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 behavioral disorders rarely yield immediate effects. For caregivers participating in behavioral therapies, the benefits from these efforts are seldom visible until after substantial time commitments. Delays associated with gains from child behavioral treatments can influence caregiver decision-making, and in turn, their extended commitments to recommended behavioral treatments. This study applied methods from behavioral economics to evaluate how delays associated with treatments affected caregiver choices among treatment options. Results indicated that caregivers often elected to pursue suboptimal behavioral strategies over recommended, superior alternatives that were associated with delays before improvements would be observed. These findings are consistent with research that has highlighted temporal preferences as a factor that may be predictive of adherence to recommended, evidence-based treatments and encourage the use of behavioral economic methods to better understand caregiver decision-making.

Keywords behavioral economics · treatment adherence · caregiver decision-making

1 Introduction

A range of effective behavioral therapies is available to treat many childhood behavior problems and behavioral disorders (Christophersen and Mortweet, 2001; 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 (Allen and Warzak, 2000; MacNaughton and Rodrigue, 2001). That is, behavioral therapies must be implemented correctly and consistently to produce the desired effects. Whereas behavioral and mental health professionals typically render therapy within systems and settings designed to implement evidence-based treatments, non-professionals (e.g., caregivers) implementing therapeutic strategies typically use them in settings that are not designed to support behavioral strategies, e.g., homes, communities (Nock and Ferriter, 2005; MacNaughton and Rodrigue, 2001). Various barriers exist in homes and community settings and these barriers may contribute to low levels of treatment adherence, or worse, caregiver discontinuation of recommended behavioral strategies (Armbruster and Kazdin, 1994).

The existing literature has highlighted numerous challenges associated with caregiver adherence to recommended behavioral treatments and these are represented across many childhood issues and disorders. For example, caregiver adherence to recommended treatments 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), various childhood anxiety disorders (Kendall and Sugarman, 1997; Santana and Fontenelle, 2011), and other childhood mental health (Gearing et al., 2012) and disruptive behavior disorders (Schoenwald et al., 2011, 2005). As such, issues associated with adherence cut across nearly all child behavior disorders that require parental participation. A large number of studies have been conducted to determine factors predictive of caregiver adherence to treatment (Chacko et al., 2016a,b; Dadds et al., 2018).

These studies have evaluated how 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; 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 (Kazdin and Mazurick, 1994; 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 aspects of behavioral therapies (e.g., acceptability, therapeutic alliance). Relatively little research has evaluated patterns of caregiver decision-making as a predictor of treatment adherence.

In one of the few studies that evaluated caregiver decision-making, Call et al. (2015b) examined how caregivers perceived behavioral outcomes when delays were involved. This study presented caregivers with choices between immediate, small improvements in their child's behavior (smaller, sooner; SS) or delayed, but larger improvements in their child's behavior (larger, later; LL). This decision is analogous to choices available to caregivers implementing behavioral strategies in naturalistic settings—do you commit to a recommended, evidence-based approach that entails weeks and months of therapy (LL) or do you choose to instead rely on short-term, less effective alternatives that provide some immediate relief from undesired behavior (SS)? The results from Call et al. (2015b) found that caregivers were differentially sensitive to the delays associated with optimal behavioral treatments (LL) and suggested that caregivers particularly sensitive to these delays may warrant additional consideration regarding implementation.

1.1 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 hold true in how animals (Ainslie, 1974; Chung and Herrnstein, 1967) and human beings make choices (Ainslie, 1975, 1992). Among the merits of behavioral economics, this framework has been particularly useful for modeling how and when individuals commit suboptimal or "irrational" patterns of decision-making .

The behavioral economic perspective has been applied to many areas of decision-making, especially those in which irrational patterns of decision-making emerge as optimal outcomes are delayed. This framework has been used to examine individual choice related to health and healthcare (Chapman, 1996, 2002), whether or not to pursue vaccination (Chapman and Coups, 1999; Chapman et al., 2010; Jit and Mibei, 2015), discontinuation of individual psychotherapy (Swift and Callahan, 2008, 2010), and behavioral outcomes when delays (Call et al., 2015b) and levels of time and effort vary among options (Call et al., 2015a). Further, this experimental methodology is increasingly used to understand choice and preferences in complex individuals, such as those diagnosed with intellectual and developmental disabilities (Gilroy et al., 2018).

The purpose of the current study was to replicate and extend findings from Call et al. (2015b). This 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 cared for children that required inpatient hospitalization for behavioral 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 struggling with more general behavioral challenges. Further, this replication and extension incorporates recent advances in methods used to evaluate intertemporal choice. The following research questions were posed: first, to what degree do delays affect preferences for behavioral treatments (e.g., SS vs. LL); second, to what degree do temporal preferences for behavioral results relate to temporal preferences for monetary outcomes; third, to what degree do demographic variables (e.g., number of reported children, level of challenging behavior) correlate with temporal preferences for behavioral treatments?

Table 1: Total Sample Demographics

Participant Demographics (n = 62)			
Age (years)		**Age (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 (Q1-Q3)	32 (51.6%)	Some college but no degree	17 (27.4%)
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%)		

2 Methods

2.1 Sample Size Estimation

A power analysis was performed using the G*Power program (Faul et al., 2007) with published results from Call et al. (2015b). Data from the original analyses were extracted, and a log10 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.

2.2 Population and Demographics

Caregivers endorsing behavioral concerns were recruited using the Amazon Mechanical Turk platform (mTurk). A total of 104 caregivers completed the survey and 62 were used in the final statistical analyses. The survey was posted as a Human Intelligence Task (HIT) to the mTurk framework, and eligible Workers (i.e., caregivers) were able to accept and complete the HIT if they met the requisite qualifications. Workers were eligible to accept the HIT if they had completed at least 1,000 HITs, maintained a 99% approval rating, and resided in the United States. These qualifications were consistent with criteria used in similar studies using the mTurk framework (Henley et al., 2016; Roma et al., 2016).

Eligible Workers completed a survey designed using the Qualtrics Research SuiteTM. The survey instrument and all study procedures were approved by the Institutional Review Board at Louisiana State University. The initial criteria for completing the survey were that the Worker had at least one child and that their child had at least occasional undesired behavior that warranted intervention. 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 complete the survey. 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 receive a $1.00 payment. Individual batches were posted to the mTurk framework until the target sample size was achieved.

Caregiver demographics are listed in Table 1. In the final sample (n = 62), twenty-five caregivers identified as male, thirty-two 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

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)	$A * e^{-(kD)^s}$

at least an associate degree. Most caregivers reported being married (n = 39, 62.90%) and identified as White/Caucasian (n = 49, 79.03%).

2.3 Monetary Decision-making Task

Caregiver preferences for hypothetical monetary outcomes were assessed using procedures derived from Frye et al. (2016) and Du et al. (2002). This adaptive assessment, the Monetary Decision-making Task (MDT), was designed to minimize the length of the assessment used in Call et al. (2015b). Procedures in the earlier study required approximately forty-five minutes to complete. In the MDT, caregivers made choices between a delayed choice (e.g., 7 days) with a fixed value (LL; $100) and an immediately available option with an adjusting value (the SS). The value of the immediately available monetary reward was adjusted, following each choice, from an initial midpoint value of $50. For example, selecting the smaller, sooner option (SS) would decrease the value of the SS while selecting the larger, later option (LL) would increase the value of the SS. The changes between each choice became progressively smaller at a pre-set rate (i.e., 50/2n; 50/21 = 25; 50/22 = 12.5). This iterative process repeated a total of six times at each delay point, with the final value of the SS characterizing temporal preferences for the corresponding delay. Caregiver preferences for monetary outcomes were assessed at delays of 1 week, 2 weeks, 1 month, 3 months, 9 months, 1 year, and 2 years. A more thorough description of the titration algorithm can be found in Frye et al. (2016).

2.4 Behavioral Decision-making Task

The Behavioral Decision-making Task (BDT) was designed using the same methods as the MDT. Whereas the MDT involved choices between monetary outcomes, the BDT involved choices between behavioral treatments (e.g., SS vs. LL). For example, the BDT included choices between treatments with defined outcomes (i.e., 50% fewer behavioral concerns for one year) rather than monetary amounts (i.e., $50). That is, caregivers were provided a choice between an option associated with a smaller, immediate effect on behavior (SS) for a period of one year and an option associated with a larger, but delayed effect on behavior (LL). 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; 1 month or 4 sessions).

2.5 Screening for Non-systematic Discounting Data

Individual caregiver data were screened for systematic responding using criteria derived from Johnson and Bickel (2008). Briefly, the criteria specified in Johnson and Bickel (2008) highlight two features of systematic discounting data. First, systematic responding entails successive decreases in value as delays grow larger (i.e., increases in value are unexpected), and 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. For this study, the second criterion was amended to accommodate aspects of caregiver preferences related to treatments. That is, it is possible that some caregivers may not discount the value of optimal treatment for their child (LL) and remain fully committed to a behavioral treatment even after years of treatment without observable improvements in behavior. To accommodate this type of decision, the second criteria was reframed to permit instances where the final delay was equal to the initial value but did not increase. Of the 104 submitted surveys, 62 caregivers (60%) provided complete records that met these criteria for both the MDT and the BDT.

2.6 Analytical Plan

Although Call et al. (2015a) modeled caregiver choices using a single-parameter Hyperbolic model (Mazur, 1987), more robust models for examining decision-making exist (Doyle, 2013). To entertain a broader range of possible

Table 3: Model Candidates and AIC 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

decision-making processes, the Hyperbolic, Exponential Constant Sensitivity (Ebert and Prelec, 2007), and Hyperboloid (Green and Myerson, 2004; Rachlin, 2006) models were fitted and evaluated to caregiver decision-making. The individual structure of each model is indicated in Table 2. Individual models were fitted using a multi-level approach (Young, 2017) and compared using the Akaike Information Criterion (AIC; Akaike, 1974). Each model was fitted using the nlme package (Pinheiro, Bates, DebRoy, & Sarkar, 2014) in the R statistical program (R Core Team, 2017) and individual parameters were entered as group-level fixed effects and as random effects at the individual level. Starting values were derived from the results of nonlinear regression at the group level using the nls package (DebRoy, Bates, & Pinheiro, 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, Doncker-Kapenga, Überhuber, & Kahaner, 1983) using the highest and lowest delays as the upper and lower bounds to be integrated upon. Whereas Call, Reavis, et al. (2015) compared fitted statistical parameters and point-based AUC separately (Myerson, Green, & Warusawitharana, 2001), MB-AUC jointly represents decision-making processes as fitted parameters and AUC simultaneously (Gilroy & Hantula, 2018). This measure is more easily compared in cases when the presence of multiple parameters complicates comparisons. 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."

3 Results

3.1 Decision-making across monetary and behavioral treatments

Model comparisons using the AIC revealed that the Rachlin hyperboloid performed better than the other candidates, see Table 3, and individual fittings using the Rachlin model are displayed in Figure 1. Numerical integration was performed upon individual discounting processes to generate a summary MB-AUC measure in both normal and log10 scaled delays (Gilroy and Hantula, 2018). From these AUC measures, the more normally-distributed AUC (log10) was then logit transformed to support parametric comparisons, see Figure 2. A Kolmogorov-Smirnov test with the transformed MB-AUC measure indicated preferences for monetary and behavioral treatments emerged from a similar distribution, $D = 0.1542$, $p = .531$. Levene's test for equality of variance was not significant, $F = 0.8374$, $p = .362$, and a paired-samples t-test assuming equal variance revealed that transformed 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, $t = -0.62$, $df = 122$, $p = .536$. The distribution of aggregated indifference points and transformed AUC across outcomes are illustrated in Figure 3.

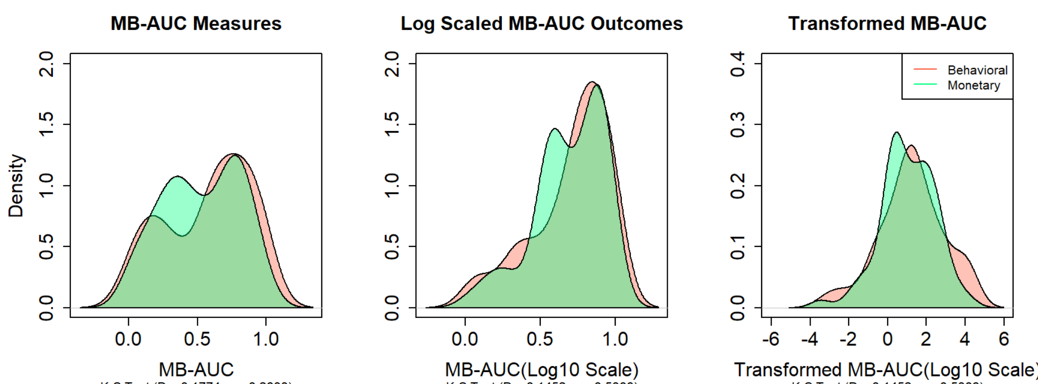

Figure 2: These density plots illustrate the distribution of MB-AUC in normal (left) and log-scaled form (center). The log-scaled MB-AUC was logit-transformed (right) to provide the measure used in the final analyses.

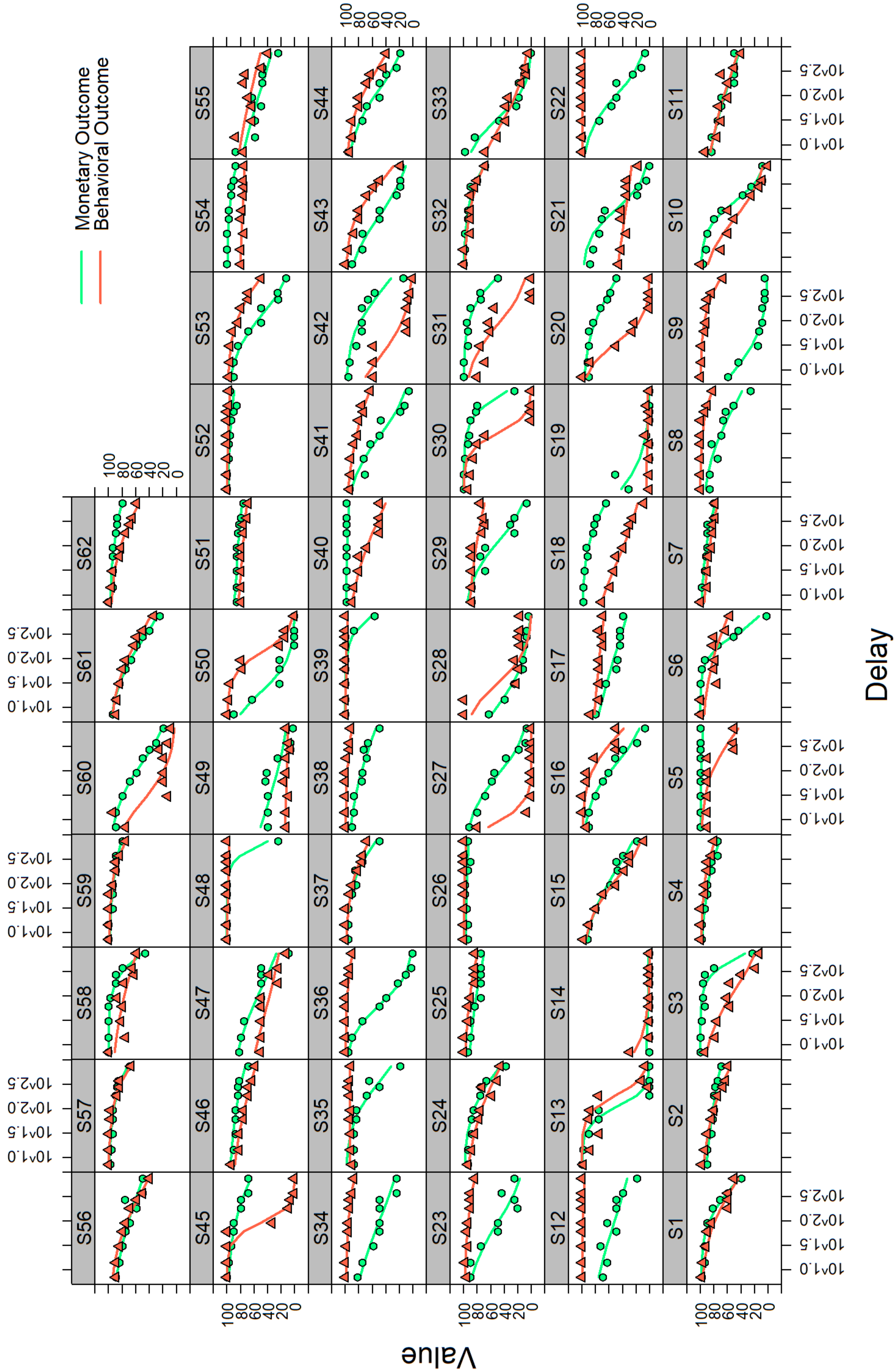

Figure 1: This figure depicts individual responding fitted to the Rachlin model across delayed Monetary and Behavioral Outcomes at the individual level. Series were fitted using multilevel modeling with individual parameters entered as fixed and random effects.

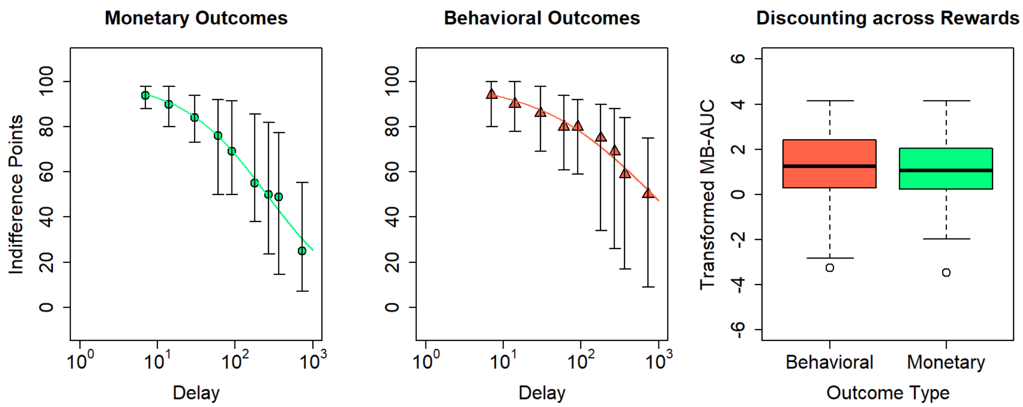

Figure 3: These plots illustrate the distribution of temporal preferences for monetary (left) and behavioral outcomes (center). These outcomes are depicted following logit transform across outcomes in the rightmost plot.

3.2 Correlates of caregiver preferences for behavioral treatments

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) = .021, p = .866 or parental age, r(57) = -.02, p = .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, rs(62) = 0.003, p = .980, and educational level, rs(62) = -.086, p =.501, were also not significant.

4 Discussion

Caregiver decision-making related to adherence to recommended behavioral treatments used with their children is complex and jointly influenced by a range of cultural factors, environmental barriers, individual characteristics, and specific behavioral therapies (Chacko et al., 2016b; Armbruster and Kazdin, 1994; Kazdin and Mazurick, 1994). Despite decades of research in this area, substantial research continues to be necessary to better understand challenges related to caregiver adherence (MacNaughton and Rodrigue, 2001; Chacko et al., 2016a). Research on decision-making seems especially relevant to behavioral therapies, as issues of adherence to recommended treatments seem to be less of an issue for psychopharmacological therapies (MacNaughton and Rodrigue, 2001; Bennett et al., 1996; Dreyer et al., 2010). 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 options for behavioral strategies. 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; third, 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. (2015a). Caregiver preferences for behavioral outcomes (i.e., SS vs. LL) were influenced by delays and caregiver preferences were comparable across both monetary and behavioral contexts. That is, all caregivers reported a strong preference for optimal treatments when delays were minimal but each differed in terms of their own sensitivity to delays. The results of this study provide converging evidence that suggests that the delays associated with behavior therapies are a factor in how caregivers decide whether or not to implement recommended, evidence-based behavioral therapies (LL) rather than reactive, immediate strategies associated with much less substantial effects (SS). For example, some caregivers may forego a reinforcement-based treatment for their child's behavior because this intervention entails weeks of training and implementation and instead pursue punitive procedures that provide an immediate, albeit minor, temporary suppression of undesired behavior.

Although behavioral economic methods require novel methods to evaluate individual decision-making, a priori knowledge of temporal preferences is potentially valuable for several reasons. First, preferences skewed towards more immediate outcomes has 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, e.g., diabetes management (Lebeau et al., 2016; Stoianova et al., 2018). With information regarding caregiver decision-making at hand, clinicians might use this information to match goals and strategies that more closely align with the temporal preferences of caregivers (Call et al., 2015a). That is, caregivers more sensitive to immediate outcomes may be better suited to strategies associated with more immediately observable benefits. Second, if temporal preferences emerge as a significant 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 sensitivity to delays. That is, further research in this area may yield strategies that can further support initial and on-going adherence to behavioral recommendations.

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 that temporal sensitivity to be more related to individual cognitive biases (DeHart and Odum, 2015), (Ludwig et al., 2015), or individual personality traits (Odum, 2011) rather than simple environmental or demographic factors.

4.1 Limitations and Next Steps

While this study extends earlier findings regarding caregiver temporal preferences, several limitations warrant noting. First, it is unknown to what degree that caregiver-report related to future gains relate to real-world participant in parent behavioral therapy. 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), and other barriers are likely to jointly influence treatment-related decisions made by caregivers (Pinheiro et al., 2014; Miller et al., 2012). 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.

References

Ainslie, G. W. (1974). Impulse control in pigeons. *J Exp Anal Behav*, 21(3):485–9.

Ainslie, G. W. (1975). Specious reward: a behavioral theory of impulsiveness and impulse control. *Psychol Bull*, 82(4):463–96.

Ainslie, G. W. (1992). *Picoeconomics: The strategic interaction of successive motivational states within the person*. Cambridge University Press.

Allen, K. D. and Warzak, W. J. (2000). The problem of parental nonadherence in clinical behavior analysis: effective treatment is not enough. *J Appl Behav Anal*, 33(3):373–91.

Armbruster, P. and Kazdin, A. E. (1994). Attrition in child-psychotherapy. *Advances in Clinical Child Psychology, Vol 16*, 16:81–108.

Bennett, D. S., Power, T. J., Rostain, A. L., and Carr, D. E. (1996). Parent acceptability and feasibility of adhd interventions: Assessment, correlates, and predictive validity. *Journal of Pediatric Psychology*, 21(5):643–657.

Borges, A. M., Kuang, J., Milhorn, H., and Yi, R. (2016). An alternative approach to calculating area-under-the-curve (auc) in delay discounting research. *J Exp Anal Behav*, 106(2):145–55.

Bromberg, U., Lobatcheva, M., and Peters, J. (2017). Episodic future thinking reduces temporal discounting in healthy adolescents. *PLoS One*, 12(11):e0188079.

Call, N. A., Delfs, C. H., Reavis, A. R., and Mevers, J. L. (2015a). Factors influencing treatment decisions by parents for their children with autism spectrum disorder. *Research in Autism Spectrum Disorders*, 15-16:10–20.

Call, N. A., Reavis, A. R., McCracken, C. E., Gillespie, S. E., and Scheithauer, M. C. (2015b). The impact of delays on parents' perceptions of treatments for problem behavior. *J Autism Dev Disord*, 45(4):1013–25.

Camerer, C. and Loewenstein, G. (2004). *Behavioral Economics: Past, Present, Future*, book section 1. Princeton University Press, Princeton, NJ.

Carr, T., Shih, W., Lawton, K., Lord, C., King, B., and Kasari, C. (2016). The relationship between treatment attendance, adherence, and outcome in a caregiver-mediated intervention for low-resourced families of young children with autism spectrum disorder. *Autism*, 20(6):643–52.

Chacko, A., Jensen, S. A., Lowry, L. S., Cornwell, M., Chimklis, A., Chan, E., Lee, D., and Pulgarin, B. (2016a). Engagement in behavioral parent training: Review of the literature and implications for practice. *Clin Child Fam Psychol Rev*, 19(3):204–15.

Chacko, A., Wymbs, B. T., Rajwan, E., Wymbs, F., and Feirsen, N. (2016b). Characteristics of parents of children with adhd who never attend, drop out, and complete behavioral parent training. *Journal of Child and Family Studies*, 26(3):950–960.

Chapman, G. B. (1996). Temporal discounting and utility for health and money. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 22(3):771–791.

Chapman, G. B. (2002). Your money or your health: time preferences and trading money for health. *Med Decis Making*, 22(5):410–6.

Chapman, G. B. and Coups, E. J. (1999). Time preferences and preventive health behavior: acceptance of the influenza vaccine. *Med Decis Making*, 19(3):307–14.

Chapman, G. B., Li, M., Colby, H., and Yoon, H. (2010). Opting in vs opting out of influenza vaccination. *JAMA*, 304(1):43–4.

Christophersen, E. R. and Mortweet, S. L. (2001). *Treatments that work with children: Empirically supported strategies for managing childhood problems*. American Psychological Association.

Chung, S. H. and Herrnstein, R. J. (1967). Choice and delay of reinforcement. *J Exp Anal Behav*, 10(1):67–74.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Routledge.

Dadds, M. R., Sicouri, G., Piotrowska, P. J., Collins, D. A. J., Hawes, D. J., Moul, C., Lenroot, R. K., Frick, P. J., Anderson, V., Kimonis, E. R., and Tully, L. A. (2018). Keeping parents involved: Predicting attrition in a self-directed, online program for childhood conduct problems. *J Clin Child Adolesc Psychol*, pages 1–13.

Dallery, J. and Raiff, B. R. (2007). Delay discounting predicts cigarette smoking in a laboratory model of abstinence reinforcement. *Psychopharmacology (Berl)*, 190(4):485–96.

Daniel, T. O., Stanton, C. M., and Epstein, L. H. (2013). The future is now: comparing the effect of episodic future thinking on impulsivity in lean and obese individuals. *Appetite*, 71:120–5.

DeHart, W. B. and Odum, A. L. (2015). The effects of the framing of time on delay discounting. *J Exp Anal Behav*, 103(1):10–21.

Doyle, J. R. (2013). Survey of time preference, delay discounting models. *Judgment and Decision Making*, 8(2):116–135.

Dreyer, A. S., O'Laughlin, L., Moore, J., and Milam, Z. (2010). Parental adherence to clinical recommendations in an adhd evaluation clinic. *J Clin Psychol*, 66(10):1101–20.

Du, W., Green, L., and Myerson, J. (2002). Cross-cultural comparisons of discounting delayed and probabilistic rewards. *The Psychological Record*, 52(4):479–492.

Ebert, J. E. J. and Prelec, D. (2007). The fragility of time: Time-insensitivity and valuation of the near and far future. *Management Science*, 53(9):1423–1438.

Faul, F., Erdfelder, E., Lang, A.-G., and Buchner, A. (2007). G*power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, 39(2):175–191.

Fishburn, P. C. and Rubinstein, A. (1982). Time preference. *International economic review*, pages 677–694.

Frye, C. C., Galizio, A., Friedel, J. E., DeHart, W. B., and Odum, A. L. (2016). Measuring delay discounting in humans using an adjusting amount task. *J Vis Exp*, (107).

Gaudiano, B. A., Weinstock, L. M., and Miller, I. W. (2008). Improving treatment adherence in bipolar disorder: a review of current psychosocial treatment efficacy and recommendations for future treatment development. *Behav Modif*, 32(3):267–301.

Gearing, R. E., Schwalbe, C. S., Dweck, P., and Berkowitz, J. (2012). Investigating adherence promoters in evidence-based mental health interventions with children and adolescents. *Community Ment Health J*, 48(1):63–70.

Gilroy, S. P. and Hantula, D. A. (2018). Discounting model selection with area-based measures: A case for numerical integration. *J Exp Anal Behav*, 109(2):433–449.

Gilroy, S. P., Kaplan, B. A., and Leader, G. (2018). A systematic review of applied behavioral economics in assessments and treatments for individuals with developmental disabilities. *Review Journal of Autism and Developmental Disorders*, 5(3):247–259.

Goin-Kochel, R. P., Myers, B. J., and Mackintosh, V. H. (2007). Parental reports on the use of treatments and therapies for children with autism spectrum disorders. *Research in Autism Spectrum Disorders*, 1(3):195–209.

Green, L. and Myerson, J. (2004). A discounting framework for choice with delayed and probabilistic rewards. *Psychol Bull*, 130(5):769–92.

Henley, A. J., DiGennaro Reed, F. D., Reed, D. D., and Kaplan, B. A. (2016). A crowdsourced nickel-and-dime approach to analog obm research: A behavioral economic framework for understanding workforce attrition. *J Exp Anal Behav*, 106(2):134–44.

Jit, M. and Mibei, W. (2015). Discounting in the evaluation of the cost-effectiveness of a vaccination programme: A critical review. *Vaccine*, 33(32):3788–94.

Johnson, M. W. and Bickel, W. K. (2002). Within-subject comparison of real and hypothetical money rewards in delay discounting. *J Exp Anal Behav*, 77(2):129–46.

Johnson, M. W. and Bickel, W. K. (2008). An algorithm for identifying nonsystematic delay-discounting data. *Exp Clin Psychopharmacol*, 16(3):264–74.

Kazdin, A. E. and Mazurick, J. L. (1994). Dropping out of child psychotherapy: Distinguishing early and late dropouts over the course of treatment. *Journal of Consulting and Clinical Psychology*, 62(5):1069–1074.

Kazdin, A. E. and Wassell, G. (1999). Barriers to treatment participation and therapeutic change among children referred for conduct disorder. *J Clin Child Psychol*, 28(2):160–72.

Kendall, P. C. and Sugarman, A. (1997). Attrition in the treatment of childhood anxiety disorders. *Journal of Consulting and Clinical Psychology*, 65(5).

Krishnan-Sarin, S., Reynolds, B., Duhig, A. M., Smith, A., Liss, T., McFetridge, A., Cavallo, D. A., Carroll, K. M., and Potenza, M. N. (2007). Behavioral impulsivity predicts treatment outcome in a smoking cessation program for adolescent smokers. *Drug Alcohol Depend*, 88(1):79–82.

Lavigne, J. V., Lebailly, S. A., Gouze, K. R., Binns, H. J., Keller, J., and Pate, L. (2010). Predictors and correlates of completing behavioral parent training for the treatment of oppositional defiant disorder in pediatric primary care. *Behav Ther*, 41(2):198–211.

Lebeau, G., Consoli, S. M., Le Bouc, R., Sola-Gazagnes, A., Hartemann, A., Simon, D., Reach, G., Altman, J. J., Pessiglione, M., Limosin, F., and Lemogne, C. (2016). Delay discounting of gains and losses, glycemic control and therapeutic adherence in type 2 diabetes. *Behav Processes*, 132:42–48.

Ludwig, V. U., Nusser, C., Goschke, T., Wittfoth-Schardt, D., Wiers, C. E., Erk, S., Schott, B. H., and Walter, H. (2015). Delay discounting without decision-making: medial prefrontal cortex and amygdala activations reflect immediacy processing and correlate with impulsivity and anxious-depressive traits. *Front Behav Neurosci*, 9:280.

MacNaughton, K. L. and Rodrigue, J. R. (2001). Predicting adherence to recommendations by parents of clinic-referred children. *Journal of Consulting and Clinical Psychology*, 69(2):262.

Madden, G. J., Begotka, A. M., Raiff, B. R., and Kastern, L. L. (2003). Delay discounting of real and hypothetical rewards. *Exp Clin Psychopharmacol*, 11(2):139–45.

Mazur, J. E. (1987). *An adjusting procedure for studying delayed reinforcement*, pages 55–73. Erlbaum, Hillsdale, NJ.

Miller, L. M., Southam-Gerow, M. A., and Allin, R. B. (2008). Who stays in treatment? child and family predictors of youth client retention in a public mental health agency. *Child Youth Care Forum*, 37(4):153–170.

Miller, V. A., Schreck, K. A., Mulick, J. A., and Butter, E. (2012). Factors related to parents' choices of treatments for their children with autism spectrum disorders. *Research in Autism Spectrum Disorders*, 6(1):87–95.

Moore, T. R. and Symons, F. J. (2009). Adherence to behavioral and medical treatment recommendations by parents of children with autism spectrum disorders. *J Autism Dev Disord*, 39(8):1173–84.

Morrison, K. L., Madden, G. J., Odum, A. L., Friedel, J. E., and Twohig, M. P. (2014). Altering impulsive decision making with an acceptance-based procedure. *Behav Ther*, 45(5):630–9.

Nock, M. K. and Ferriter, C. (2005). Parent management of attendance and adherence in child and adolescent therapy: A conceptual and empirical review. *Clinical Child and Family Psychology Review*, 8(2):149–166.

Odum, A. L. (2011). Delay discounting: trait variable? *Behav Processes*, 87(1):1–9.

Peters, J. and Buchel, C. (2010). Episodic future thinking reduces reward delay discounting through an enhancement of prefrontal-mediotemporal interactions. *Neuron*, 66(1):138–48.

Pinheiro, J., Bates, D., DebRoy, S., and Sarkar, D. (2014). R core team (2014) nlme: linear and nonlinear mixed effects models. r package version 3.1-117. *Available at http://CRAN.R-project.org/package=nlme*.

Rachlin, H. (2006). Notes on discounting. *J Exp Anal Behav*, 85(3):425–35.

Roma, P. G., Hursh, S. R., and Hudja, S. (2016). Hypothetical purchase task questionnaires for behavioral economic assessments of value and motivation. *Managerial and Decision Economics*, 37(4-5):306–323.

Santana, L. and Fontenelle, L. F. (2011). A review of studies concerning treatment adherence of patients with anxiety disorders. *Patient Prefer Adherence*, 5:427–39.

Schoenwald, S. K., Garland, A. F., Southam-Gerow, M. A., Chorpita, B. F., and Chapman, J. E. (2011). Adherence measurement in treatments for disruptive behavior disorders: Pursuing clear vision through varied lenses. *Clin Psychol (New York)*, 18(4):331–341.

Schoenwald, S. K., Letourneau, E. J., and Halliday-Boykins, C. (2005). Predicting therapist adherence to a transported family-based treatment for youth. *J Clin Child Adolesc Psychol*, 34(4):658–70.

Snider, S. E., LaConte, S. M., and Bickel, W. K. (2016). Episodic future thinking: Expansion of the temporal window in individuals with alcohol dependence. *Alcoholism: Clinical and Experimental Research*, 40(7):1558–1566.

Springer, C. and Reddy, L. A. (2010). Measuring parental treatment adherence in a multimodal treatment program for children with adhd: A preliminary investigation. *Child Family Behavior Therapy*, 32(4):272–290.

Stoianova, M., Tampke, E. C., Lansing, A. H., and Stanger, C. (2018). Delay discounting associated with challenges to treatment adherence and glycemic control in young adults with type 1 diabetes. *Behav Processes*, 157:474–477.

Swift, J. K. and Callahan, J. L. (2008). A delay discounting measure of great expectations and the effectiveness of psychotherapy. *Professional Psychology: Research and Practice*, 39(6):581–588.

Swift, J. K. and Callahan, J. L. (2010). A delay discounting model of psychotherapy termination. *International Journal of Behavioral Consultation and Therapy*, 5(3-4):278–293.

Thompson, L. and McCabe, R. (2012). The effect of clinician-patient alliance and communication on treatment adherence in mental health care: a systematic review. *BMC Psychiatry*, 12:87.

Watson, T. S. and Gresham, F. M. (2013). *Handbook of child behavior therapy*. Springer Science Business Media.

Weisz, J. R., Weiss, B., and Langmeyer, D. B. (1987). Giving up on child psychotherapy: Who drops out? *Journal of Consulting and Clinical Psychology*, 55(6):916–918.

Yoon, J. H., Higgins, S. T., Heil, S. H., Sugarbaker, R. J., Thomas, C. S., and Badger, G. J. (2007). Delay discounting predicts postpartum relapse to cigarette smoking among pregnant women. *Exp Clin Psychopharmacol*, 15(2):176–86.