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We have no conflicts of interest to disclose. The source code necessary to reproduce this work is publicly archived at https://www.github.com/miyamot0/TreatmentDemandCBA

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Abstract

Behavior analysts and psychologists advocate for the use of therapies and strategies based on credible, scientific evidence. Researchers and clinicians regularly advocate for Evidence-based Practices (EBPs) over questionable “alternatives” because caregivers seldom choose interventions based on scientific evidence alone. This study applied methods and concepts from Consumer Behavior Analysis to conduct a reinforcer-based evaluation of the consequences that influence treatment choices. Hypothetical Treatment Purchase Tasks (HTPTs) were designed to evaluate how utilitarian (UR; i.e., the efficacy of treatment) and informational sources of reinforcement (IR; i.e., community support for treatment) jointly influence treatment-related choices. A total of 104 caregivers were recruited using the Amazon Mechanical Turk (MTurk) framework to complete two HTPTs. Results indicated that caregivers overall favored treatments with greater IR over those with greater UR, suggesting that indirect contingencies for treatment choices exerted greater overall influence than the direct contingencies of treatment choices (i.e., efficacy). This finding extends the literature on treatment choice by providing a reinforcer-based perspective on why ‘fad’, questionable, and pseudoscientific practices can achieve and maintain high levels of adoption by caregivers. This work concludes with a discussion of Consumer Behavior Analysis and how reinforcer-based interpretations of choice can be used to improve efforts to support and advocate for evidence-based child behavior treatments.

Keywords: **consumer behavior analysis, behavior economics, public policy, evidence-based practices**

Introduction

Scientific evidence is critical in the design and delivery of effective behavior therapy (APA Presidential Task Force on Evidence-Based Practice, 2006). In behavior analysis, Evidence-based Practices (EBPs) refer to those that are those guided by behavioral principles that have been rigorously evaluated in research (Behavior Analyst Certification Board, 2017; Smith, 2013). Apart from behavior analysis, specifically, various foundations and groups have developed systems to categorize and grade the levels of support for specific therapeutic approaches and procedures (e.g., National Autism Center, 2015; What Works Clearinghouse, 2016).

In a recent review by Kaminski and Claussen (2017), these authors presented several designations that highlighted qualitatively different degrees of scientific support. At the highest and most established extreme, treatments characterized as being "well-established" had been evaluated using randomized assignment and controls, had well-defined independent variables and populations, included reliable and valid measures, and applied appropriate analyses (Kaminski & Claussen, 2017, p. 482). Furthermore, well-established treatments had demonstrated efficacy across both multiple research settings and teams, with evidence that the treatment was superior to other forms of active treatment or at least equivalent to another well-established treatment.

Evidence-based and "Alternative" Treatments

Whereas EBPs typically refer to those rooted in established behavioral principles, not all of the treatments marketed to consumers are based on established behavioral principles or scientific knowledge (Smith, 2015). Rather, such "alternatives" to EBPs include practices that are based on questionable scientific evidence, or worse, outright pseudoscience (Normand, 2008;

Zane et al., 2008). Unfortunately, the range and the number of these "alternative" therapies marketed to caregivers and educators have steadily increased over time (Metz et al., 2005) and behavior analysts must now regularly advocate for EBPs and against these unsupported "alternatives" (Bailey & Burch, 2016).

The risks associated with pursuing unsupported treatments can be considerable. These may range from the loss of time and resources up to physical harm, and potentially, to death. For example, some providers have marketed the use of chelation therapy to families of children diagnosed with autism spectrum disorder (ASD). This practice entails the injection of chemicals into the body to remove "toxins" that are presumed to contribute to, and maintain, the symptoms characteristic of various disorders (see Davis et al., 2013, for a review). Although this treatment has approved medical uses, such as in the treatment of heavy metal poisoning, there is no scientific evidence supporting its use in treating the core symptoms of ASD (Sinha et al., 2006). Furthermore, unnecessary chelation therapy may even result in accidental death (Baxter & Krenzelok, 2008). Despite these risks and a continued lack of evidence for this practice, an estimated 500,000 individuals diagnosed with ASD are subjected to chelation therapy in the United States every year (Brent, 2013). Although the most severe risks associated with "alternative" treatments are quite rare, time and resources are limited for families and the consumption of such practices ultimately detracts from those that could otherwise be allocated to effective treatments (Zane et al., 2008).

A Consumer Behavior Analytic Approach to Evidence-based Practices

In a consumer behavior analytic approach to evaluating choice, the emphasis is placed on the ecological events that precede and follow choice (Foxall, 2016; Foxall et al., 2011; Foxall et al., 2007). That is, consumer behavior analysis can be viewed as an extension of applied behavior analysis and operant behavioral economics (Foxall, 1987; Foxall et al., 2011). The Behavioral Perspective Model (BPM), as outlined in Foxall (2016), applies the three-term-contingency to a range of competing forms of purchasing behavior. For instance, consumption is viewed in light of the relevant context (i.e., discriminative stimuli) as well as its relation to future behavior (e.g., reinforcement, punishment).

In the BPM, consumer behavior occurs at the intersection of the individual's learning history and the immediate environment. This context is referred to as the "consumer situation" and is defined as "…the social and physical environment in which the consumer is exposed to stimuli signaling a choice situation," (Foxall et al., 2007, p. 5). In this context, the transformation of neutral stimuli into discriminative stimuli signaling choice behavior relies on how the individual responds to these stimuli. The learning history of the individual informs this interpretation, with previous experiences guiding the individual's appraisal of the consequences for the available choices (Foxall, 2016).

According to the BPM, three types of consequences influence consumer behavior: Utilitarian Reinforcement (UR), Informational Reinforcement (IR), and aversive consequences (Foxall, 2016; Foxall et al., 2011). All goods and services entail varying degrees of each type of these consequences. Utilitarian reinforcement is defined as the direct benefits that result from consuming a good or service. For example, the UR of buying a car is the practical, functional consequences of car ownership, such as having ready access to transportation and being able to travel to locations inaccessible by public transit. When considering therapies for children with behavior problems, UR can be represented by the putative effects of effective behavior treatment that result from consuming the therapy service (e.g., behavior change, acquisition of age-appropriate skills). Evidence-based therapies, thus, can be considered to have higher UR than "alternative" or unsupported therapies, given that they have more evidence and a greater likelihood of producing the putative effect of interest.

Informational reinforcement is defined as the indirect and symbolic consequences of consuming a good or service. Put simply, IR refers to the social consequences of making a purchasing choice; namely, how the verbal community responds to such choices (i.e., the consequences mediated). For example, the IR of buying a car might result in an elevation of social status or an increase of desirable attention mediated by others, especially in the case of premium cars. The IR of therapies for children with behavior problems can also be understood in terms of how the verbal community of the family might respond to a certain form of behavior therapy. For example, the verbal community may affirm certain therapies, regardless of efficacy, and the mediation of this stream of reinforcement would be considered IR. Aversive consequences are defined as the costs to consume goods and services, such as surrendering money, waiting in line, etc. The most obvious aversive consequence of buying a car is relinquishing a significant amount of money (Foxall, 2016). Although aversive consequences are relevant to treatment-related choices, the focus of this specific work was on evaluating how IR and UR relate to the consumption of behavior therapies.

The Operant Demand Framework

The Operant Demand Framework refers to a collection of methods and procedures used to evaluate how various ecological factors (e.g., unit price) influence consumption (Hursh, 1980, 1984; Reed et al., 2013). Within this framework, Hypothetical Purchase Tasks (HPTs) are often used to sample how individuals would make choices under some form of constraint, e.g. budget (Roma et al., 2017). Within an HPT, a marketplace is simulated, and participants are presented with a variety of goods or services available for purchase. Data is collected regarding which prospect, and how much of it, would be consumed as prices increase from low to high (Jacobs & Bickel, 1999). These data are then analyzed to examine the demand for those goods and services (Reed et al., 2013; Roma et al., 2016).

Hypothetical Purchase Tasks have been used to examine the consumption of a variety of goods, such as tobacco (e.g., Wilson et al., 2016), alcohol (e.g., Amlung et al., 2012; Kaplan et al., 2018; Zvorsky et al., 2019), drugs (e.g., Jacobs & Bickel, 1999; MacKillop et al., 2019), and food (e.g., Epstein et al., 2018). However, evaluations of treatment services using Hypothetical Treatment Purchase Tasks (HTPTs) are quite rare and the ecological factors that influence the consumption (or substitution) of EBPs are still not yet well-understood (see Gilroy & Feck, 2022; Gilroy et al., 2022, for empirical evaluations). For instance, Gilroy et al. (2022) evaluated caregiver demand for EBPs and found that caregivers readily consumed "alternatives" to EBPs as if they were functional substitutes (i.e., used them as if they were equivalent). Gilroy and Feck (2022) investigated this further, evaluating whether *differences* in levels of evidence influenced the substitutability of EBPs with "alternatives." Taken together, the results of these works suggest that evidence is relevant to treatment choice—but is unlikely to be the only relevant factor. It warrants noting that the existing demonstrations of treatment-related decision-making using HTPTs focused exclusively on UR (i.e., evidence of efficacy), which is just one type of contingencies that influences treatment choice (Gilroy & Feck, 2022; Gilroy et al., 2022). As such, it is unknown to what degree IR and the verbal community influence how caregivers make choices between available treatments.

The purpose of this study was to translate concepts and methods derived from Consumer Behavior Analysis to evaluate how varying types of contingencies differentially influence caregiver treatment choices. Specifically, HTPTs were constructed to evaluate the alone- and own-price demand for a child behavior therapy high in both UR and IR. That is, a behavior therapy high in both UR (i.e., high evidence of efficacy) and IR (i.e., practices supported or encouraged by the participant's community) would represent the optimal arrangement of contingencies supporting the consumption of EBPs (i.e., maximizes available *types* of reinforcement). This maximal treatment approach was then featured in a cross-price task wherein an unpopular, but effective treatment (High UR, Low IR) and a popular, but ineffective treatment (Low UR, High IR) were concurrently available at a lower fixed price. This arrangement provided a means to evaluate which type of reinforcement (i.e., UR or IR) most influenced treatment choice when increasing costs eliminated the ability to maximize *both* contingencies.

The specific research questions included in this work were: 1) to what degree do specific demographic factors appear to be associated with the demand for behavior therapy associated with High UR and High IR (i.e., popular EBP; alone-price), 2) to evaluate how the introduction of additional treatments influenced the consumption of an EBP high in both UR and IR (e.g., alone- vs. own-price demand), and 3) to determine whether caregiver choice related to behavior therapy is differentially sensitive to different types of reinforcer contingencies when unable to maximize both types of reinforcement (UR, IR; cross-price).

Methods

Participants

A total of 104 participants were recruited using the Amazon Mechanical Turk (MTurk) platform. The MTurk platform allows researchers (i.e., "requesters") to assign tasks to users (i.e., "workers") and compensate them for their participation in research tasks (Chandler & Shapiro, 2016). The task was made available to workers on the MTurk platform if they met the following qualifications: 1) they had completed at least one thousand total tasks; 2) they maintained an overall 99% approval rating for their submitted work; 3) they held the ‘parent’ qualifier in the MTurk framework; 4) and they resided in the United States. Such qualifications are consistent with recommended practices when gathering “crowdsourced” participant data (Chandler & Shapiro, 2016). Eligible workers were able to accept the task and access survey designed using the Qualtrics Research Suite™.

Criteria for inclusion

Eligible participants in the study were parents or caregivers of children that endorsed a degree of child behavior problems and interest in parent-implemented behavior therapy. Before completing the study instrument, prospective participants completed a brief qualifying questionnaire that featured questions about their present level of concern about their child(ren)’s behavior. Prospective participants who indicated that they had no children, were not concerned about their child’s current behavior, or were not interested in pursuing parent-implemented behavior therapy were informed that they were not eligible to participate in the study. Caregivers who completed the task, or were determined ineligible to participate, were flagged in the MTurk framework so that they could not re-attempt the task. Eligible caregivers were compensated with 2 USD, delivered through the MTurk framework, for an estimated 11 minutes of participation time.

Procedures

Characterizing Utilitarian and Informational Reinforcement

Rankings of UR/IR were determined before participants completed the HTPTs. Specifically, a total of three behavior therapies were selected based on relative UR and IR rankings, see Table 1 for a depiction of this arrangement. Prior to disseminating study measures, a range of behavior therapies was classified as High UR or Low UR by the study team. Given that the UR (i.e., evidence of efficacy) for behavior therapies was not expected to vary across individuals, the ranking (i.e., High UR, Low UR) was based on a review of the scientific literature.

Therapies that were well-supported in the literature were considered to have High UR (i.e., evidence-based practices). These consisted of The Incredible Years (Webster-Stratton, 2001), Brief Parent Training (Kjobli & Ogden, 2012), Parent-Child Interaction Therapy (Hembree-Kigin & McNeil, 2013), Parent Management Training (Kazdin, 1997), and Enhanced Triple P interventions (Positive Parenting Program; Sanders et al., 2000). In contrast to these High UR options, a total of ten therapies that were not supported by credible research were chosen to represent therapies considered to have Low UR. These specific treatments were drawn from a treatment resource for parents related to pseudoscientific practices (Sandberg & Spritz, 2012) and consisted of the Gluten-free and Casein-free diet (Elder et al., 2006), Sensory Integration Therapy (Lang et al., 2012), Earthing/Grounding Therapy (Ober et al., 2010), Hyperbaric Oxygen Therapy (Rossignol et al., 2007), Chelation Therapy (Sinha et al., 2006), various dietary supplements (Kawicka & Regulska-Ilow, 2013), Music Therapy (Geretsegger et al., 2014), the Miller Method (Miller & Chrétien, 2007), Collaborative and Proactive Solutions (Maddox et al., 2018), and Essential Oils (Worwood, 2016).

Whereas UR was determined a priori, levels of IR were expected to vary across individuals (Foxall, 2016). As such, the level of IR for each type of behavior therapy (High UR and Low UR) was determined by querying caregivers about how their friends and family would respond to their consumption of a specific type of behavior therapy. Participants rated each type of behavior therapy for IR after reading a short vignette about each of the therapies using a short questionnaire. Interested readers may consult Oliveira-Castro and Foxall (2017) for examples of how IR has been previously evaluated for goods. Specifically, caregivers answered two questions for each treatment using a 0-100 sliding scale: 1) How likely would you be to try this therapy; and 2) How likely would you be to talk about this therapy with others? Responses to each question yielded a numerical value from the sliding scale and these were combined to create an omnibus index of IR. That is, higher numerical values suggested higher IR and a greater likelihood of caregivers trying the therapy and being willing to share this information with others.

The combination of UR and IR scores was used to form the basis of the HTPT options. Specifically, the High UR treatment with the highest IR (High UR/High IR) was used as the primary service in the alone- and own-price analyses. Additionally, the High UR treatment with the *lowest* IR (High UR/Low IR) and the Low UR treatment with the *highest* IR (Low UR/High IR) were included as fixed price alternatives in the cross-price task.[1]

Hypothetical Treatment Purchase Tasks

Two HTPTs were constructed using caregiver-specific UR and IR ratings. The first HTPT evaluated the demand for a High UR/High IR option across a range of prices (alone-price demand). Caregivers were instructed to respond as if that they had a hypothetical budget of 4000 USD and up to 16 hours available to spend towards parent-implemented behavior therapy each week. Hours of treatment consumption were available in 15-minute increments (0.25 hours) and caregivers were instructed to respond as if that they could not direct their available resources anywhere else and that unspent weekly resources would not be carried forward. The price assay was determined using an average hourly rate of 200 USD with a standard deviation of 50 USD,

[1] High IR and Low IR designations referred to rankings at the upper and lowest extremes of the combined IR values.

yielding a price assay ranging from 50 to 400 USD. This pricing was consistent with earlier demonstrations using HTPTs (Gilroy & Feck, 2022; Gilroy et al., 2022).

The second HTPT evaluated the demand for a High UR/High IR behavior therapy across a range of prices when High UR/Low IR and Low UR/High IR alternatives were concurrently available at a fixed price (100 USD; cross-price demand). The price assay for the High UR/High IR treatment remained the same across tasks. In both HTPTs, relevant vignettes were re-presented to caregivers before they started the respective tasks.

Evaluations of Systemic Purchase Task Data

Purchase task data were screened for features of systematic responding (Stein et al., 2015) and the overall instrument contained items to detect inattentive patterns of responding. A total of three attention checks were embedded in the instrument. The three criteria for systematic purchase tasks data described in Stein et al. (2015) were evaluated using the *beezdemand* R package (Kaplan et al., 2019). The first criterion, trend, draws from the law of demand. That is, that things being equal, increasing the price of a commodity should drive the consumption of that commodity downward and there should be a non-negligible change in consumption from the first (cheapest) price point to the last (most expensive). The second indicator of systematic purchase behavior is bounce. Bounce describes proximal change between adjacent price points (i.e., from one price to the next). Frequent increases in consumption as prices increase are not expected and often correspond with inattention or a misunderstanding of the task. The final indicator, reversals from zero, reflects instances in which a participant ceases consumption at one price point only to then resumes consumption at a higher price point. As with bounce, this instance is not characteristic of the prototypical demand curve and may be indicative of inattention or a misunderstanding of the task.

A total of 78 caregivers (*n*=78/104, 75%) met all three indicators of systematic responding and 70 caregivers (*n*=70/104; 67.31%) failed no more than 1 attention check. All study analyses were conducted with and without nonsystematic responders and the full data was analyzed if the inclusion of such data significantly did not alter the findings of the analysis. This approach was consistent with approaches using a multilevel approach to analyzing purchase task data (Kaplan et al., 2021).

Analytical Plan

Alone- and Own-price Demand

Caregiver consumption of behavior therapies was analyzed using the Zero-Bounded Exponential (ZBE) model of demand (Gilroy et al., 2021). Specifically, the ZBE model was used to assess caregiver consumption of units of therapy (Q) as a function of price (P) per hour of therapy. This model extends the framework presented in Hursh and Silberberg (2008) by using a modified scale (Inverse Hyperbolic Sine) to support a true lower bound at zero consumption (for a discussion of issues with zero limits, see Gilroy, 2022). The ZBE model also has multiple forms (see Eqs. 1-3) that optionally support a non-zero lower limit. Furthermore, parameter α can be normalized in units of Q_0 to support comparisons in the absence of an explicit span parameter (Gilroy et al., 2021). Each of these forms is illustrated below:

$$IHS(Q) = IHS(Q_0) + k\,(e^{-\alpha Q_0 P} - 1) \quad 1)$$

$$IHS(Q) = IHS(Q_0) * e^{-\frac{\alpha}{IHS(Q_0)} Q_0 P} \quad 2)$$

$$IHS(Q) = IHS(Q_0) \quad 3)$$

Each variant of the ZBE model exists on the same scale (IHS) and can be evaluated using traditional model selection procedures (e.g., Sum of Squares F-test). That is, both Equations 2 and 3 were considered restricted forms of Equation 1. For each of the research questions, the complexity of the model was determined before performing the final analysis.

Study analyses were performed using a multilevel modeling approach (Kaplan et al., 2021) in the R statistical program (R Core Team, 2017). Alone- and own-price consumption of EBPs (High UR/High IR) was fitted to individual data (i.e., not aggregated into means). Elasticity, a term describing the relationship between changes in price and subsequent changes in consumption (Gilroy et al., 2020), was determined by optimizing the peak levels of responding on the natural scale (Gilroy et al., 2021). Consistent with commitments to open science in behavior analysis (Gilroy & Kaplan, 2019), all analytical syntax and study data have been included as supplemental materials and are hosted in a repository managed by the corresponding author, see Author Note.

Cross-price Demand

Although alone- and own-price demand for EBPs was fitted using a multilevel modeling approach, a Generalized Estimating Equation (GEE) was applied to evaluate the factors influencing the consumption of the treatment alternatives (i.e., High UR/Low, Low UR/High IR). The GEE was applied using the *geeglm* method included in the *geepack* R package (Halekoh et al., 2006). This approach is favorable for this type of analysis for several reasons. First and foremost, GEE is easily extended to explore the effects of multiple covariates (e.g., caregiver demographics) beyond Price. Specific to Price, this estimate can be used to describe the relationship between the consumption of an alternative and the primary service of interest (i.e., complementary or substitutive relationship). Further, the GEE approach circumvents challenges associated with the *I* parameter in the Hursh and Roma (2013) model this quantity approaches zero (Gilroy & Feck, 2022; Gilroy et al., 2022). The GEE was applied with an exchangeable correlation structure and model comparisons were performed using the QIC metric included in the *MuMin* R package (Barton, 2015).

Results

Alone-Price Demand

A total of 104 participants were included in the final analysis and the demographics of included participants are listed in Table 2. The alone-price demand for EBPs (High UR/High IR) was first evaluated using aggregated data with each of the ZBE models before analysis. Using generalized nonlinear least squares, comparisons between the full (3-parameter) and abbreviated (2-parameter) ZBE models indicated that the 2-parameter model better characterized the data ($F [1, 829] = 0.536$, $p = .464$). Similarly, the 2-parameter model better characterized the data than the intercept-only (1-parameter) alternative ($F [1, 830] = 82.469$, $p = 0$).

The 2-parameter form of the ZBE model was used to estimate Q_0 and α across reported levels of education (College, No College), gender (Male, Female), and family size (Single, Multiple children) using all individual-level consumption in a multilevel modeling approach. There was no separate span parameter included in the analysis. The results of this regression are listed in Table 3 and displayed in Figure 1. Model fits indicated that fathers endorsed lower baseline levels of demand for treatment than mothers (Q_0 *[Male]* $= -3.957$, $T = -1.990$, $p < .05$). No other significant differences were observed across levels of education or family size for either Q_0 or α. Population-level predictions revealed a peak expenditure (O_{MAX}) of 1632 USD towards EBPs, which occurred at a price (P_{MAX}) of 558.7 USD per unit hour of therapy.

Alone vs. Own-Price Demand

Evaluations of alone- and own-price demand were performed by comparing the demand for the High UR/High UR behavior therapy across HTPTs. Using aggregated levels responding in a generalized nonlinear least squares approach, model comparisons revealed that the 2-parameter ZBE model better characterized the data than the 3-parameter alternative (F *[1, 1661]* = 0.6345, p = .4258). Similarly, the 2-parameter model better characterized the data than the 1-parameter variant (F *[1, 1662]* = 130.1023, p = 0).

The 2-parameter form of the ZBE model was used to estimate Q_0 and α parameters across the HTPTs using individual-level data in a multilevel modeling approach. The results of this regression are listed in Table 3 and displayed in Figure 2. Model fits indicated an effect for the type of HTPT, whereby an open economy resulted in lower overall demand intensity for the High UR/High IR treatment prospect (Q_0 *[Own-Price]* = -4.048, T = -4.604, p = 0). All other factors were nonsignificant in the model.

Cross-Price Demand

Evaluations of cross-price demand for treatment alternatives used GEEs and model comparisons were performed using the QIC. The factors in the GEEs included price, prospect (High UR/Low IR, Low UR/High IR), gender, family size, and education, and all possible interactions. Model selection favored the model with price (β *[Price]* = 0.001, W = 5.42, $p < .05$) and prospect as the sole factors (β *[Low UR/High IR]* = 0.734, W = 4.22, $p < .05$) without the interaction. Fits across both the alone- and cross-price HTPTs are illustrated together in Figure 2.

Results of cross-price analyses indicated that caregivers substituted the primary therapy with both treatment alternatives. That is, results replicated earlier findings that caregivers substituted EBPs regardless of the level of evidence for the alternative (Gilroy & Feck, 2022; Gilroy et al., 2022). However, there was a main effect for prospect, whereby caregivers substituted the primary therapy with the High IR alternative at a significantly greater level than they did for the High UR alternative. That is, when unable to maximize for both types of reinforcement contingencies, most caregivers favored IR contingencies (i.e., more related to those mediated by the verbal community) over UR contingencies (i.e., related to likely efficacy of treatment).

Discussion

Choices related to child behavior therapy are complex and are likely influenced by a confluence of various factors. Caregivers seeking behavior therapy for their children likely make such decisions under the pressure of various stressors (e.g., financial), cultural factors (e.g., conformity with the community), and contrasting sources of information (e.g., professionals vs. peers and colleagues). The purpose of this study was to expand upon an Operant Behavioral Economic account of treatment-related choice to evaluate how various types of reinforcement differentially contribute to caregiver choices. The results from this study confirmed the notion that treatment-related choices are multidimensional, with treatment choices being jointly influenced by both the levels of scientific evidence (UR) as well as by contingencies specific to the individual and their verbal community (IR). Specifically, caregiver choice related to behavior therapy was not driven primarily by scientific evidence (i.e., UR) and this finding is consistent with earlier research on caregiver choice in this context (see Gilroy & Feck, 2022; Gilroy et al., 2022 for earlier demonstrations). This study extended the earlier findings using HTPTs by identifying another relevant class of reinforcement that appears particularly meaningful in these types of choices—informational reinforcement.

Although the findings from this study are likely to be considered novel in a (traditional) reinforcer-based approach, most fields beyond Behavior Analysis would be unsurprised that treatment choices are strongly influenced by contingencies that are rooted in community norms, views, and practices, i.e. cultures (Sue, 1999, 2003). Indeed, a recent review by Kelly et al.

(2019) communicated various successes and challenges associated with disseminating Behavior Analysis when consumer values and culture differ from those traditionally reflected in the history and development of behavior analysis. That is, despite a large body of evidence supporting the use of applied behavior analysis, the dissemination and adoption of behavior analysis has been a challenge outside of the United States. Kelly et al. (2019) highlighted the importance of culture and encouraged behavior analysts to be sensitive to the social contingencies that exist for families in other cultures. For example, Liao et al. (2018) provided several notable examples of effective delivery of behavior analytic services to children with autism in China; specifically, how child development is often viewed through the lens of the family and how parent-mediated forms of intervention are more accepted within the existing norms, views, and practices of the local verbal community in that culture. Even within North America, there have been continued calls for additional training in, and emphasis on, cultural awareness and culturally-responsive practices in Behavior Analysis (Fong et al., 2016; Fong et al., 2017; Fong & Tanaka, 2013).

The findings from this experiment advance the study of treatment-related choice, evidence-based or otherwise, in two important ways. First, this study systematically replicated and extended the existing HTPT methodology in several regards. Specifically, this study replicated earlier findings (i.e., caregivers substituted EBPs with other treatments—evidence-based or not) and successfully expanded the HTPT methodology to feature a wider range of treatment options. As such, this is a more representative and broadly applicable approach to evaluating treatment choice moving forward. Second, this is an initial application of consumer behavior analysis to a treatment-related context. The use of a consumer behavior analytic approach to service consumption is substantial because prior accounts of treatment choice did not provide a reinforcer-based account of *both* optimal and sub-optimal patterns of treatment choice. The results of this study suggest that consumers maximized the *combined* utility of their therapy options (i.e., High UR/High IR), and when their resources were insufficient to maintain that consumption, they indicated an overall preference to pursue treatments associated with higher IR than UR. This approach and these findings are significant in that they reveal some of the additional contingencies that are relevant to treatment choice.

Limitations and Future Directions

Although this work successfully extends earlier demonstrations in both Operant Behavioral Economics and consumer behavior analysis, some limitations must be discussed. First and foremost, the design of this study was focused on broad-level comparisons of how different contingencies influence treatment choice (i.e., IR vs UR). As such, the current sampling was sufficiently powered to answer the primary questions (i.e., the substitution of IR vs UR) but likely underpowered to detect the potential effects of various other covariates (e.g., specific demographics). This may be one reason why effects for certain demographics were not observed in this demonstration but in previous demonstrations (Gilroy & Feck, 2022; Gilroy et al., 2022). It is also possible that the added degree of customizability featured in this study minimized the effect of such differences (i.e., individuals self-selected into preferred treatment). Second, participants were real caregivers interested in parent-implemented behavior therapy, but the choices presented to them were hypothetical. As such, it is unclear to what degree these choices are related to real-world decision-making. Although this is reported as a potential limitation, HPTs have been found to have good correspondence with various forms of real-world purchase behavior (Roma et al., 2017). Third, this extension expanded upon the range of breadth of treatment choices, but the pricing structure remained largely unchanged. Future extensions of this work should explore the "real-world" costs to families participating in child behavior therapy and better align these with hypothetical purchase tasks. Notwithstanding, the approach and methodology presented here provide an important avenue towards better understanding the factors that influence the consumption (and non-consumption) of EBPs.

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Figure Captions

Figure 1. This figure illustrates the Alone-Price demand for Evidence-based Practices across reported gender, number of children in the household, and level of education.

Figure 2. This figure illustrates the differential degrees of substitutability observed for alternatives with high utilitarian/low informational and high informational/low utilitarian value in cross-price analyses of treatment demand.

Table 1

Behavioral Perspective Model

		Informational Reinforcement	
		Low	High
Utilitarian Reinforcement	Low	Alternative therapies not highly reinforced by the verbal community*	Alternative therapies highly reinforced by the verbal community (Low UR/High IR)
	High	Evidence-based therapies not highly reinforced by the verbal community (High UR/Low IR)	Evidence-based therapies highly reinforced by the verbal community (High UR/High IR)

*Note: The Low UR/Low IR classification was not explored.

Table 2

Participant Demographics

Participant Demographics (n = 104)			
Age (years)		**Number of Children**	
Mean (SD)	38.2 (7.63)	Median (Q1-Q3)	2 (1-3)
Median (Q1-Q3)	32-43.2	Mean (SD)	2.24 (1.13)
Sex		**Education**	
Male	36 (34.6%)	High School graduate	10 (9.62%)
Female	68 (65.4%)	Some college but no degree	16 (15.4%)
Income		Associate degree	9 (8.65%)
Q1	45,000	Bachelor's degree	50 (48.1%)
Median	59,500	Master's degree	17 (16.3%)
Q3	90,500	Doctoral degree	1 (0.09%)
Behavior Concern		Professional Degree	1 (0.09%)
A little	26 (25%)	**Race/Ethnicity**	
A moderate amount	28 (26.9%)	Black/African-American	18 (17.3%)
A lot	31 (29.8%)	Asian	7 (6.73%)
A great deal	19 (18.3%)	Hispanic/Latinx	2 (1.92%)
Marital Status		White/Caucasian	74 (71.2%)
Single	13 (12.5%)	Native American	2 (1.9%)
Married	71 (74%)	Other	1 (0.9%)
Divorced	10 (9.62%)		
Other	4 (3.85%)		

Table 3

Results of Demand Curve Analysis across Closed and Open Economies

	Alone-Price Demand for EBPs			
	Estimate	*Std. Err*	*T-value*	*p*
Q_0 [Intercept; >= Bachelors, Female, Single]	15.4573	2.0641	7.4888	0.0000**
Q_0 [Education < Bachelors]	-0.1884	2.0435	-0.0922	0.9266
Q_0 [Male]	-3.9572	1.9883	-1.9902	0.0469*
Q_0 [Multiple Child Family]	1.1883	2.1015	0.5655	0.5719
α [Intercept; >= Bachelors, Female, Single]	0.0002	0.0000	4.3154	0.0000**
α [Education < Bachelors]	0.0000	0.0000	-0.1770	0.8596
α [Male]	0.0000	0.0000	0.1614	0.8718
α [Multiple Child Family]	-0.0001	0.0000	-1.2373	0.2164

	Alone- vs. Own-Price Demand for EBPs			
	Estimate	*Std. Err*	*T-value*	*p*
Q_0 [Intercept; Alone-Price]	13.8457	0.9349	14.8098	0.0000**
Q_0 [Own-Price]	-4.0482	0.8791	-4.6049	0.0000**
α [Intercept; Alone-Price]	0.00013	0.00002	8.3297	0.0000**
α [Own-Price]	0.00001	0.00001	1.0878	0.2769

†: Evidence-based Practices (EBPs) in Own-Price did not include the High UR/Low IR prospect.
* $p < .05$, ** $p < .0001$

Figure *1. Alone-Price Demand for Evidence-based Practices (High UR/High IR)*

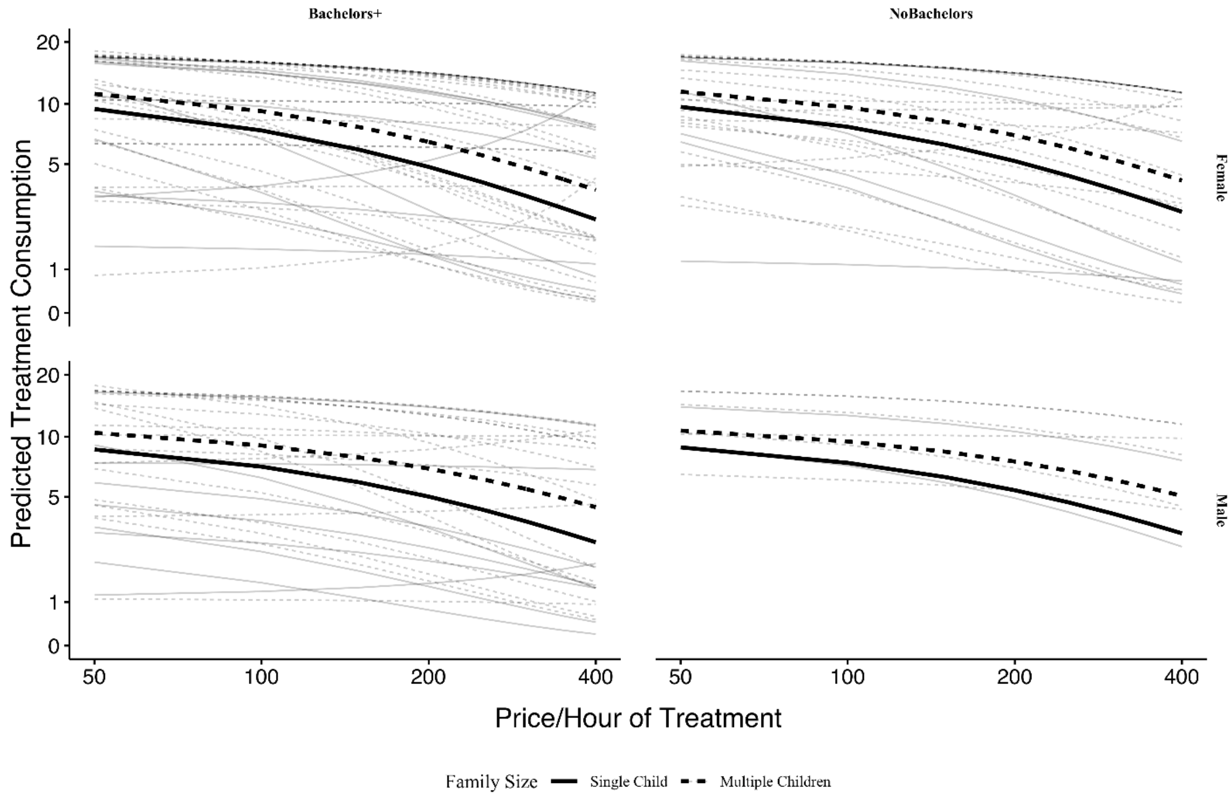

Figure 2. Substitution of Evidence-based Practices by Reinforcer Quality