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Modeling Treatment-Related Decision-Making Using Applied Behavioral Economics: Caregiver Perspectives in Temporally-Extended Behavioral Treatments

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Abstract
Evidence-based behavioral therapies for children with disruptive and challenging behavior rarely yield immediate improvements in behavior. For caregivers participating in behavioral therapies, the benefits from these efforts are seldom visible until after substantial time commitments. Delays associated with relief from challenging behavior (i.e., improved behavior) can influence how caregivers decide to respond to instances of problem behavior, and in turn, their continued commitment (i.e., integrity, adherence) to treatments that require long-term implementation to produce improvements in child behavior. This study applied delay discounting methods to evaluate how delays affected caregiver preferences related to options for managing their child's behavior. Specifically, methods were designed to evaluate the degree to which caregiver preferences for a more efficacious, recommended approach was affected by delays (i.e., numbers of weeks in treatment). That is, methods evaluated at which point caregivers opted to disregard the optimal, delayed strategy and instead elected to pursue suboptimal, immediate strategies. Results indicated that caregivers regularly discounted the value of the more efficacious treatment, electing to pursue suboptimal approaches when delays associated with the optimal approach grew larger. Caregivers demonstrated similar patterns of suboptimal choice across both clinical (i.e., intervention) and non-clinical (i.e., monetary) types of decisions. These findings are consistent with research that has highlighted temporal preferences as an individual factor that may be relevant to caregiver adherence to long-term evidence-based treatments and encourage the incorporation of behavioral economic methods to better understand caregiver decision-making.

Keywords Behavioral economics · Treatment adherence · Caregiver decision-making · Delay discounting

Introduction

A range of effective behavioral therapies is available to treat many childhood behavior problems and behavioral disorders (Christophersen and Mortweet 2013; Watson and Gresham 2013). Positive responses to these therapies are jointly driven by the efficacy of the treatment as well as the degree to which it is implemented as recommended (Hogue et al. 2008; Sanetti and Kratochwill 2009). That is, behavioral therapies must be implemented correctly and consistently to produce optimal effects. Adherence to effective behavioral therapies is particularly problematic in approaches that require caregiver implementation in home and community settings, as additional challenges are often encountered outside of more specialized settings such as clinics (MacNaughton and Rodrigue 2001; Nock and Ferriter 2005). That is, there are various barriers to consistently implementing behavioral therapies across environments and these barriers contribute to lower levels of treatment adherence, or worse, caregiver discontinuation of recommended therapeutic approaches (Chacko et al. 2012).

The existing literature has highlighted numerous challenges associated with caregiver adherence to recommended behavioral treatments and these challenges are well represented across many childhood disorders. For example, caregiver adherence to recommended treatments

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has been endorsed as a challenge in attention-deficit/hyperactivity disorder (Springer and Reddy 2010), autism spectrum disorder (ASD) (Carr et al. 2016; Moore and Symons 2009), conduct disorder (Kazdin and Wassell 1999), bipolar disorder (Gaudiano et al. 2008), and various childhood anxiety (Kendall and Sugarman 1997; Santana and Fontenelle 2011), mental health (Gearing et al. 2012), and disruptive behavior disorders (Schoenwald et al. 2011; Schoenwald et al. 2005). As such, issues associated with adherence cut across nearly all treatments for child behavior disorders that require caregiver participation.

A large number of studies have been conducted to determine factors predictive of caregiver adherence in behavioral treatments (Chacko et al. 2016a, 2016b; Dadds et al. 2018). These studies have evaluated factors such as age, sex, socioeconomic status, stress, marital status, ethnic minority status, treatment cost, treatment length, treatment acceptability, treatment alliance, and others (Armbruster and Kazdin 1994; Bennett et al. 1996; Dadds et al. 2018; dosReis et al. 2017; Kazdin and Wassell 1999; Lavigne et al. 2010; Nock and Ferriter 2005; Thompson and McCabe 2012; Weisz et al. 1987). However, few have emerged as consistent predictors of adherence to treatment (Kazdin and Mazurick 1994; L. M. Miller et al. 2008). For example, factors such as socioeconomic status have been found to be a positive predictor of poor adherence in some studies but a negative predictor in others (Armbruster and Kazdin 1994). Research predicting caregiver adherence has focused largely on family characteristics (e.g., demographics, socioeconomic status) and select aspects of behavioral therapies (e.g., acceptability, therapeutic alliance). Relatively little research has evaluated caregiver decision-making and how intertemporal preferences relate to choices made regarding behavior therapies Call et al. 2015b; Cunningham et al. 2013).

Among the few studies that evaluated caregiver decision-making, Cunningham et al. (2013), Cunningham et al. (2015), and Call et al. (2015b) evaluated caregiver choices in the context of delayed treatment outcomes. With regard to delays in the form of delayed treatment onset (i.e., waitlisted for treatment), both Cunningham et al. (2013) and Cunningham et al. (2015) evaluated temporal preferences related to interim services prior to participating in children's mental health services. Using Latent Class Analyses, both studies found significant variability with respect to caregiver preferences for behavioral treatment in the presence of delays. That is, some caregivers preferred group-based parent training (Group Contact segment) and support groups in the interim waiting period while others were content with occasional updates (Limited Contact segment) related to the waitlist alone (Cunningham et al. 2013). Similarly, Cunningham et al. (2015) revisited caregivers on waitlists for child mental health services and found that caregivers varied both in their preference for specific services as well as in the frequency of supports during this period (e.g., weekly, biweekly, monthly).

Whereas Cunningham et al. (2013) and Cunningham et al. (2015) evaluated aggregated caregiver preferences during delayed treatment *onset*, Call et al. (2015b) examined how individual caregivers perceived behavioral outcomes in the face of delayed treatment *improvements*. Using the delay discounting framework, this study presented caregivers with choices between smaller, but immediate improvements in their child's behavior (smaller, sooner; SS) and larger, but delayed improvements in their child's behavior (larger, later; LL). Such choices underpin long-term adherence to the implementation of evidence-based behavioral strategies. That is, would a caregiver currently involved in therapy commit to the recommended, long-term evidence-based approach that entails weeks and months of therapy (LL; i.e., without immediate results) or would they instead rely on shorter-term, less effective strategies that provide more immediate relief from undesired behavior (SS)? Such choices are often encountered by caregivers and individual decision-making here would influence adherence because deviations from the LL option, a suboptimal decision-making pattern, would be considered a departure from the methods considered to be evidence-based (i.e., non-adherence). The results from Call et al. (2015b) indicated that individual caregivers were differentially sensitive to delays to behavioral improvements and that caregivers demonstrated similar patterns of suboptimal decision-making across both therapeutic (i.e., behavioral outcomes) and economic (i.e., monetary) contexts.

Applied Behavioral Economics and Treatment-Related Decision-Making

Behavioral economics emerged as an area of study designed to extend classical economic interpretations with research from the behavioral sciences (Camerer and Loewenstein 2004). For example, the classical economic axiom of stationarity states that an individual's preferences between prospects should not change (e.g., Choice 1 vs. Choice 2) when both are translated by some constant fixed constant, i.e. both become more delayed (Fishburn and Rubinstein 1982). Put simply, individual preferences should not change when all prospects become more delayed or more immediate. However, behavioral scientists have found that this economic assumption (and others) seldom holds true in how animals (Ainslie 1974; Chung and Herrnstein 1967) and human beings make choices (Ainslie 1975, 1992). Among the various methods subsumed under the behavioral economic approach, the delay discounting framework has been particularly useful for modeling how individuals come to demonstrate suboptimal or "irrational" patterns of decision-making.[1]

The delay discounting framework has been applied to many areas of decision-making, especially those in which suboptimal patterns of decision-making emerge as optimal outcomes become delayed. Several examples of these phenomena have been observed in individual choices related to health and healthcare (Chapman 1996, 2002), decisions of whether or not to pursue vaccination (Chapman and Coups 1999; Chapman et al. 2010; Jit and Mibei 2015), the discontinuation of individual psychotherapy (Swift and Callahan 2008, 2010), and behavioral outcomes when delays (Call et al. 2015b) and the levels of time and effort vary among options (Call et al. 2015a). Further, there is emerging support that applied behavioral economics can be one avenue for better understanding individual preferences in complex individuals, such as those diagnosed with ASD and other intellectual and developmental disabilities (Gilroy et al. 2018).

The purpose of this study was to replicate and extend findings from Call et al. (2015b). Specifically, the current study addresses limitations related to the size ($n = 17$) and the composition of the sample drawn in Call et al. (2015b). Caregivers in the original study were parents of children that required inpatient hospitalization for the treatment of severe behavior. Given the severity of this disorder and this tier of behavioral treatment, the perspectives of those caregivers may not be representative of caregivers managing more general behavioral challenges. Additionally, the limited size of the sample may have obscured small but potentially relevant differences between decision-making in clinical and traditional economic contexts. Further, this extension incorporates recent advances in methods used to evaluate intertemporal choice (i.e., multilevel modeling) across decision-making contexts. The following research questions were posed: first, do caregiver preferences for optimal treatments change following the introduction of delays (i.e., SS vs. LL); second, if temporal preferences for treatment outcomes change as a function of delays, do temporal preferences specific to behavioral treatments differ from those in an economic, non-treatment context (i.e., monetary outcomes); and, third, do caregiver-reported demographic variables (e.g., number of reported children, level of challenging behavior) correlate with temporal preferences for behavioral treatments?[2]

[1] We make note that behavioral economics draws from various areas of behavioral science, e.g. neuroscience, cognitive science, behavior analysis. While we discuss behavioral economics broadly here, the methodology used here most directly relates to operant behavioral economics and the experimental delay discounting framework.

[2] All elements of this study (e.g., data) and materials necessary to recreate these findings (e.g., statistical scripts, figure rendering) are included as supplemental materials as well as archived on the corresponding author's GitHub account under the repository "Caregiver-Delay-Discounting" at https://github.com/miyamot0/Caregiver-Delay-Discounting.

Methods

Sample Size Estimation

A power analysis was performed using the G*Power program (Faul et al. 2007) using published results from Call et al. (2015b). Data from the original analyses were extracted, and a $\log_{10}$ scaled Area Under the Curve (AUC) measure was calculated for caregivers included in the earlier analysis (Borges et al. 2016). An AUC measure was used to make no assumptions that the underlying model would remain the same across studies. Using the scaled calculation from the data listed in Call et al. (2015b), a small-medium effect size of 0.366 was observed (Cohen 1988). Using Type I (α) and Type II (β) error rates of 0.05 and 0.80, respectively, and parametric paired samples comparisons, the proposed sample size to detect the earlier effect was 61 caregivers.

Participants

Caregivers endorsing behavioral concerns were recruited using the Amazon Mechanical Turk platform (MTurk). MTurk is an online crowdsourcing platform whereby "workers" (participants) who meet certain criteria complete Human Intelligence Tasks (HITs) for "requesters" (e.g., researchers) and are compensated for their time and satisfactory completion of the task (Chandler and Shapiro 2016), see also Strickland and Stoops (2019). In order to increase the likelihood of high quality data (Paolacci and Chandler 2014) and consistent with criteria used in similar studies using MTurk (Henley et al. 2016; Roma et al. 2016), workers were eligible to accept the HIT if they had completed at least 1000 HITs, maintained a 99% approval rating, and resided in the United States.

Criteria for Inclusion

Eligible workers completed a survey designed using the Qualtrics Research Suite™. The survey instrument and all study procedures were approved by the Louisiana State University Institutional Review Board. An initial screener was used for eligibility and workers who had at least one child with at least occasional undesired behavior that warranted intervention were able to complete the full HIT. Workers indicating that they either had no children, no behavioral concerns, or were not interested in pursuing behavior therapies were subsequently informed they were not eligible to participate. Workers who completed the survey received a unique string at the end of the survey which was then submitted to MTurk portal to complete the HIT and received a $1.00 payment for the approximately 10 min task (consistent with recommended guidelines; Chandler and Shapiro 2016).

Individual batches were posted to the MTurk framework until the target sample size was achieved for the final analyses.[3]

Systematicity of Delay Discounting Data

Individual caregiver data gathered from the MTurk platform were screened for systematic (i.e., non-random) responding using criteria derived from Johnson and Bickel (2008). The inspection of data gathered using this platform is indicated to ensure that participants adequately understood and completed the assigned tasks as designed. Briefly, Johnson and Bickel (2008) specify two criteria indicative of systematic discounting data: first, systematic responding entails successive decreases in value as delays grow larger (i.e., increases in value are unexpected); second, subjective values at the largest delay point should be lower than the values recorded at the smallest delays (i.e., the first delay point). These criteria assist in identifying participants who may have either incorrectly completed the task or did not understand the directions. That is, these criteria were used to provide an additional level of validation with respect to data quality when using data gathered from workers on the MTurk framework.

For this study, the second criterion was amended to accommodate the first research question. Specifically, the base Johnson and Bickel (2008) criteria would have rendered data indicating a null effect for delay ineligible for inclusion (i.e., the absence of discounting would be considered ineligible). A modification was warranted in order to entertain the possibility that some caregivers may not discount the value of an optimal treatment for their child (LL) and remain committed to a behavioral treatment even if it would take years of treatment without immediately observable improvements in behavior. To accommodate the first research question, the second criterion was reframed to permit instances where the final delay was equal to the initial value but *did not increase*. The final study analyses were completed with both the screened and full data set to ensure that excluding non-systematic responding did not alter the overall findings or conclusions.

Intertemporal Choice Tasks

The intertemporal preferences of caregivers were assessed separately across two contexts—delayed monetary choices and delayed treatment choices. Caregiver preferences were assessed at delays of 1 week, 2 weeks, 1 month, 3 months, 9 months, 1 year, and 2 years and these delays were identical across monetary and treatment choice contexts. In each context, preferences were assessed in an adaptive, adjusting-amount fashion using procedures derived from Frye et al. (2016) and Du et al. (2002). An adaptive assessment was used to minimize the length of the assessments used in Call et al. (2015b), as methods used in the earlier study required approximately 45 min to complete. A more thorough description of this assessment can be found in Frye et al. (2016) and individual descriptions of each task are presented below.

Monetary Decision-Making Task

A Monetary Decision-making Task (MDT) was used to evaluate intertemporal choices in an economic context (i.e., money now or money later). In the MDT, caregivers chose between either a delayed option (e.g., 7 days) with a fixed value (LL; $100) or an immediately available option with an adjusting value (SS). For example, the first trial of the 7-day block read, “Would you rather have $50 now or $100 in 7 days?” The value of the SS option was adjusted, following each choice, from an initial midpoint value of $50. On subsequent trials, selecting the SS option would decrease the value of the SS option whereas selecting the LL option would increase the value of the SS. The incremental changes in the SS value became progressively smaller at a pre-set rate (i.e., $50/2^n$; $50/2^1 = 25$; $50/2^2 = 12.5$) and this process repeated a total of six times at each delay point. After the sixth choice, the final value of the SS option characterized the temporal preferences for the corresponding delay.

Behavioral Decision-Making Task

The Behavioral Decision-making Task (BDT) was designed using the same methodology as the MDT. Whereas the MDT modeled intertemporal choice in an economic context (i.e., monetary outcomes), the BDT modeled intertemporal choice in a clinical context (i.e., long- vs. short-term behavior management strategy). That is, caregivers were provided a choice between an option associated with a smaller, immediate effect on behavior (SS) for a period of 1 year and an option associated with a larger, but delayed effect on behavior (LL). For example, the BDT included choices between treatments with defined outcomes (i.e., 50% fewer behavioral concerns for 1 year right now vs 100% fewer behavioral concerns for 1 year after 7 days or 1 session of therapy?) rather than monetary amounts. Like the MDT, the value of the SS was adjusted following each choice from an initial amount of a 50% reduction in behavioral concerns. Identical to the procedures in the MDT, selecting the SS would decrease the SS on the following choice and selecting the LL would increase the SS on the following choice. The BDT included the same delays used in the MDT with additional language to improve clarity (i.e., delays translated to a number of weekly therapy sessions; e.g., 1 month or 4 weekly sessions).

[3] We note here that HITs were published to the MTurk framework until the recommended number of caregivers meeting all criteria for use in the statistical analysis was reached ($n = 61$).

Analytical Plan

The original Call et al. (2015b) analyses examined individual rates of discounting using the single-parameter Hyperbolic model (Mazur 1987). Briefly, this single-parameter model characterizes the rate at which outcomes are discounted, as a function of the delay, using a hyperbolic form, i.e. $\frac{1}{1+kx}$, where k represents the discount rate. This model has been shown to perform well in various circumstances, however many more sophisticated models for examining decision-making exist (Doyle 2013). Although these models differ in terms of their assumptions as to how outcomes are discounting (e.g., hyperbolically, exponentially), all assume that delayed outcomes are preferred less than immediate outcomes.

The present study evaluated the Hyperbolic model as well as the following two-parameter models: the Exponential Constant Sensitivity (Ebert and Prelec 2007), the Green & Myerson Hyperboloid (Green and Myerson 2004), and the Rachlin Hyperboloid (Rachlin 2006). A range of models was included to entertain the possibility that a more sophisticated model might better characterize discounting than the one used in Call et al. (2015b). A review of the model selection procedures used here is provided by Franck et al. (2015). Using a model selection approach, we had no a priori hypotheses about which model would best characterize discounting in the current study.

Parameter Estimation

Delay discounting models were fitting using a multi-level approach (Young 2017) and compared using the Akaike Information Criterion (AIC; Akaike 1974). Each delay discounting model was fitted using the *nlme* package (Pinheiro et al. 2014) in the R statistical program (R Core Team 2017). Briefly, the *nlme* package provides methods to fit nonlinear mixed-effects models, models that can fit data at both the group (i.e., "population") and individual levels simultaneously, and the individual structure of each model candidate is indicated in Table 2. In each discounting model, parameters were entered as group-level fixed effects and as individual-level random effects. Starting values were derived from the results of nonlinear regression at the group level using the *nls* package (DebRoy et al. 1999) along with the corresponding model.

Using the best performing model, a measure of model-based Area Under the Curve (MB-AUC) was derived using the *integrate* package (Piessens et al. 1983) using the highest and lowest delays as the upper and lower bounds upon which to be integrated. Whereas Call et al. (2015b) compared fitted statistical parameters and point-based AUC separately (Myerson et al. 2001), MB-AUC jointly represents decision-making processes as fitted parameters and AUC simultaneously (Gilroy and Hantula 2018). This measure is more easily compared in cases when the presence of multiple parameters complicates comparisons. Similarly, fits across each decision-making context were indexed using the Effective Delay 50 (ED50)—a measure that indicates the amount of delay needed for a delayed outcome to lose 50% of its original value (Yoon and Higgins 2008). For example, an ED50 of 1 month for a participant making decisions for a \$100 delayed outcome means that \$100 delayed by 1 month is valued at \$50 now. In other words, the ED50 specifies a point whereby the specific delay referenced, and any beyond it, is valued at 50% (or below) the original value. Both the full dataset and all associated statistical scripts have been provided as supplemental materials as well as archived on the corresponding author's GitHub account under the repository "Caregiver-Delay-Discounting."

Results

Terminal Caregiver Sample

Caregiver demographics are listed in Table 1. From a total of 104 caregivers who completed the HIT, 62 (60%) provided complete records that met the criteria for systematic discounting on *both* the monetary and behavioral outcome tasks.[4] That is, approximately 80% of responding in each of the tasks met these criteria, but only 60% of the sample jointly met criteria for both tasks and also provided complete records. In the screened sample, 25 caregivers identified as male, 32 identified as female, and five indicated they would rather not say. The median self-reported income was 60,000 USD and the 25th and 75th percentiles were 30,000 and 81,000 USD, respectively. Education levels ranged from less than a high school degree to a professional degree (e.g., MD, JD), with 50% of caregivers reporting achieving at least an associate degree. Most caregivers reported being married ($n = 39$, 62.90%) and identified as White/Caucasian ($n = 49$, 79.03%). Table 2

Caregiver Decision-Making across Contexts

Model comparisons using the AIC revealed that the Rachlin hyperboloid performed better than the other candidates overall (see Table 3), and individual fittings using the Rachlin model are displayed in Fig. 1. With respect to the first research question, these results indicated that caregiver preferences for the optimal treatment (LL) reliably decreased as the delay to behavioral improvements increased. Mean parameter fits were comparable across both treatment ($k = 0.0093$; $s = 0.77785$)

[4] The demographics, data, and results for both the screened and total example are available as supplemental materials.

Table 1 Total sample demographics

Participant Demographics ($n = 62$)			
Age (years)		**Number of Children**	
Mean (SD)	38.8 (10.1)	Median (Q1-Q3)	2 (1–3)
Median (Q1-Q3)	36.5 (32–43)	Mean (SD)	2.1 (1.2)
Sex		**Education**	
Male	25 (40.3%)	High School graduate	2 (3.2%)
Female	32 (51.6%)	Some college but no degree	17 (27.4%)
Would rather not say	5 (8.1%)	Associate degree	12 (19.3%)
Income		Bachelor's degree	21 (33.9%)
Q1	30,000 USD	Master's degree	6 (8.1%)
Median	60,000 USD	Professional degree	1 (1.6%)
Q3	81,000 USD	Would rather not say	4 (6.5%)
Behavior Concern		**Ethnicity**	
A little	31 (50%)	African-American	3 (4.8%)
A moderate amount	9 (14.5%)	Asian	5 (8.1%)
A lot	12 (19.3%)	Hispanic/Latinx	1 (1.6%)
A great deal	10 (16.1%)	White/Caucasian	49 (79%)
Marital Status		Would rather not say	4 (6.4%)
Single	9 (14.5%)		
Married	39 (62.9%)		
Divorced	7 (11.3%)		
Would rather not say	7 (11.3%)		

and monetary choices ($k = 0.00531$; $s = 0.90747$). Given that rates of discounting were jointly represented by two varying parameters, numerical integration was performed to generate a singular summary MB-AUC measure in both normal and $\log_{10}$ scaled delays (Gilroy and Hantula 2018). From these singular AUC measures across both decision-making contexts, the more normally-distributed MB-AUC ($\log_{10}$) was then logit transformed to support parametric comparisons between choices made in behavioral and monetary contexts (see Fig. 2).

A Kolmogorov-Smirnov test with the transformed MB-AUC measure indicated that preferences for monetary and behavioral treatments emerged from a similar distribution, $D = 0.1542$, $p = 0.531$. Levene's test for equality of variance was not significant, $F = 0.8374$, $p = 0.362$, and a paired-samples t-test assuming equal variance revealed that transformed MB-AUC did not differ significantly between preferences for monetary ($M = 1.04$, $SD = 1.40$) and behavioral outcomes ($M = 1.22$, $SD = 1.70$) within individuals, $t = -0.62$, $df = 122$, $p = 0.536$. The distribution of aggregated indifference points and transformed AUC across outcomes are illustrated in Fig. 3.

Additionally, the ED50 was calculated as a supplemental indicator of discounting rates across choice contexts. As noted earlier, the ED50 indicates the amount of time necessary for the optimal option to lose 50% of its original, undiscounted value. Using the logarithm of the ED50 computed from the fitted parameters of the best-performing (Rachlin) model, the overall distribution of these measures were comparable across behavioral ($Mdn = 6.67$, $Q1 = 4.64$, $Q3 = 9.37$) and monetary ($Mdn = 5.88$, $Q1 = 4.66$, $Q3 = 7.51$) choice. Represented in terms of days, the ED50 for behavioral and monetary outcomes was 788 (~2.1 years) and 357 days (~0.9 years), respectively. The relationship between temporal preferences and delays is nonlinear and, although informative, the ED50 measure does not speak to rapid changes in decision-making across each context. With respect to delayed behavioral outcomes using more common time frames, delays of 7, 30, and

Table 2 Model candidates

Model (n parameters)	Structure
Mazur's Hyperbola (1)	$\frac{A}{1+kD}$
Green-Myerson's Hyperboloid (2)	$\frac{A}{(1+kD)^s}$
Rachlin's Hyperboloid (2)	$\frac{A}{1+kD^s}$
Ebert-Prelec's Constant Sensitivity (2)	$A * e^{-(kD)^s}$

Note: This table specifies the models used evaluated in this study along with the model structure. The term A refers to the maximum value of the commodity being modeled (e.g., \$100) and D refers to delay (e.g., 1 week). The two model parameters k and s (if included) jointly determine the shape of the discounting function

Table 3 Model candidates and comparisons

Model	Rank	Log *k*	*s*	AIC
Rachlin	1	−4.954	0.842	8282.621
Ebert-Prelec	2	−6.994	0.686	8364.779
Green-Myerson	3	−3.341	0.477	8628.272
Hyperbolic	4	−5.835	–	8828.572

Note: In the table above, the parameters reported are the fixed effects estimates for the group and AIC corresponds to each model type with parameters as both fixed effects as well as random effects clustered at the individual level

180 days were associated with decreases of 5%, 12%, and 35% of the value of the optimal behavioral treatment option. Represented in this way, smaller and more proximal delays (i.e., initial weeks, months) affected intertemporal choices more heavily than larger, more distant ones (i.e., years).

Correlates of Caregiver Decision-Making

For the third research question, individual correlations were calculated to examine the relationships between MB-AUC for behavioral outcomes and various parent demographics. Using Pearson correlations, there was not a significant correlation between transformed MB-AUC and number of children, $r(62) = 0.021$, $p = 0.866$ or parental age, $r(57) = -0.02$, $p = 0.826$. Ratings of behavioral intensity and levels of education level were converted to ordinal equivalents and Spearman correlations between transformed MB-AUC and level of behavior intensity, $r_s(62) = 0.003$, $p = 0.980$, and educational level, $r_s(62) = -0.086$, $p = 0.501$, were also not significant.

Full Vs. Screened Caregiver Responding

Study analyses with the screened sample ($n = 62$) were also applied to the full sample ($n = 104$). With the full dataset, model comparisons revealed that the Rachlin model continued to be the best performing model ($AIC = 16{,}331.97$). Levene's test for equality of variance was also not significant for MB-AUC across monetary and behavioral outcomes, $F = 0.4177$, $p = 0.518$. Identical to the screened dataset, a paired-samples *t*-test assuming equal variance indicated that MB-AUC did not differ significantly between preferences for monetary ($M = 0.41$, $SD = 1.27$) and behavioral outcomes ($M = 0.65$, $SD = 1.38$) within individuals, $t = -1.31$, $df = 206$, $p = 0.191$.

Using Pearson correlations, there was not a significant correlation between transformed MB-AUC and number of children, $r(102) = 0.11$, $p = 0.247$ or parental age, $r(98) = 0.06$, $p = 0.529$. Ratings of behavioral intensity and levels of education level were converted to ordinal equivalents and Spearman correlations between transformed MB-AUC and level of behavior intensity, $r_s(104) = -0.138$, $p = 0.159$, and educational level, $r_s(104) = -0.176$, $p = 0.079$, were also not significant.

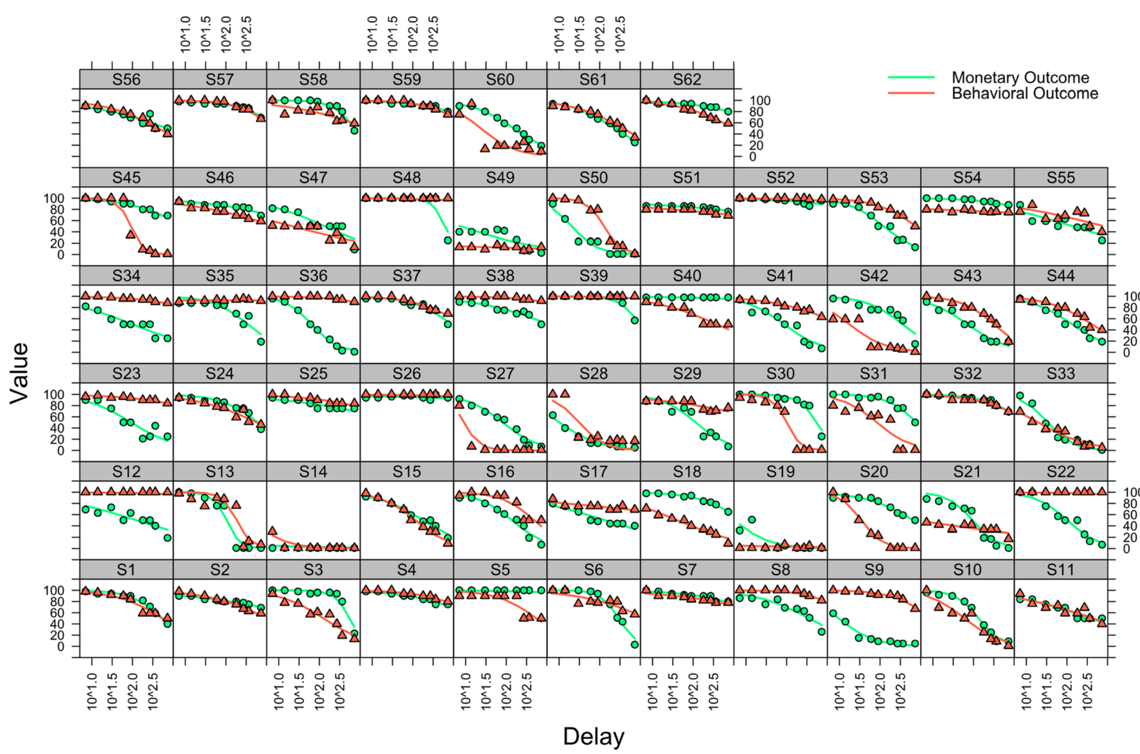

Fig. 1 This figure depicts individual responding fitted to the Rachlin model across delayed Monetary and Behavioral Outcomes at the individual level. Series were fitted using multilevel modeling with individual parameters entered as fixed and random effects

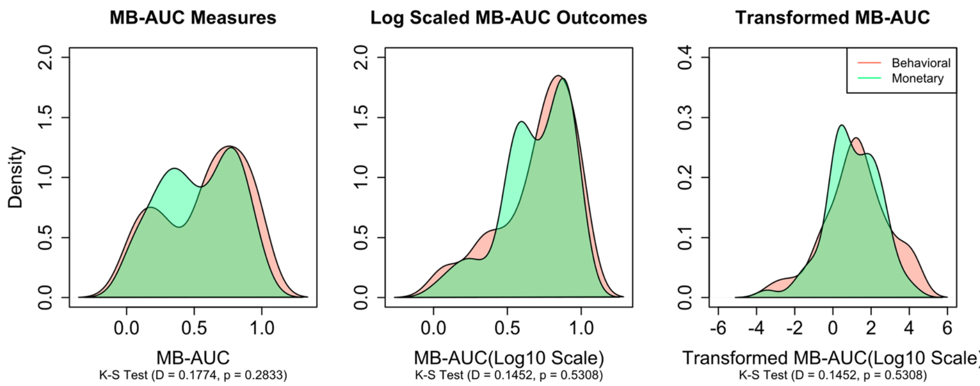

Fig. 2 These density plots illustrate the distribution of MB-AUC in normal (left) and log-scaled form (center). The log-scaled MB-AUC was logit-transformed (right) to provide the measure used in the final analyses

As such, analyses from both the screen and full datasets provided the same results.

Discussion

Caregiver decision-making related to the implementation of recommended behavioral treatments used with children is complex and jointly influenced by a range of environmental barriers, individual characteristics, and aspects of specific behavioral therapies (Armbruster and Kazdin 1994; Chacko et al. 2016b; Kazdin and Mazurick 1994). Despite decades of research in this area, substantial research continues to be necessary to better understand why caregivers struggle with long-term treatment adherence (Chacko et al. 2016a; MacNaughton and Rodrigue 2001). Further research on caregiver decision-making seems especially relevant to behavioral therapies, as issues associated with adherence to behavioral interventions appear to be distinct from those associated with adherence to medical, psychopharmacological therapies (Bennett et al. 1996; Dreyer et al. 2010; MacNaughton and Rodrigue 2001).

The purpose of this study was to extend earlier work applying behavioral economic methods to examine how delays associated with certain behavioral treatments affected caregiver choices between behavioral outcomes. Specifically, three questions were posed: First, to what degree do delays associated with behavioral treatments affect caregiver preferences? Second, to what degree does sensitivity to delays in preferences for behavioral outcomes relate to preferences for monetary outcomes? Lastly, to what degree do demographic variables (e.g., number of reported children, level of challenging behavior) correlate with temporal preferences for behavioral treatments?

Regarding the first and second research questions, the results of this sufficiently-powered study were consistent with those of Call et al. (2015b). Caregiver preferences for behavioral outcomes (i.e., SS vs. LL) were indeed influenced by delays and these preferences were comparable across both monetary and behavioral contexts. That is, all caregivers reported a consistent preference for optimal treatments when delays were minimal (or immediate) but each differed in terms of their own sensitivity to delays. The results of this study provide converging evidence suggesting that the delays associated with behavior therapies are a factor in how caregivers make decisions regarding whether or not to implement recommended, evidence-based behavioral strategies (LL) rather than short-term, reactive strategies associated with much less substantial benefits (SS). For example, some caregivers may forego a reinforcement-based treatment for their child's behavior because this intervention entails weeks of training and months of implementation and instead pursue punitive procedures that provide immediate, albeit minor, temporary relief from undesired behavior. Abstracting this observation to group-level behavior, similar trends were observed in Cunningham et al. (2013) and Cunningham et al. (2015). That is, particular

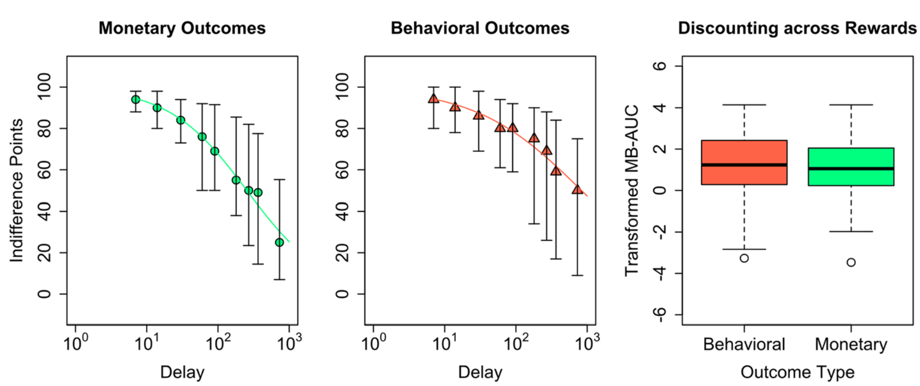

Fig. 3 These plots illustrate the distribution of temporal preferences for monetary outcomes (left) and behavioral outcomes (center). These outcomes are depicted following logit transform across outcomes in the rightmost plot

segments of the population queried in these studies were particularly sensitive to delayed treatment onset and sizable proportions of these samples disregarded recommended supports in the interim and instead preferred to pursue little-to-no consultation or training during the waiting period.

Although behavioral economic methods require novel methods to evaluate individual decision-making, a priori knowledge of a caregiver's temporal preferences is potentially valuable for several reasons. First, individual preferences skewed towards more immediate outcomes have been found to be predictive of poorer responses certain behavioral treatments, e.g., cigarette cessation (Dallery and Raiff 2007; Krishnan-Sarin et al. 2007; Yoon et al. 2007) and adherence to medication regimens, such as diabetes management (Lebeau et al. 2016; Stoianova et al. 2018). With information regarding caregiver decision-making at hand, clinicians might use this information to better match goals and strategies that more closely align with the temporal preferences of caregivers (Call et al. 2015b). That is, caregivers more sensitive to immediate outcomes may be better suited to strategies associated with more immediately observable benefits. Such efforts were explored in Cunningham et al. (2013) and Cunningham et al. (2015) but in aggregate form and not specific to caregivers.

Second, if temporal preferences emerge as a factor that influences adherence, additional strategies may be beneficial in these circumstances. For example, treatment elements such as Episodic Future Thinking (Bromberg et al. 2017; Daniel et al. 2013; Peters and Buchel 2010; Snider et al. 2016) and approaches such as Acceptance and Commitment Therapy (Morrison et al. 2014) have been found to reduce overall sensitivity to delayed outcomes. Indeed, similar initiatives have already been proposed to support caregiver engagement in behavioral parent training, e.g. the Strategies to Enhance Positive Parenting (STEPP) program (Chacko et al. 2012). Although not specific to discounting phenomena, the findings from Chacko et al. (2012) indicated that addressing caregiver expectations and preferences before beginning treatment can serve to support implementation and improve outcomes. As such, further evaluation of caregiver decision-making using behavioral economic methods may lead to more effective, integrated methods for improving initial and ongoing engagement in long-term behavioral therapies.

The third research question evaluated the relationship between caregiver preferences for behavioral outcomes (SS vs. LL) and reported family demographics. Unsurprisingly, caregiver preference was not strongly related to any individual environmental factors. This finding is consistent with earlier findings, which has found temporal sensitivity to be more related to individual cognitive biases (DeHart and Odum 2015), neurological correlates (Ludwig et al. 2015), or individual personality traits (Odum 2011) rather than any single environmental or demographic factor.

Limitations and Next Steps

While this study extends earlier findings regarding caregiver temporal preferences, several limitations warrant noting. First, to what degree that caregivers' intertemporal preferences relate to real-world participation in parent behavioral therapy is unknown. Although there is good support that hypothetical tasks correspond to their real-world equivalents (Johnson and Bickel 2002; Madden et al. 2003), additional real-world research is necessary in this regard. Second, it is unlikely that delays alone will emerge as the sole (or even primary) factor in how caregivers arrive at treatment-related decisions for their children. Various other treatment factors such as effort, cost (i.e., time, money), efficacy (i.e., probability or magnitude of behavior improvement), and other barriers are likely to jointly influence treatment-related decisions made by caregivers (Call et al. 2015a; V. A. Miller et al. 2012). Third, this study included a relatively larger sample of fathers than most studies evaluating treatment-related decision-making for children. As such, the sample derived here was sufficiently powered to perform the desired test but may not be representative of caregivers who typically implement these procedures. Lastly, caregivers of children with complex disorders, such as autism, regularly participate in multiple treatments simultaneously (Goin-Kochel et al. 2007). Future experimental research evaluating parental decision-making should account for the influence of other complementary, or even competing, options for behavioral treatments pursued by caregivers.

Compliance with Ethical Standards All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Conflict of Interest The authors declare that they have no conflicts of interest. The study materials (e.g., scripts) and data are released under an open source license (MIT).

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