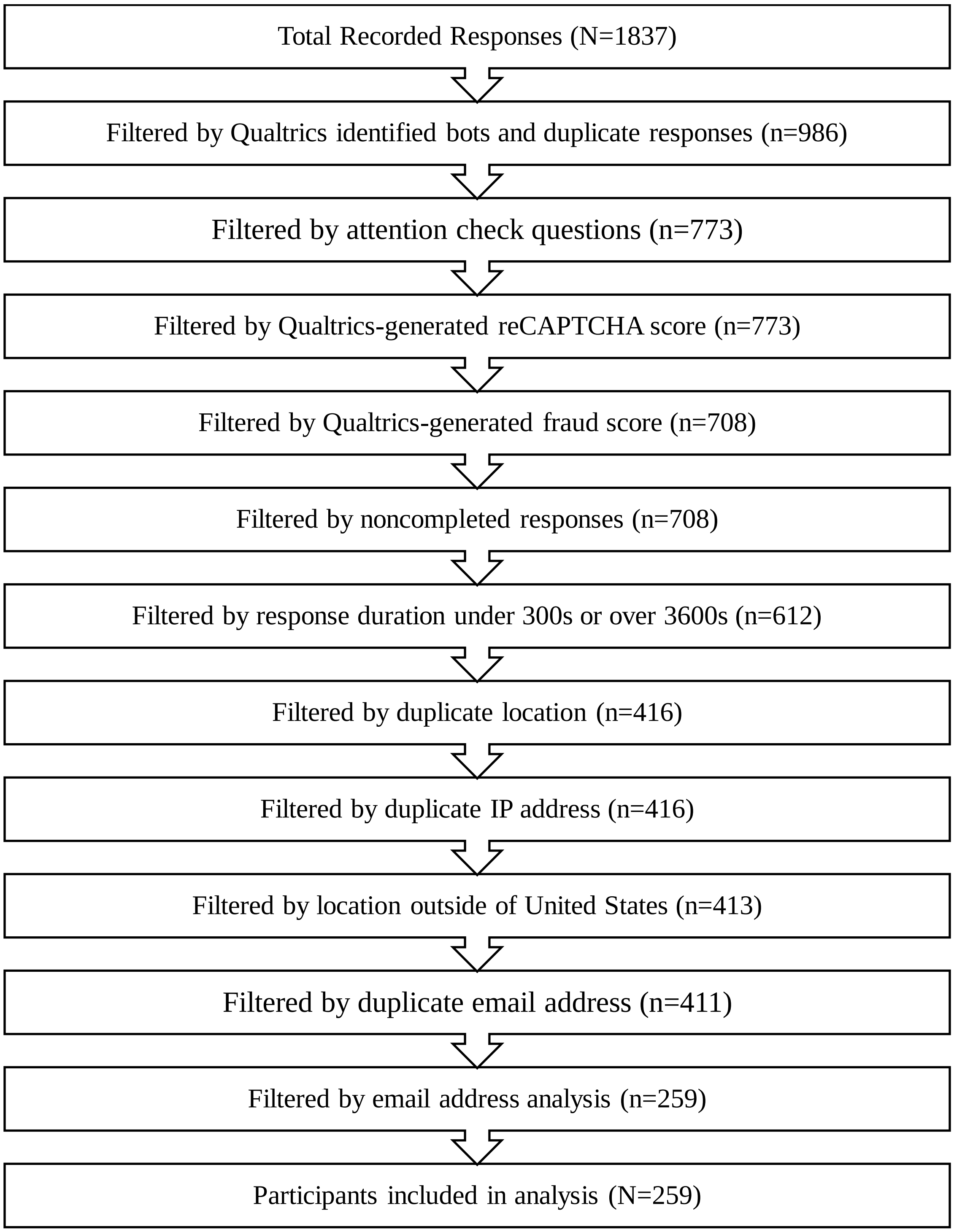


Table 9

Participant Demographic Information

Participants (N=259)			
Age (years)		**Special Education License**	
< 20	0 (0%)	Yes	167 (64.5%)
20 - 29	46 (17.8%)	No	92 (35.5%)
30 - 39	102 (39.4%)		
40 - 49	70 (27%)	**Teaching Area**	
50 - 59	31 (12%)	Early Childhood	35 (13.5%)
> 60	10 (3.9%)	Elementary	125 (48.3%)
		Middle	85 (32.8%)
Ethnicity		High	50 (19.3%)
White - Non-Hispanic	216 (83.4%)	Post-Secondary	7 (2.7%)
Latino/Hispanic	17 (6.6%)	Other	4 (1.5%)
Black	14 (5.4%)		
Asian/Pacific Islander	5 (1.9%)	**Teaching Environment**	
Native Indian	4 (1.5%)	General Education	112 (43.2%)
Native Hawaiian	2 (.8%)	Early Intervention	69 (26.6%)
Multiethnic	1 (.4%)	Resource Setting	60 (23.3%)
		Self-Contained Classroom	67 (25.9%)
Gender		Specialized Day Program	45 (17.4%)
Male	56 (21.6%)	Residential Facility	17 (6.6%)
Female	199 (76.8%)	Home Program	3 (1.2%)
Transgender Male	1 (.4%)	Hospital	3 (1.2%)
Transgender Female	1 (.4%)	Other	7 (2.7%)
Nonconforming	1 (.4%)		
Prefer not to say	1 (.4%)	**Students Receiving Free/Reduced Lunch (%)**	
		0	7 (2.7%)
Highest Level of Education		1 - 25	61 (23.6%)
Some College	5 (1.9%)	26 - 50	84 (32.4%)
Associate Degree	11 (4.2%)	51 - 75	50 (19.3%)
Bachelor Degree	100 (38.6%)	76 - 100	57 (22%)
Master's Degree	126 (48.6%)		
Doctoral Degree	17 (6.6%)	**Students Engage in Challenging Behavior (%)**	
		1 - 25	109 (42.1%)
Teaching Experience (years)		26 - 50	92 (35.5%)
< 1	2 (.8%)	51 - 75	29 (11.2%)
1 - 5	84 (32.4%)	76 - 100	29 (11.2%)
6 - 10	73 (28.2%)		

Table 9 (cont'd)

11 - 15	35 (13.5%)	**Professional Development (Developing)**	
16 - 20	29 (11.2%)	Yes	215 (83%)
> 20	36 (13.9%)	No	44 (17%)
Teaching Region (USA)		**Professional Development (Implementing)**	
Northeast	57 (22%)	Yes	223 (86.1%)
Midwest	93 (35.9%)	No	36 (13.9%)
South	64 (24.7%)		
West	45 (17.4%)	**Collaboration with Related Service**	
		Yes	225 (86.9%)
		No	34 (13.1%)

Figure 10
Recruitment Flier

MICHIGAN STATE
UNIVERSITY

Recruiting Teachers to Take a Survey About Challenging Behavior

Doctoral Candidate Allison Cascarilla and Dr. Matthew Brodhead are recruiting teachers to participate in a survey about educators' perceptions of challenging behavior.

Description of survey: We are recruiting teachers of students who engage in challenging behavior to take an online survey evaluating how teachers make decisions regarding treatments for challenging behavior. The survey should take 10 - 20 minutes to complete.

General requirements: In order to participate, you must be (1) a current teacher who (2) currently serves a student who engages in challenging behavior.

Compensation: Participants will receive an Amazon.com gift card.

To participate, please scan the QR code or visit the link:

Password: education

https://msu.co1.qualtrics.com/jfe/form/SV_0OqVy9A5mHkaaeG

For additional information or any questions please contact Dr. Matthew Brodhead at mtb@msu.edu.

Table 10

Response differences between survey one and survey 2

Survey	Days Open	Total Number of Responses	Average Number of Responses per Day
1	6	5,240	873
2	27	1,837	68

Table 11
Delay Discounting Variables used in Data Analysis

	MCQ		TCQ - Mild		TCQ - Severe	
Participant ID	Overall *k* value	Log geomean *k* value	Overall *k* value	Log geomean *k* value	Overall *k* value	Log geomean *k* value
1	.0097	-2.1448	.0039	-2.5408		
2	.0157	-1.7358			.0060	-2.1357
3	.0255	-1.598	.0016	-2.6695		
4	.2494	-0.6046			.2494	-0.6046
5	.0002	-3.8007	.0002	-3.8007		
6	.0157	-1.7358			.0159	-1.8666
7	.0002	-3.8007			.1009	-1.0626
8	.0097	-1.869			.0039	-2.4058
9	.0410	-1.4603	.0039	-2.2735		
10	.0097	-2.0048			.0097	-1.8736
11	.0644	-1.5995	.0157	-2.008		
12	.0016	-2.8039			.0159	-1.5993
13	.0025	-2.3982			.0060	-2.2735
14	.0157	-1.8668	.0325	-1.5958		
15	.1584	-0.7992	.0644	-1.1942		
16	.0002	-3.6	.0004	-3.367		
17	.0157	-1.7358	.0060	-1.9998		
18	.0025	-2.3982	.0025	-2.536		
19	.1584	-0.7992	.2494	-0.7036		
20	.1584	-0.7345			.2494	-0.7036
21*	.0410	-1.1919	.2494	-1.4031		
22	.0097	-1.9979	.0060	-2.0068		
23	.0025	-2.2671			.0410	-1.4639
24	.0410	-1.3235			.0410	-1.4576
25	.0652	-1.1899	.1265	-1.1319		
26	.0002	-3.8007			.0010	-2.9329
27	.0016	-2.7985	.0025	-2.6695		
28*	.0002	-3.7004	.2494	-0.9147		
29	.2494	-0.6682	.2494	-0.6046		
30	.1009	-1.0618			.0157	-1.7352
31	.0097	-1.8736	.0039	-2.4103		
32	.0157	-1.7358	.0157	-1.8711		
33	.0002	-3.7338			.0097	-2.1448

Table 11 (cont'd)

34	.1584	-0.8638	.0253	-1.5988		
35	.2494	-0.6046			.2494	-0.6682
36	.0157	-1.868			.0048	-2.407
37	.0157	-1.8668	.0410	-1.3235		
38	.0072	-1.869	.0097	-2.0114		
39	.0002	-3.8007			.0002	-3.8007
40	.0003	-3.4329	.1988	-0.7329		
41	.0255	-1.5384			.2494	-0.6046
42	.0025	-2.5393			.0124	-2.0071
43	.0025	-2.6695	.0025	-2.4072		
44	.0410	-1.3235			.0097	-1.8754
45	.0255	-1.598			.0255	-1.598
46*	.2489	-2.2712			.1584	-1.0998
47	.0025	-2.3982			.0025	-2.536
48	.1013	-1.1947	.2494	-0.6046		
49	.0002	-3.8007	.0002	-3.8007		
50	.1009	-1.066	.1013	-1.6009		
51	.0039	-2.2771	.0254	-1.5998		
52	.0016	-2.7985			.0255	-1.598
53*	.0002	-2.7363			.0016	-2.5383
54	.0410	-1.4576	.0039	-2.1421		
55	.1988	-0.7329			.0097	-1.869
56	.0025	-2.6695	.0039	-2.4103		
57	.2494	-0.6046	.2494	-0.6046		
58	.0025	-2.6695	.0157	-1.7358		
59	.0025	-2.6695	.0002	-3.8007		
60	.0157	-1.7358	.0325	-1.4589		
61	.0016	-3.1378	.0097	-2.0114		
62	.0097	-2.1417			.2494	-0.7683
63	.2494	-0.6046	.2494	-0.6046		
64	.0157	-1.7358	.0097	-1.869		
65	.0811	-1.0582			.0157	-1.7358
66	.0255	-1.598			.0025	-2.5298
67	.0157	-1.7358			.2494	-0.6046
68	.0025	-2.6695			.0652	-1.2263
69	.0048	-2.278	.0652	-1.1899		
70	.0060	-2.1384	.0016	-2.8056		
71	.0060	-2.0068			.0025	-2.6695
72*	.0652	-1.1899			.0010	-2.5573

Table 11 (cont'd)

73	.0048	-2.278	.0060	-2.0068		
74	.1009	-0.9289			.0410	-1.3235
75	.0097	-1.8736			.0060	-2.0068
76	.0157	-1.7358	.0157	-1.8711		
77	.0006	-3.2	.2494	-0.6046		
78	.0048	-2.278			.0048	-2.278
79	.2494	-0.6046	.2494	-0.6046		
80	.0410	-1.4639	.0159	-1.7334		
81	.0410	-1.3235			.0097	-2.0043
82	.0185	-1.4687	.0097	-2.0114		
83	.0025	-1.9979			.0157	-1.8711
84	.0097	-1.8736			.0157	-1.8711
85	.1584	-0.7992	.1584	-0.7992		
86	.0652	-1.0602	.0410	-1.1919		
87	.2494	-0.6046	.2494	-0.6046		
88	.2494	-0.6046			.2494	-0.6046
89	.0410	-1.5944	.0652	-1.1899		
90	.1267	-0.9309	.0002	-2.979		
91	.0410	-1.4639	.0060	-2.0068		
92	.0255	-1.7312			.0410	-1.3235
93	.0157	-1.7358			.0072	-2.1412
94	.1009	-0.9289			.0097	-2.0114
95	.0025	-2.3982			.0157	-2.0034
96	.0097	-1.8736	.0025	-2.6701		
97	.0016	-2.8039			.0258	-1.7298
98	.0002	-3.8007			.0072	-2.1412
99	.0157	-1.7358	.0097	-1.8736		
100	.0410	-1.4639	.0157	-2.008		
101	.0255	-1.598			.0254	-1.5998
102	.0002	-3.7338	.0002	-3.8007		
103*	.1013	-1.0974	.0002	-2.8335		
104	.2494	-0.6046	.2494	-0.6046		
105	.1009	-0.9289			.0060	-2.1446
106	.0076	-2.0058			.0060	-2.1446
107	.1013	-1.0606			.1584	-0.7992
108*	.2489	-1.505	.0652	-1.8548		
109*	.0517	-1.7708			.0003	-3.133
110	.0644	-1.1942	.1013	-1.0606		
111	.2484	-0.8321	.2494	-0.8005		

Table 11 (cont'd)

112	.0060	-2.0068	.0097	-2.1426		
113*	.0003	-3.0641			.1010	-1.7286
114	.0097	-1.8736	.0097	-2.0114		
115*	.0410	-2.2653			.0475	-2.0746
116	.0025	-2.6695	.0016	-2.9325		
117	.0097	-2.1448			.0410	-1.3283
118	.2494	-0.6694	.2494	-0.6046		
119	.0097	-2.1448	.0097	-2.0114		
120	.0410	-1.4576			.0410	-1.4576
121*	.1842	-0.8919			.0652	-1.1955
122	.0255	-1.7312			.0255	-1.598
123	.2494	-0.6046	.2494	-0.6046		
124	.2494	-0.6046			.2494	-0.6046
125	.0410	-1.3235			.0097	-2.0114
126	.0255	-1.7312	.0048	-2.278		
127	.1013	-1.0606	.1009	-0.9289		
128	.0811	-1.0582	.0097	-2.0114		
129*	.0652	-1.733			.2494	-1.669
130	.0255	-1.598			.0157	-1.8711
131	.0410	-1.4576			.0159	-1.8666
132*	.1013	-1.6684	.1583	-1.3361		
133	.2494	-0.6046			.2494	-0.6046
134	.0410	-1.3235			.0097	-1.8754
135	.0255	-1.598	.0410	-1.3235		
136	.0039	-2.267	.0016	-2.6704		
137	.0157	-1.7358	.0157	-1.6065		
138	.0060	-2.0068	.0097	-2.0114		
139	.0002	-3.8007	.0002	-3.8007		
140	.0002	-3.8007			.2494	-0.6046
141	.0517	-1.324			.0002	-3.8007
142	.0255	-1.598			.0410	-1.3235
143	.2494	-0.6046	.2494	-0.6046		
144	.0039	-2.267	.0025	-2.5383		
145*	.0039	-2.401			.2494	-1.5332
146	.0097	-2.0046	.0039	-2.5402		
147	.0157	-1.5987	.0002	-3.8007		
148	.0255	-1.598	.0097	-1.8736		
149	.0002	-3.8007	.0159	-2.0034		
150	.0349	-1.461			.0002	-3.8007

Table 11 (cont'd)

151	.0060	-2.0068			.0157	-1.8711
152	.0097	-1.869			.0255	-1.598
153	.0185	-1.7358	.0159	-1.601		
154	.0652	-0.9612			.2494	-0.6046
155	.0410	-1.5944	.0517	-1.324		
156	.0025	-2.4082			.0053	-2.1369
157	.0048	-2.278	.0060	-2.1446		
158*	.0021	-2.5408			.0003	-2.4691
159	.0097	-1.869	.0025	-2.4082		
160*	.2489	-0.6709			.0003	-2.6671
161	.0157	-1.7358			.2494	-0.6046
162	.0039	-2.268	.0097	-2.0114		
163	.0039	-2.4103			.0097	-2.0043
164*	.0049	-2.5125	.0002	-3.5017		
165	.0652	-1.1899	.0097	-1.8684		
166	.0060	-2.0068			.0097	-2.0043
167	.2494	-0.6046			.2494	-0.6046
168	.0157	-1.6065			.0097	-2.0114
169	.2494	-0.7991	.2494	-0.7036		
170	.0097	-1.8736	.0258	-1.593		
171	.2494	-0.7018	.0157	-2.1353		
172	.0025	-2.3982	.0025	-2.536		
173	.0255	-1.598			.0072	-2.1412
174	.2494	-0.6046	.2494	-0.6046		
175	.0157	-1.7358			.0159	-1.7334
176	.0002	-3.8007	.0002	-3.7004		
177	.0410	-1.4576	.0255	-1.4687		
178	.0410	-1.3235	.0097	-1.8736		
179	.0157	-1.9991			.2489	-0.6709
180	.2494	-0.6682	.2494	-0.6046		
181	.0025	-2.6695	.0255	-1.598		
182	.0039	-2.1302	.0255	-1.598		
183	.0644	-1.1942			.0410	-1.5944
184	.0517	-1.324			.0039	-2.4103
185	.0097	-1.869			.0060	-2.1446
186*	.0060	-1.8084	.0025	-2.6695		
187	.0039	-2.4103	.0072	-2.1412		
188*	.2494	-1.6034			.0013	-2.6654
189	.0255	-1.598			.0258	-1.4593

Table 11 (cont'd)

190	.0255	-1.598			.0124	-1.8736
191	.0025	-2.3939			.0159	-2.0034
192	.0157	-1.7358	.0060	-2.1446		
193	.0097	-1.869	.0097	-1.8754		
194*	.1267	-0.9309			.2494	-1.602
195	.0255	-1.598			.0325	-1.3273
196	.0097	-2.0002			.0124	-2.0071
197*	.0076	-1.9189	.0533	-1.7703		
198*	.2484	-0.7357			.0020	-2.8015
199	.0097	-1.8736	.0048	-2.278		
200	.0097	-1.8736			.2494	-0.6694
201	.0255	-1.6348	.2494	-0.6046		
202	.0010	-2.9329	.0060	-2.2768		
203*	.0060	-2.138			.2494	-1.669
204	.0025	-2.6695	.0255	-1.4651		
205	.0060	-2.139	.0039	-2.6424		
206*	.0021	-2.7829	.0060	-2.033		
207	.0060	-2.0068			.0157	-1.8711
208	.0097	-1.869	.0258	-1.593		
209	.0025	-2.3982			.0002	-3.8007
210	.0097	-1.8736			.0060	-2.0068
211	.0157	-1.6065	.1013	-1.0606		
212	.2494	-0.6046	.2494	-0.6046		
213	.0517	-1.324	.0410	-1.4576		
214	.0016	-2.7985	.0060	-2.1418		
215	.1584	-0.7992	.1584	-0.7992		
216*	.1179	-1.89	.0157	-1.6065		
217	.0097	-1.8736			.0159	-1.7334
218	.2494	-0.6046	.2494	-0.6046		
219	.2494	-0.6046			.2494	-0.6046
220	.0006	-3.2	.0020	-2.8011		
221	.0157	-1.7358			.0002	-3.4672
222	.0002	-3.8007	.0002	-3.8007		
223	.0039	-2.267			.0325	-1.4589
224	.0157	-1.7376			.0060	-2.0068
225	.0410	-1.3259	.0410	-1.4576		
226	.0410	-1.3283			.0048	-2.278
227	.1267	-0.9309	.0255	-1.7312		
228	.0349	-1.461	.0157	-1.8711		

Table 11 (cont’d)

229	.0255	-1.598			.1588	-1.0649
230	.0157	-1.7358			.0410	-1.4576
231	.0157	-1.7358			.0097	-1.8736
232	.0097	-1.8736	.0097	-2.0114		
233	.0652	-1.1899			.0652	-1.1899
234	.0517	-1.332	.0135	-1.8675		
235	.0025	-2.5383			.0255	-1.7312
236*	.2494	-1.3318			.0003	-2.0658
237	.2494	-0.6046			.2494	-0.6046
238	.0652	-1.5971	.1013	-1.1929		
239	.0410	-1.3235			.0157	-1.8711
240*	.0517	-1.324	.0157	-1.7355		
241	.0157	-1.7358			.0255	-1.598
242	.0060	-2.1357	.0255	-1.598		
243	.0410	-1.5954	.0025	-2.4014		
244	.0039	-2.4103			.0031	-2.5405
245	.0025	-2.6695			.0325	-1.4589
246	.0097	-2.0048	.0039	-2.4058		
247	.1584	-0.7992	.1584	-0.7992		
248	.0255	-1.598	.0410	-1.4639		
249	.0016	-2.7985			.0159	-1.8666
250	.0255	-1.598			.0097	-1.869
251*	.1842	-0.7682	.1421	-1.8329		
252	.0025	-2.3982	.0097	-2.1426		
253	.0039	-2.267	.0025	-2.5383		
254	.0072	-1.869	.0159	-1.7334		
255	.0060	-2.0068			.0097	-2.1426
256	.0644	-1.3346			.0255	-1.4687
257	.2494	-0.6046			.2494	-0.6046
258*	.0517	-1.3293	.0005	-1.501		
259	.0255	-1.598	.0039		.0410	-1.4576
All mean	.0566	-1.8032	.0607	-1.8444	.0632	-1.7743
(SD)	(.0809)	(.7908)	(.0889)	(.826)	(.092)	(.7213)
Included	.0578	-1.8054	.0589	-1.8363	.0634	-1.7265
mean (SD)	(.0819)	(.7962)	(.0868)	(.8401)	(.0924)	(.7268)

Note. The asterisk indicates that the participant was excluded in the statistical analysis due to consistency score being less than 75% in both the MCQ and TQC.

Figure 11

Proportion of SIR choices at each k rank in the MCQ at the group level

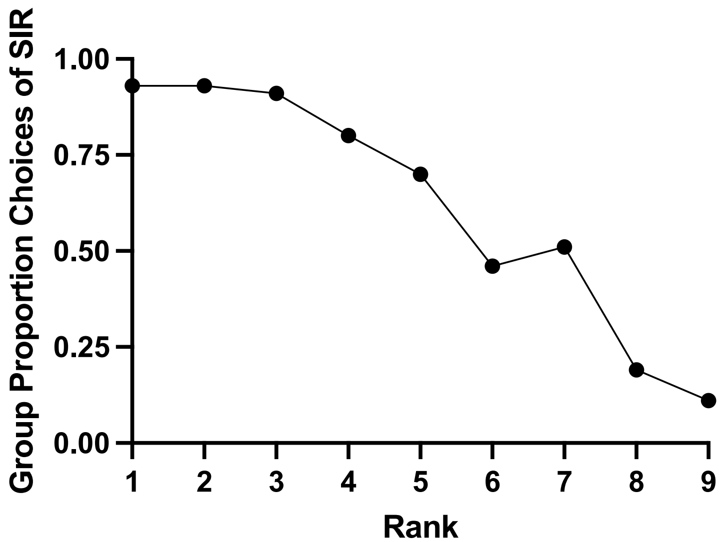


Figure 12

Proportion of SIR choices at each k rank in the mild TCQ at the group level

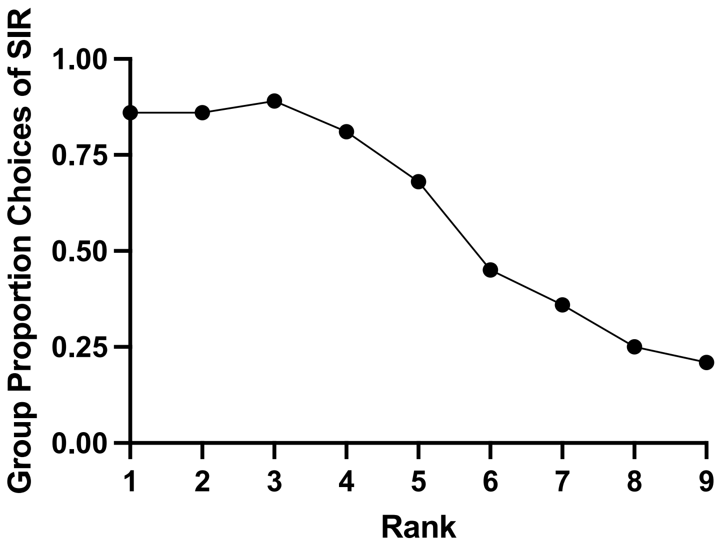
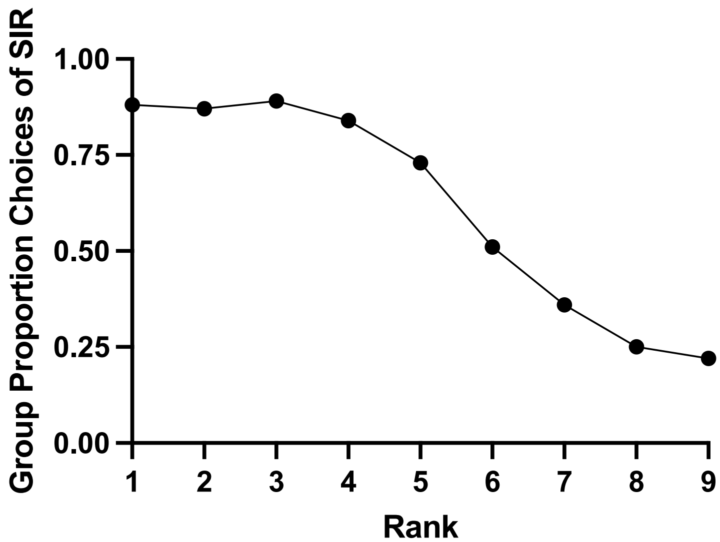


Figure 13

Proportion of SIR choices at each k rank in the severe TCQ at the group level



CHAPTER 4

A TUTORIAL ON CREATING, DISSEMINATING, AND PREVENTING FRAUD IN DELAY DISCOUNTING SURVEY RESEARCH

Researchers interested in the temporal properties of decision-making commonly use delay discounting to understand how people make choices between smaller immediate rewards (SIR) and larger delayed rewards (LDR; Reed et al., 2012). Delay discounting is the process whereby the value of a reward decreases as the delay to access the reward increases (Critchfield & Collin, 2001); the longer a person must wait for a reward, the less valuables that reward becomes (Critchfield & Collins, 2001). Due to the increasing awareness of delay discounting as a method to analyze human decision-making, researchers have published technical articles and tutorials designed to guide researchers through scoring of delay discounting tasks (Kaplan et al., 2016), analysis of discount rates (Reed et al., 2012), and processing of discounting data (Grey et al., 2016).

The goal of the current tutorial is to extend previously published delay discounting tutorials to the context of teacher decision-making to further aid in increasing the accessibility of discounting research and encourage the quantitative analysis of human behavior (Reed et al., 2012). First, we briefly describe translational research, delay discounting, and teacher decision-making. Second, we provide researchers with a step-by-step description on how to collect delay discounting data using survey research methodology and fraud protections. Third, we describe areas for future research using delay discounting to examine teacher decision-making.

Translational Research, Delay Discounting, and Teacher Decision-Making

An Introduction to Translational Research

Pure basic research often ignores problems in the "real world" and practice, and pure applied research often avoids theory and fundamental processes that shape practice (Mace & Critchfield, 2010). Translational research attempts to address the disconnect between basic and applied research by integrating research principles to solve "real world" problems (Mace & Critchfield, 2010). For example, researchers in local Ohio communities used translational research as a problem-solving approach to reduce risky youth behaviors associated with substance misuse and abuse (Julian et al., 2022). The researchers gained knowledge of the community needs, implemented evidence-based practices in the community (e.g., public schools, community centers), and influenced policy aimed to reduce opioid-related deaths in Ohio. The Ohio project is ongoing; however, initial evidence supports translational research as a framework for implementing evidence-based practices in local communities to address problems identified by community members and stakeholders (Julian et al., 2022).

As described by Neuhauser et al. (2007), translational research consists of two domains: (1) using research outcomes to guide clinical practice, and (2) disseminating research findings and clinical applications to community members. As such, the translational research process is an iterative cycle in which research guides practice to enhance society and societal outcomes influence the research agenda (Jones et al., 2015). In doing so, research becomes more representative of the problems facing society and society benefits from turning research findings into practice (Jones et al., 2022).

Because the current tutorial discusses translational research in the context of teacher decision-making, we use Jones et al. (2022) definition of translational research: "a systematic educational inquiry or investigation, where the findings have been developed by and/or shared effectively with practitioners, with the purpose of informing educational practices." Implicit in the definition is the process of turning research findings into practical knowledge. Indeed, the goal of educational research should be to improve the outcomes of students, school personnel, and relative stakeholders. Translational research attempts to meet this goal by using research outcomes to encourage best practice, including education settings (Laxton et al., 2020).

Translational research is commonly associated with the fields of medicine, public health, and public policy and is emerging in the field of education (Jones et al., 2022). Translational research can be especially useful in school settings because the iterative exchange of knowledge between researchers and educators supports teachers' use of evidence-based practices, aids researchers in understanding the day-to-day problems faced by both educators and students, and influences policy designed to enhance public education (Jones et al., 2022). Teachers make many practice-related decisions that impact their students; as such, educators and policy makers must stay up to date on research to inform these decisions (Jones et al., 2022).

Delay Discounting

Translational research presents a framework for researchers interested in analyzing decision-making. Specifically, translational researchers can use delay discounting, a commonly studied pattern of choice in behavioral economics, to describe the diminishing value of a reward as the delay to receive the reward increases (Critchfield & Collins, 2001), to understand humans' decision-making, such as decisions regarding behavioral interventions. Delay discounting is relevant to teacher decision-making of behavioral interventions, for example, because the decrease in challenging behavior followed by implementing behavioral interventions may serve as a reward for the teacher. Put another way, when teachers adhere to behavioral interventions, that adherence is often “rewarded” by the students abstaining from engaging in challenging behavior. Using delay discounting, researchers can analyze how teachers make decisions about behavioral interventions as delays to challenging behavior reduction increase. In fact, a study by White et al. (2023) investigated discounting of delayed reductions to challenging behavior in special education teachers and found that special education teachers did discount delays to behavioral treatment outcomes (i.e., reductions to challenging behavior). In the sample of 22 special educators, as a group, they did make selections that indicated a preference for immediate behavior reduction.

A key outcome of delay discounting research over the last 30 years is that humans often prefer smaller more immediate rewards compared to larger delayed rewards (Weatherly et al., 2010). That is, humans often discount the subjective value of a reward if that reward is delivered after some delay. Applications of delay discounting have become increasingly popular as delay discounting tasks (experiments) allow researchers to analyze the temporal relationships of rewards and decision-making of socially important problems (Kaplan et al., 2016; Reed et al., 2012). For example, Callan et al. (2011) used delay discounting to understand the relationship between personal relative deprivation (i.e., feelings of resentment or dissatisfaction based on the belief that one is deprived of a desired or deserved outcome) and gambling disorders. Callan et al. found that people experiencing personal relative deprivation are more likely to prefer smaller immediate rewards – indicating an increase in gambling behavior. The outcomes derived from the study contribute to the development of treatment strategies and interventions for people at-risk for gambling addiction or those with existing gambling problems. As a second example, Naudé et al. (2022) used delay discounting to understand problematic alcohol consumption and impaired driving in underage college women. Results of the study indicate that high degrees of discounting predicted significant increases in the odds of impaired driving. From a public health perspective, future researchers may be able to utilize a delay discounting survey to identify and intervene with individuals who are likely to drive impaired.

Monetary Choice Questionnaire

Delay discounting studies provide individuals with a choice between two rewards: one that is available immediately and one that is available after a delayed period of time. When rewards only differ in immediacy (e.g., $100 reward today vs $100 reward in 7 days), most people choose the immediate reward (Call et al., 2015; Meyerson & Green, 1995). When the amount of the immediate reward decreases and the delay between reward stays constant (e.g., $25 reward today vs $100 reward in 7 days), most people will eventually select the delayed reward (Call et al. 2015). By systematically varying reward amounts and delays, overall patterns of choice can be calculated and analyzed (Grey et al., 2016). Delay discounting tasks are a valid method for collecting discount rates as discounting of hypothetical rewards correlates to how humans make decisions in the "real world" (Kaplan et al., 2016).

The monetary choice questionnaire (MQC) was developed by Kirby et al. (1999) as a tool to efficiently analyze degrees of discounting. While a variety of delay discounting tasks exists, the MCQ is the most widely used and validated task for analyzing discounting (see Kaplan et al., 2016 & Kirby, 1999 for a discussion of the MCQ). The MCQ has a test-retest reliability score of .71 across 1-year (Hamilton et al., 2015; Towe et al., 2015) and diminishes floor and ceiling effects (Myerson et al., 2014). The MCQ presents a fixed set of 27 dichotomous choices between a monetary smaller immediate reward (SIR) and a larger delayed reward (LDR) (see Table 12). A person's patterns of choices across trials allows researchers to estimate a person's discount rate (Kaplan et al., 2016; Kirby, 2009; Kirby et al., 1999). Discount rates (*k* values) are a robust quantitative indicator of discounting of delayed rewards and describe a temporally extended pattern of behavior (Kaplan et al., 2016); higher discount rates indicate a preference for smaller immediate rewards (SIR) as opposed to larger delayed rewards (LDR) (Kirby et al., 1999). Because the scoring procedures of the MCQ can be complex (Kaplan et al., 2016), Kaplan et al. (2014) created a freely available automated MCQ spreadsheet scoring tool in Excel[1] to assist researchers with calculating discount rates (visit Kaplan et al., 2016 for a discussion of the tool's scoring logic). The tool computes standard hyperbolic-based *k* values, log transformed and natural log transformed *k* values, and supplementary measures (e.g., proportion of LDR choices and summary statistics) for overall discounting.

Case Example: Using Delay Discounting to Analyze Teacher Decision-Making

Next, we describe how delay discounting can be used to analyze teacher decision-making, in particular, the management of challenging behavior. We have chosen challenging behavior to illustrate how delay discounting can be used to study teacher decision-making because challenging behavior is often one of the greatest concerns in school settings. Further, teachers consistently report a lack of professional development, training, and support in the area of behavior management (Briere et al., 2015; McGuire & Meadan, 2022). As a result, teachers commonly collaborate with behavioral consultants as a method to address challenging behavior in the classroom (Briere et al., 2015). Behavioral consultants recommend interventions to reduce challenging behavior, and consultants intend for teachers to adhere to their recommended interventions upon future instances of challenging behavior (Anderson & Daly, 2013). Therefore, the next section of this tutorial will describe a situation where delay discounting is applied to teacher decision-making in the context of treatment of challenging behavior.

[1] You can download the automated MCQ scoring tool at https://kuscholarworks.ku.edu/handle/1808/15424

Consider an example where a teacher has been recommended to implement an intervention to reduce a student's engagement in challenging behavior. Here, the teacher has two choices: (1) adhere to intervention as was recommended or (2) do not adhere to the intervention as recommended. We hope the teacher will adhere to the intervention; however, there may be many barriers (e.g., availability of school resources) that prevent the teacher from adhering to the recommend intervention. Using delay discounting, researchers can evaluate what variables impact discount rates that may be an indicator of future teacher adherence to recommended behavioral interventions.

Administering a Delay Discounting Survey: A Step-by-Step Description

Next, this tutorial will provide a step-by-step description of how to create and disseminate a delay discounting task using the survey program Qualtrics (Qualtrics, Provo, UT). For this tutorial, pretend you are investigating if a specific variable, severity of challenging behavior, impacts teachers' discount rates using the MCQ in a web-based survey. Online data collection can be extremely advantageous as it allows for recruitment of large samples across geographic regions (Pellicano et al., 2023), decreases barriers for participation in research (Ballard et al., 2019), increases diversity in research participants (Chandler & Paolacci, 2017), and allows for relatively quick data collection (Griffin et al., 2021).

For this tutorial, please ensure that you have access to and can login to Qualtrics. Second, if you are unfamiliar with the MCQ, we recommend you review Kaplan et al. (2016) and Kirby et al. (1999). Finally, please ensure you have downloaded or have access to Excel. Of note, we use the abbreviation "TCQ" for treatment choice questionnaire. The TCQ was modeled from the MCQ to assess discount rates of treatment outcomes (i.e., reductions in challenging behavior).

Creation of Delay Discounting Survey

1. To begin, open Qualtrics and select CREATE A NEW PROJECT.
2. Find the heading, ‘From scratch,” and select SURVEY.
3. In the right panel select GET STARTED.
4. Create a title for your survey in the UNTITLED PROJECT box.
5. In the dropdown menu titled HOW DO YOU WANT TO START YOUR SURVEY, select CREATE A BLANK PROJECT.
6. Click CREATE PROJECT.

Entering Trials in Qualtrics Survey

1. You will already have one block in your survey titled DEFAULT QUESTION BLOCK.
2. Now, at a minimum, add five additional blocks to your survey by clicking ADD BLOCK. Label block one “Captcha,” block two “Directions and Consent,” block three “MCQ,” block four “TCQ Mild,” and block five “TCQ Severe.” If you aim to collect demographic information and provide compensation for participation, label block six “Demographics,” and block seven “Compensation.”
3. Delete the block titled DEFAULT QUESTION BLOCK. To delete this block, click on the three dots in the upper right corner of the block, and click DELETE. A warning box will appear. Click the red box labeled DELETE. The block will be deleted, and you will be left with the five blocks you added.
4. In block one, select ADD A NEW QUESTION, and in the dropdown menu, select CAPTCHA VERIFICATION. This will assist in preventing fraudulent responses (discussed in detail below). Then, look to the left panel titled EDIT QUESTION. Scroll down in this section to find RESPONSE REQUIREMENTS. Under RESPONSE

REQUIREMENTS, turn on ADD REQUIREMENTS and select FORCED RESPONSE. We recommend FORCED RESPONSE for all survey questions.

5. In block two, select ADD A NEW QUESTION, and in the dropdown menu, select MULTIPLE CHOICE. Replace “Click to write the question text,” with your IRB consent information. Note, you will replace “Click to write the question text,” for all multiple-choice questions.
6. Select “Click to write Choice 1,” and enter, “I have read the informed consent and agree to participate.” For choice two, enter, “I have read the informed consent and do not agree to participate.”[3] Note, you will replace “Click to write Choice X,” for all multiple-choice questions.
7. If you have any inclusion criteria for participation, enter the screening questions into block two. To do so, add as many multiple-choice questions needed to screen your participants. For example, we used two multiple-choice questions, “Are you currently a teacher?” and “Do you currently serve a student that engages in challenging behavior?” The choice options were, “yes,” and “no.”
8. In block three, select ADD A NEW QUESTION, and in the dropdown menu, select TEXT/GRAPHIC. Here is where you will provide directions for the MCQ (see Table 13 for an example).
9. In block three, select ADD A NEW QUESTION, and in the dropdown menu select MULTIPLE CHOICE 27 times. These 27 questions will be the MCQ trials (see Table 12 for the order and information for each trial). As an example, for trial one, you will type, “Would you prefer $54 today or $55 in 117 days?” The choices will be, from left to right,

[3] The language may vary depending on your IRB requirements or preferences.

"$54 today," and "$55 in 117 days." For these questions, we recommend presenting the choices horizontally. To present choices horizontally, select the question, on the left panel find FORMAT, click the dropdown menu under ALIGNMENT, and select HORIZONTAL. Once you have entered all 27 MCQ trials, confirm you have selected FORCED RESPONSE for all trials.

10. Blocks four and five will be the TCQs evaluating discounting of delays to treatment outcomes. Remember, there are two TCQs: one evaluating mild challenging behavior and the second evaluating severe challenging behavior. Setting up blocks four and five follow the same steps as 6 and 7; however, the directions will be different in blocks four and five (see Table 13 for an example). In block four, add the directions for the mild TCQ, and in block five, add the directions for the severe TCQ. When you enter the 27 choice trials into blocks four and five, you will replace monetary rewards with treatment outcomes. For example, for trial one in blocks four and five, you will type, "Would you prefer a treatment that will result in 54 days without challenging behavior immediately or a treatment that will result in 55 days without challenging behavior after 117 days of treatment implementation?" The choices will be, "54 days without challenging behavior immediately," and, "55 days without challenging behavior after 117 days of treatment implementation."
11. If you plan to collect demographic information from participants, begin by entering a TEXT/GRAPHIC question in block six that states, "Please answer the following questions to help us better understand the results of our study." Then, enter your demographic questions.

12. If you plan to provide compensation for participation, select block seven. For this tutorial, the researchers provided financial compensation. Enter a TEXT ENTRY question that states, "Please enter your email address below to receive [compensation]."
13. Qualtrics automatically provides an END OF SURVEY message. We recommend customizing the message. To the original Qualtrics message we added, "If your response is not flagged as fraudulent, you will first receive an email from the research team thanking you for your participation. Then, you will receive [compensation]."

Preventing Fraudulent Responses in Qualtrics

Qualtrics, and our research team, have many fraud detection procedures that can help prevent the collection of fraudulent/bot responses. Those procedures are described in more detail below.

1. We recommend password protecting your survey. To do so, on the far-left panel, click the icon labeled SURVEY OPTIONS (icon second from the bottom). Click SECURITY, find PASSWORD PROTECTION, click the toggle to ON, and enter a password of your choosing.
2. While in SECURITY, turn ON: PREVENT MULTIPLE SUBMISSIONS, BOT DETECTION, SECURITY SCAN MONITOR, RELEVENNTID, and PREVENT INDEXING. You can read the about Qualtrics fraud detection here: https://www.qualtrics.com/support/survey-platform/survey-module/survey-checker/fraud-detection/.
3. We recommend including at least three attention check questions. Disperse these attention check questions throughout your survey. As an example, in block two, add a TEXT ENTRY question that states, "Please type the second word in the following list:

teacher, student, school." We use text entry attention checks, because researchers can easily identify correct answers later using Microsoft Excel (discussed below).

Setting Survey Logic

Survey logic allows you to control how blocks and trials are presented to participants. Here, we will add in question behavior and set up block randomization.

1. Go to block two and click on the question with the IRB consent information. In the left panel click SKIP LOGIC. In the left box, click the drop-down menu and select END OF SURVEY. In the second box select I HAVE READ THE INFORMED CONSENT AND DO NOT AGREE TO PARTCIPATE. In the third box, select IS SELECTED. By following these steps, if participants do not consent to participate in the study, they will be immediately redirected to the end of the survey.
2. If you have screening questions, select the question, and in the left panel select DISPLAY LOGIC. In the left box select QUESTION. In the second box select your IRB consent question. In the third box select I HAVE READ THE INFORMED CONSENT AND AGREE TO PARTCIPATE. In the fourth box, select IS SELECTED.
3. On the same screening question, add SKIP LOGIC as you did in step 1. In the second box, select NO.
4. Complete steps 2 and 3 for all screening questions.
5. You will now design the survey flow. On the far-left panel click the icon labeled SURVEY FLOW (second icon from the top).
6. On block two select ADD BELOW and in the yellow box select RANDOMIZER.
7. Under the randomizer block select ADD A NEW ELEMENT HERE.
8. In the yellow box select GROUP. Label this group "Mild."

9. There will now be two ADD A NEW ELEMENT HERE. You will select the ADD A NEW ELEMENT HERE that is farthest to the left.
10. In the yellow box select GROUP. Label this group “Severe.” You now have your two groups.
11. In the purple randomizer box you will see RANDOMLY PRESENT; type “1” and check EVENLY PRESENT ELEMENTS.
12. Under the blue box that displays, “Group: Mild,” click ADD A NEW ELEMENT.
13. Select RANDOMIZER.
14. Locate block 3 labeled, “MCQ,” click on MOVE, and drag it under the randomizer block.
15. Locate block 4 labeled, “TCQ Mild,” click on MOVE, and drag it under “Show block: MCQ”.
16. Find the randomizer box under “Group: Mild.” Where it indicates RANDOMLY PRESENT, type “1” and check EVENLY PRESENT ELEMENTS.
17. Find the blue box labeled, “Group: Severe.”
18. Under the blue box that displays, “Group: Severe,” click ADD A NEW ELEMENT.
19. Select RANDOMIZER.
20. Under this randomizer box select ADD A NEW ELEMENT.
21. Select BLOCK, and in the drop-down menu select “MCQ.”
22. Locate block 5 labeled, “TCQ Severe,” click on MOVE, and drag it under “Show block: MCQ” in the severe group.
23. Find the randomizer box under “Group: Severe.” Where it indicates RANDOMLY PRESENT, type “1” and check EVENLY PRESENT ELEMENTS.
24. You have now completed the survey flow.

Administration of Delay Discounting Task

Below, we will provide directions for downloading a Qualtrics-generated QR code and survey link that you will use for recruitment and dissemination of the survey. We then provide recommendations for recruiting participants and disseminating the survey to prevent fraudulent/bot responding.

1. Download the Qualtrics-generated QR code. On the top panel click DISTRIBUTIONS.
2. Click the icon labeled MOBILE.
3. Find and select the blue box labeled USE A QR CODE (second box from the right).
4. Select DOWNLOAD QR CODE.
5. Access the survey link. On the left panel click ANONYMOUS LINK.
6. Select the blue box labeled COPY SURVEY LINK.
7. Save this link in a document.

Materials

A. Create a recruitment flier. On the flier include: the title of your research project, a description of the survey, general requirements for participation, information required to access the survey (we recommend using the Qualtrics generated QR code and survey link), the contact information of the projects primary investigator, and any additional information required by the IRB.
B. Include the password to access the survey.
C. If you will provide compensation for participation, include the reward on the flier. However, we recommend not including the exact dollar amount of the compensation in an effort to avoid bots designed to find incentive surveys (Griffin et al., 2022).

Dissemination

A. To avoid fraudulent or bot responses, avoid posting the recruitment flier on social media. If you relay on social media for recruitment, avoid posting the flier to public feeds or pages[1].

Data Cleaning

Below, we will provide the steps needed to filter out any fraudulent or bot responses.

1. Open the survey in Qualtrics.
2. On the top panel click the tab labeled DATA & ANALYSIS.
3. Find and click the tab labeled EXPORT & IMPORT. In the drop-down menu click EXPORT DATA.
4. A white box should have opened. On the top panel click EXCEL.
5. Check the box next to DOWNLOAD ALL FILES.
6. Select the circle next to USE CHOICE TEXT.
7. Click the blue box labeled DOWNLOAD. You have now downloaded all your data.
8. Label this Excel sheet, "All Data."

Fraud Detection

1. The first step in fraudulent response detection is to filter out any responses flagged as fraudulent by Qualtrics (because you set up fraud detection in Qualtrics, the platform will identify *some* fraudulent responses).
   a. Open the survey in Qualtrics, and on the top panel click the tab labeled DATA & ANALYSIS.
   b. Find a response that has a red warning triangle on the right side.

[1] We have preliminary evidence that posting the recruitment flier on private Facebook pages minimizes recruitment of fraudulent or bot responses.

c. Click the red warning triangle.

d. In the box the popped up, click VIEW DETAILS.

e. In the pop-up window, click the box that says FILTER OUT POOR QUALITY RESPONSES (bottom left corner). You have now removed fraudulent responses identified by Qualtrics.

f. Download these responses (follow steps 3 – 7 under 'data cleaning').

g. Label this sheet "Fraud detection." You will work off this excel spreadsheet for the entire fraud detection process.

h. Label the first tab "Cleaned by Qualtrics."

2. The second step is to filter out responses that incorrectly answered the attention check questions. To do so, find the columns containing the collected attention check data. Scroll through these responses and remove any response that provided an incorrect answer to the attention check question.

3. The third step is to filter out responses that have a reCAPTCHA score less than 0.5. Locate the column labeled "Q_RecaptchaScore," and remove any response with a score less than 0.5.

4. The fourth step is to filter out responses that have a fraud score greater than or equal to 30. Locate the column labeled "Q_RelevantIDFraudScore," and remove any response with a score greater than or equal to 30.

5. The fifth step is to remove any response that is not 100% complete. Find the column labeled "Progress," and remove any response less than 100.

6. The sixth step is to clean your data based on the duration to complete the survey. Specifically, you will remove responses that were completed in a very short duration and

responses that were completed after a long duration. We recommend collecting pilot data to determine an average response time to aid in defining a minimum and maximum duration criterion. Our team removed any response with a duration less than 5 min and over 1 hr (average response time was 19 min).

7. The seventh step is to remove responses with duplicate latitude and longitude coordinates. We take a conservate approach in order to remove any potential bot responses. If you have participants completing the survey in specificized locations or believe it would be reasonable for your participants to be in the same location (e.g., disseminating the survey to specific schools), you *may* be able to skip this step (and potentially step eight).
8. The eighth step is to remove responses with duplicate IP addresses. Again, we take a conservate approach in order to remove any potential fraudulent responses.
9. The ninth step is to remove responses that were completed outside of a set location. To do so, identify the target location of your participants, and remove any response with latitude and longitude coordinates outside of your target location. Our target location was the United States, so we remove any response with latitude and longitude coordinates outside of the United States.
10. The tenth step is to remove any response that has the same email address as another response as this indicates a duplicate response. We included this step, because our respondents were asked to enter their email address to receive compensation. If you do not ask participants for any identifying information, you can skip this step.
11. If you have participants provide an email address to receive compensation, the final step is to remove responses based on an email filtration process. There are five filtration steps.

a. The first step is to remove any response that did not include an email address (i.e., blank or text that is not an email address).
b. The second step is to remove email address that end in more than 4 numbers as these email addresses are likely fraudulent (CITE).
c. The third step is to remove email address that contains more than one "@," ".com," or email system (e.g., gmail).
d. The fourth step is to remove any email address that contains the words "bot," "poll," or "survey." We found these terms during our fraudulent analysis – there may be more trigger words that we did not identify.
e. The fifth step is to remove any email address that is comprised of a random string of characters (e.g., hsgev4jfnfj@email.com). Note, this may be the most difficult step in the fraud detection process. We recommend having at least one other person complete this step, comparing the removals, and discussing any disagreements.

Future Research Directions

In this tutorial, we described how applied researchers can use translational research, delay discounting, and survey research methodology to explore the underling determinants of decision-making. We provided a rational as to why delay discounting can be used to assess variables that may impact teacher decision-making, specially, adherence to recommend behavioral interventions. We hope this tutorial encourages applied researchers to explore delay discounting in the context of educational research.

The use of delay discounting to analyze teacher decision-making is a ripe area for research as teachers are constantly making in the moment and long-term decisions that directly impact their students (Jones et al., 2022). There are many variables that impact teacher decision-making, and delay discounting provides researchers with a framework to directly analyze the impact of variables on how teachers make decision regarding behavior interventions. Collier-Meek et al. (2017) describes variables that impact teacher decision-making of behavioral interventions into four categories: intervention level, implementer level, organizational level, and external level. And we expand on these categories below.

Within the intervention level, variables that can be assessed using delay discounting may include, but are not limited to, intervention complexity/feasibility (e.g., number of steps in the plan), time it takes to implement the intervention, materials needed, resources required to implement the intervention, and the quality of the intervention (Charlton et al., 2021; Collier-Meek et al., 2017). For example, a study by Charlton et al. (2021) found that teachers' adherence to behavior intervention plans (BIP) was linked to the complexity/feasibility of the intervention. As the plans became more technical, teachers believed that adhering to the plan was not feasible (Charlton et al., 2021). One explanation may be that as the complexity or technicality of a BIP increases, teachers may not have the skills to adhere to the intervention (Charlton et al., 2021). Future research may consider analyzing how teachers make decisions for highly complex interventions (e.g., treatment package containing multiple interventions) verses decisions for relatively simple interventions (e.g., single interventions with few steps). The implications may be that consultants recommending complex interventions may need to allocate additional time to training and ongoing supervision and feedback (Verschuur et al., 2020).

Teacher's adherence to interventions has also been linked to the "helpfulness" or quality of the intervention (Biggs et al., 2008; Charlton et al., 2021). That is, teachers are more likely to adhere to interventions if the teacher perceives the intervention as helping (i.e., being of high quality) the student(s), classroom, or school. A study by Thomas & Lafasakis, 2019 investigated four classroom aids' adherences to a student's behavioral intervention plan (BIP). Prior to the study, the aids rarely adhered to the student's BIP. To begin, the aids completed an acceptability questionnaire asking them to rate how acceptable they found components in the BIP. Based on the results of the acceptability questionnaire, a behavior analyst created a new BIP including components that the aids found acceptable and were evidence-based and related to the behavioral function. Results of the study indicate that aids' adherence to the BIP that included components found acceptable was much higher compared to the original BIP. This is unsurprising as teacher input and collaboration with a behavior consultant prior to and during intervention creation is associated with increased adherence to the intervention (Long et al., 2018). An interesting avenue for future research may be in analyzing how teachers make decisions for interventions that are specifically designed to decrease a students' engagement in challenging behavior (e.g., function-based interventions) verses interventions designed to generally decrease challenging behavior (e.g., antecedent interventions). This may lend insight to the initial and ongoing collaboration process between a consultant and teacher – consultants may need to enhance the collaboration process with teachers when designing behavioral interventions.

At the implementer level, additional variables that may be analyzed include previous history with professional development and training, personal philosophies of the intervention itself, previous experience implementing behavioral interventions, and psychological wellbeing (Collier-Meek et al., 2017). A study by Verschuur et al. (2020) investigated the relationship between treatment implementation and behavior therapist personal characteristics (e.g., personality traits, therapist-student relationships, experience). Results of the study indicate that therapists' attitudes towards evidence-based practice (i.e., openness to innovation) and therapist's previous experience implementing the intervention significantly predicted therapist adherence to the intervention. When therapists were open to innovation (i.e., the extent to which the therapist was open to trying a new evidenced-based intervention) or had previous experience with the intervention, they were more likely to adhere to the intervention. Expanding from Verschuur et al., researchers can use delay discounting to explore how teachers make decisions for novel behavioral interventions verses behavioral interventions in which they have experience implementing. Analyzing how teachers make adherence decisions based on their familiarity with interventions may lend insight to (1) how behavioral consultants recommend interventions – either recommending an intervention that is new to the teacher or one that the teacher has previous experience implementing, (2) how often or how much training may be needed – providing additional high-quality training for new interventions, or (3) how much additional support the teacher may require – providing adherence checklists, evaluating adherence more often.

At the organizational level, researchers may consider analyzing school culture or climate, the use of school-wide behavioral supports, availability of school resources, and classroom and school characteristics (Collier-Meek et al., 2017; Fallon et al., 2019). For example, teachers that have few students that engage in challenging behavior are more likely to adhere to interventions compared to teachers that have a large proportion of students that engage in challenging behavior (Biggs et al., 2008; Foreman et al., 2021). An avenue for future research may be in comparing discount rates of teachers with a small proportion of students that engage in challenging behavior to discount rates of teachers with a large proportion of students that engage in challenging behavior. The implications for this line of research would be to give insight to how consultants amend their consultative supports for teachers based on classroom demographics. Teachers in classrooms with a large proportion of students that engage in challenging behavior may require additional consultative supports to ensure adherence to behavioral interventions.

Additionally, future research may analyze decision-making of teachers with supportive leadership teams verses unsupportive leadership teams as previous research supports that teachers are more likely to adhere to recommended interventions if their administration or leadership teams support the intervention (Biggs et al., 2008). The perceptions of school-based leadership teams do impact teachers' implementation of behavioral interventions, and resistance to behavioral support from school leadership teams has been cited as a significant barrier to implementing behavioral interventions (Long et al., 2016). In fact, school leadership teams that resist behavioral supports are less likely to have the staff, resources, and professional development aimed to increase teachers implementation of behavioral interventions (Long et al., 2016). Addressing how teachers make decisions for behavioral interventions as a function of leadership support may lead to broader school changes as focusing on how leadership teams or administration impacts teacher decision-making draws specific attention to the importance of a supportive school climate. Disseminating this research may further educate leadership teams on how their support ultimately influences how teachers make decisions that impact their students (Kim et al., 2018).

Within the external level, future research may examine district or state policy, educational funding sources, and community involvement (Adelman & Tylor, 2003; Collier-Meek et al., 2017). Community-university partnerships have proven to increase teachers' implementation of behavior support plans and evidence-based practices (Domitrovich et al., 2008). For example, the Ohio opioid prevention program discussed in the introduction was a community-university partnership. Schools involved in the program received resources, training, and consultative services to support teachers' adherence to the prevention program (Domitrovich et al., 2008). An area for future research may be in analyzing teacher decision making within schools that have university-based partnerships verses schools that are not involved in university-based partnerships. University to school partnerships can greatly impact student success, and future research may prove valuable to school districts when considering a university partnership (Kearney et al., 2021).

Additionally, many schools rely on federal, state, local, or private funding to support teachers' implementation of evidence-based interventions (Domitrovich et al., 2008). Future research may investigate teacher decision-making of interventions that are supported by external funding verses interventions that are not supported by external funding. As noted by Zhang et al. (2022), schools that receive external funding to support the implementation of evidence-based practices may have additional time allocation for staff reflection, collaboration, and professional development/training. If this is the case, teachers that are employed at schools that have additional funds to support implementation of behavioral interventions may be more likely to adhere to consultant recommended interventions. Additionally, these teachers may not require additional consultative training and evaluation – minimizing the cost of consultative services or maximizing the consultants' time for other clients.

In this tutorial we included methods for preventing fraudulent responses and outline a 11-step process for detecting fraudulent responses. We recognize that the fraudulent response detection process can be laborious and time consuming, but it is necessary step for ensuring the validity of data. Based on our previous experience, embedding Qualtrics fraudulent protections, careful design of materials (e.g., recruitment flier), and cautious dissemination of the survey (e.g., avoiding public social media pages) can minimize the time and effort spent filtering through collected survey responses. We encourage all researchers, not just delay discounting researchers, to apply, analyze, and refine our proposed plans for fraudulent prevention and detection. At this point, there is no perfect model for preventing and detecting all fraudulent responses, but future replications of our proposed process will hopefully provide more insight to the extent to which and how fraudulent responders gain access to research surveys. We recommend that researchers continue to review the research literature on fraudulent response detection because technology used to create bots is rapidly advancing (Zhang et al., 2022).

Despite the threats posed by fraudulent responses (e.g., misuse of funds, dissemination of inaccurate data), we encourage researchers to continue to use internet-based survey research to continue to reach a wide variety of participants (Griffin et al., 2021). Our tutorial provides an integrated approach to avoiding and identifying fraudulent responses that can protect against bot infiltration starting at the conception of the survey project. Proactively building in fraudulent protections can effectively limit the number of fraudulent or bot responses and aid researchers in identifying fraud in collected data (Griffin et al., 2021). We urge researchers to stay vigilant on the advancement of bots as they continue to advance, mimic human-like response patterns, and infiltrate internet research (Griffin et al., 2021).

Conclusion

Translational research is often described a process whereby scientific knowledge and principles are imbedded into everyday practice to enhance the overall wellbeing of humans (Edwards, 2017; Julian et al., 2022). Using translational research, educational researchers can investigate how teachers make decisions regarding behavioral interventions. Delay discounting presents a framework for researchers to analyze variables that may impact how teachers make decisions after delayed periods of time. Identifying variables that may impact rates of discounting is critical for understanding teacher decision-making and treatment non-adherence in order to create environments that decrease the chances of treatment non-adherence and ultimately improve the outcomes and lives of students that receive behavioral interventions (Xu et al., 2022).

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APPENDIX

Table 12
Choice Trial Values

Trial Order	SIR	LDR	Delay (days)
13	34	35	186
1	54	55	117
9	78	80	162
20	28	30	179
6	47	50	160
17	80	85	157
26	22	25	136
24	54	60	111
12	67	75	119
22	25	30	80
16	49	60	89
15	69	85	91
3	19	25	53
10	40	55	62
2	55	75	61
18	24	35	29
21	34	50	30
25	54	80	30
5	14	25	19
14	27	50	21
23	41	75	20
7	15	35	13
8	25	60	14
19	33	80	14
11	11	30	7
27	20	55	7
4	31	85	7

Note. This table was edited from Kirby et al. (1999).

Table 13
Directions for the MCQ and TCQ

Task	Directions
MCQ	For this part of this experiment you will be asked to make choices about hypothetical amounts of money. You will not receive any money, however, we ask that you make choices as if you were to receive the money. For each trial, you will see two options. One option will offer money today. The other option will offer money after some delay. Pick the option that you would rather have. You will continue to see two options presented to you after each choice that you make. Please continue to pick the option that you would rather have.
TCQ – Mild	For this part of this experiment you will be asked to make choices about treatment options for a hypothetical student that engages in **problem behavior defined as: student leaving their seat without permission from their teacher**. The treatment outcomes are hypothetical, but we ask that you make choices as they were real. Each treatment outcome represents a problem behavior no longer occurring for different amounts of time. You will see two options. One option will offer you a treatment that will stop your student's problem behavior immediately. The other option will offer you a treatment that will stop your student's problem behavior after some delayed period of time. Pick the option that you would rather have. You will continue to see two options presented to you after each choice that you make. Please continue to pick the option that you would rather have.
TCQ – Severe	For this part of this experiment you will be asked to make choices about treatment options for a hypothetical student that engages in **problem behavior defined as: open-handed strike to another person's face resulting in a mark**. The treatment outcomes are hypothetical, but we ask that you make choices as they were real. Each treatment outcome represents a problem behavior no longer occurring for different amounts of time. You will see two options. One option will offer you a treatment that will stop your student's problem behavior immediately. The other option will offer you a treatment that will stop your student's problem behavior after some delayed period of time. Pick the option that you would rather have. You will continue to see two options presented to you after each choice that you make. Please continue to pick the option that you would rather have.

CHAPTER 5

CONCLUSION

Overview

This dissertation explored teacher decision-making by using delay discounting to analyze how teachers make decisions as a function of delay to treatment outcomes. Chapter 2 used the MCQ to assess discounting of delayed rewards by teachers of students who engage in challenging behavior and evaluated associations between demographic variables and group mean discount rate. Chapter 3 extend the findings of Chapter 2 by administering two treatment choice questionnaires (one targeting mild challenging behavior and one targeting severe challenging behavior) to assess behavior severity as a state influence. Additionally, Chapter 3 replicated and extended the fraudulent response detection and prevention process outlined in Chapter 2. Chapter 4 (a) described translational research, teacher decision-making, and delay discounting, (b) presented readers with a tutorial on how to collect discounting data using survey research methodology and fraud protections, and (3) recommended future research using delay discounting to examine teacher decision-making.

The purpose of this dissertation was not to encourage practicing behavior consultants to use the MCQ or the TCQ modeled from the MCQ to assess whether their consultee will adhere to their recommended intervention(s). Further, I do not intend to imply that all teachers do not adhere to consultant-recommended interventions. Instead, I used delay discounting as a framework for understanding variables that may impact teachers' adherence to recommended behavioral interventions. Before making practice recommendations that will hopefully increase teachers' adherence to recommended interventions, I wanted to analyze possible barriers to treatment adherence. There are many reasons why teachers may not adhere to recommended interventions, and this dissertation explored how delays to reductions in problem behavior impact how teachers make decisions about behavioral interventions. By examining the variables that may impact how teachers make decisions, my goal is to enhance the implementation and evaluation stages of the behavioral consultation model. Advances in behavioral consultation will ultimately improve the outcomes for students that engage in challenging behavior.

Delay Discounting, Teacher Decision-Making, and Behavioral Consultation

Identifying variables that may impact teachers' rates of discounting is critical for understanding treatment non-adherence and creating interventions designed to increase adherence (Xu et al., 2022). Because managing student challenging behavior is often one of the greatest concerns in school settings (Briere et al., 2015; McGuire & Meadan, 2022), and approximately 60% of individuals with intellectual disability and 94% of individuals with autism engage in challenging behavior in school settings (David et al., 2022), continued research in the area of teacher decision-making of interventions designed to decrease challenging behavior is of upmost importance for students, teachers, school districts, communities, and related stakeholders. Further, students with behavioral support needs are increasingly served in general education classes; all teachers, including general educators, need behavioral consultative support now more than ever (Charlton et al., 2021).

Delay discounting is especially relevant to teacher decision-making because interventions targeting challenging behavior may take extensive periods of time (e.g., six or more months) for behavior to decrease to intended therapeutic levels (Call et al., 2015). Delays to reductions in challenging behavior are concerning, because, when immediate changes in student challenging behavior are not experienced by the teacher, behaviors that support adherence are effectively placed on extinction and are likely punished (Allen & Warzak, 2000). That is, when teachers adhere to an intervention but challenging behavior does not decrease, the motivation to adhere to the intervention again in the future may be diminished.

Consultants commonly collaborate with teachers when designing and implementing behavioral interventions. An important responsibility of the consultant is to routinely evaluate their consultees' adherence to their recommended intervention (Erdy et al., 2020). Recognizing that delay to treatment outcomes may impact whether or how teachers adhere to behavioral treatments, consultants may need to change their consultative strategies when providing treatment recommendations to teachers. For example, consultants may need to address the teacher's expectations or tolerance for the length of time required to achieve treatment effects – this may address implementer level barriers. By clarifying delay expectations, consultants can better match behavior goals and treatments to the temporal preferences of the teacher (Call et al., 2015). Additionally, consultants may need to consider the difficulty of recommended interventions, because, as treatment plans become more technical, adhering to the plan becomes increasingly more difficult (Charlton et al., 2021).

Fraudulent Response Prevention and Detection

A major take away from this dissertation is that the collection of fraudulent and bot responses is almost inevitable within internet-based survey research, especially for surveys that promise compensation upon completion. Chapter 1 and Chapter 2 both received a large proportion of fraudulent and bot responses; the proportion decreased from Chapter 2 to Chapter 3. In Chapter 2, we implemented a a10-step fraud detection process whereby 5,240 responses were filtered to 317; 94% of responses were removed. In Chapter 3, we made procedural changes to protect against fraud (i.e., removing the compensation amount from the recruitment flyer, enabling additional Qualtrics fraud protects, avoiding disseminating the survey to public social media pages) and detect fraudulent responses (i.e., inclusion of attention-check questions). We then implemented an 11-step fraud detection process where we filtered 1,837 responses to 259; 86% of responses were removed.

The main limitation to our fraudulent response detection and response removal process is that we risk removing responses that are legitimate. Within our fraudulent response removal process, the steps that comprise of filtering out responses with duplicate IP addresses, duplicate latitude and longitude coordinates, and email addresses that are comprised of a random string of characters are of most concern. In fact, some previous research (Ballard et al., 2019) has cautioned against removing duplicate IP addresses or locations, because genuine respondents may complete the survey in a common place of work (e.g., teachers at the same school), shared household (e.g., two partners in a household that are both teachers), or a community space (e.g., social gathering of teachers). However, upon examining groups of responses with duplicate IP addresses or coordinates, we found that many of the responses with duplicate IP addresses did not have the same latitude and longitude coordinates as one another (which would be logical as IP addresses identify a network). Additionally, when searching duplicate groups of latitude and longitude coordinates on the internet, we discovered that many of these locations were common points of interest (e.g., Central Park, Carnegie Center located in Phenix, Civic Garden Downtown Dallas). Based on the patterns of some duplicate locations being points of interest or common locations, we decided to take a conservative approach to response filtration and removed all responses that had duplicate locations.

The collection of fraudulent responses is extremely concerning as these responses can impact the validity of a study's results. Fraudulent responses can conceal actual relationships and associations between variables or can create artificial relationships between variables (Chandler

& Paolacci, 2017). Not only do fraudulent responses cause problems to the validity of data, if undetected, these responders can essentially steal money from the research team, relative stakeholders, and funding agencies. If we did not identify and remove the fraudulent responses submitted in this dissertation, the research team would have lost $65,010 compensating fraudulent responders.

As noted in a recent discussion about the inadvertent collection of fraudulent responses in web-based research (Pellicano et al., 2023), researchers must engage in constant reflection about how to best ensure the quality and validity of data. Researchers must balance prevention, detection, and removal of fraudulent responses with the ethical obligations to (1) maintain trust between the research team and honest participants, (2) increase accessibility to participate in research (and earn compensation for participation), and (3) avoid stereotyping groups of participants that may be more or less likely to be a fraudulent respondent (Pellicano et al., 2023). Balancing the motivation for open and inclusive research with the obligation to ensure quality and validity of data can be complex. Researchers may inadvertently remove legitimate responses from a data set or may accidentally include a fraudulent response that passed fraudulent detection. As fraudulent and bot responses increasingly infiltrate online research, we, as researchers, must stay up to date on the fraudulent prevention and detection process and the advances in technology that make bot responses difficult to detect.

Future Research Directions

Results of this dissertation have led to the creation of research questions that can be addressed in my future research endeavors. Below, I have stated some possible research questions and describe a series of studies aimed to answer these research questions.

Delay Discounting

The first question that can be addressed in future research is: Are discount rates obtained in an adherence delay discounting task associated with teachers' adherence to recommended behavioral interventions? To answer my research question, I intend to first create and validate a delay discounting task specifically designed to evaluate treatment adherence – the Treatment Adherence Questionnaire (TAQ). To do so, I may follow the task creation and validation processes outlined by Hendrickson et al. (2015). Hendrickson et al. describes the process whereby the researchers created and validated the Food Choice Questionnaire (FCQ), a delay discounting task modeled from the MCQ to assess discounting of hypothetical food items. To validate the FCQ, the researchers compared discount rates of monetary outcomes and food-related outcomes across different delay discounting tasks (i.e., the MCQ and an adjusting amount procedure for money). Here, I may be able to replicate the Hendrickson et al. study to validate the TAQ. Validating the TAQ will allow for researchers to continue to explore teacher decision-making of delayed outcomes with a task specifically designed to evaluate treatment adherence.

Second, I aim to (a) administer the validated TAQ to teachers requesting behavior support, (b) recommend behavioral interventions to these teachers, and (c) examine the associations between discount rates from the TAQ and teachers' adherence to the recommended behavioral interventions. A study by Reed at al. (2011) investigated a similar question – the researchers examined the relationship between young students' discount rates and their responses to immediate and delayed rewards as part of a token economy. Reed at al. created a framework for using discount rates of a hypothetical reward to predict real-word choices between an immediate and delayed reward. Expanding from the study, I could examine associations between discount rates obtained in the TAQ and treatment adherence data from teachers requesting behavioral support. The goal would be to determine if discount rates obtained in the TAQ predict teachers' adherence to interventions. If discount rates in the TAQ predict adherence to recommended interventions, the TAQ may be an evaluation tool be used by consultants when planning and creating recommended behavioral interventions.

Behavioral Consultation

The second question to be addressed by future research is: How can behavioral consultants ameliorate the effects of delays to behavior reduction? To answer this question, I will analyze the effects of a goal setting intervention on teachers adherence to behavioral interventions. The goal setting intervention would emphasize smaller, more immediate reductions in challenging behavior (e.g., small decreases in challenging behavior) as opposed to emphasizing the larger delayed reduction in challenging behavior (e.g., complete behavior reduction). White et al. (2023) provided an example where a student engages in an average of 20 instances of disruption a day while attending school (2.5 instances/hr). In this scenario, the long-term goal is to decrease the number of instances of disruption to two a day (0.1 instances/hr). Here, the consultant may set a few short-term behavior goals such as: reduce the target behavior to (goal 1) 2.0 instances/hr, (goal 2) 1.5 instances/hr, and (goal 3) 1.0 instances/hr. The goal of this study would be to evaluate if setting, and meeting, multiple short-term goals increases teachers' adherence to a recommended intervention. Because teachers discount delayed treatment outcomes, meeting multiple short-term goals may increase the likelihood the teacher will adhere to the recommended treatment, because they would be contacting rewards more quickly (i.e., they are seeing the behavior reduce after short delays; White et al., 2023).

An additional consultative approach that can be evaluated may be in recommending additional behavioral supports to ameliorate delay to treatment outcomes. Keeping with the DRO example above, researchers can evaluate the effects of evidence-based antecedent interventions (e.g., visual schedule, token economy system, student choice) prescribed with the recommended DRO on teachers adherence to the DRO intervention. Because antecedent interventions can effectively decrease challenging behavior and increase appropriate behavior (Rivera et al., 2019), incorporating an additional antecedent strategy may yield reductions in problem behavior enough to where the teacher continues to adhere to the recommended DRO treatment long term (White et al., 2023).

Fraudulent Response Prevention and Detection

The third research question to be addressed is: What methods effectively prevent and detect fraudulent responses in internet-based survey research? To answer this third research question, my goal would be to first disseminate a short survey across various online platforms (e.g., Twitter, Facebook, Reddit, LinkedIn) to see which platforms elicit small proportions and large proportions of fraudulent responses. For example, a study by Paolacci et al. (2010) compared response consistency across three different sources (i.e., Amazon Mechanical Turk, a Midwestern University, online discussion boards) exploring the validity of Amazon Mechanical Turk respondents. Expanding from Paolacci et al., I may disseminate a brief survey that promises compensation across multiple platforms in order to determine which platform recruits the largest and smallest proportion of fraudulent or bot responses. Results of this study can inform how and where future researchers should, or should not, disseminate online surveys.

Second, I aim to analyze different types of attention check questions to determine which question type most accurately identifies fraudulent responses. A study by Liu & Wronski (2018) evaluated the effectiveness of trap questions (i.e., attention check questions) as a preventative measure against fraudulent or bot responses. Expanding from the Liu & Wronski study, future research can examine different types of attention check questions (e.g., free response, multiple choice, knowledge questions), surveys with different amounts of attention check questions (i.e., one attention check verses three attention checks), and placement of attention check questions (i.e., all at the beginning, dispersed throughout). Results of this study can provide recommendations regarding inclusion of attention check questions for future researchers creating online surveys.

Conclusion

This dissertation analyzed teacher decision-making of behavioral outcomes using delay discounting. There are several reasons why teachers may not adhere to a consultant recommended behavioral intervention, including: (a) difficulty of the intervention (b) previous classroom responsibilities, (c) personal philosophies of the intervention, and (d) administrative limitations (Kasari et al., 2013). Results of this dissertation support the hypothesis that the delay in treatment outcomes (i.e., delay before reduction in challenging behavior) may serve as an additional variable that affects teacher decision-making and possibly treatment adherence. Though we did not directly assess treatment adherence, teachers increased selections of the SIR as the delay increased may indicate low treatment adherence at longer delays (White et al., 2023). Continued research in examining the relationship between delays to behavior reduction and teacher decision-making will further enhance the behavioral consultation process to support teachers adherence and students outcomes.

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