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THE DEMAND CURVE ANALYZER: BEHAVIORAL ECONOMIC SOFTWARE FOR APPLIED RESEARCH

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Free and open-source software for applying models of operant demand called the Demand Curve Analyzer (DCA) was developed and systematically evaluated for use in research. The software was constructed to streamline the use of recommended screening measures, prepare suitable scaling parameters, fit one of several models of operant demand, and provide publication-quality figures. The DCA allows users to easily import price and consumption data into spreadsheet-based controls and to perform statistical modeling with the aid of a graphical user interface. The results from computer simulations and reanalyses of published study data indicated that the DCA provides results consistent with commercially available software that has been traditionally used to apply these analyses (i.e., GraphPadTM Prism). Further, the DCA provides additional functionality that other statistical packages do not include. Practical issues and future directions related to the determination of scaling parameter *k*, screening for nonsystematic data, and the incorporation of more advanced behavioral economic methods are also discussed.

Key words: software, open source, demand, behavioral economics

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Introduction

Within an ecological approach to understanding individual choice and decision-making, empirical research has found that a range of environmental factors such as the probabilities of gains or losses (Rachlin, Raineri, & Cross, 1991), the presence of delays (Ainslie, 1974; Mazur, 1987), and the cost or levels of effort required (Hursh, Raslear, Shurtleff, Bauman, & Simmons, 1988; Tustin, 1994) influence choice and decision-making. Ecological accounts of choice and decision-making have existed for some time (see Matching Law, Baum, 1974; Herrnstein, 1961), though perspectives such as Consumer Demand Theory (Kagel & Winkler, 1972) have more recently received renewed interest following mainstream appeal of "behavioral economics" (Allison, 1983; Bickel, DeGrandpre, & Higgins, 1993; Bickel, Johnson, Koffarnus, MacKillop, & Murphy, 2014; Hursh, 1980; Hursh & Roma, 2013; MacKillop, 2016; Rachlin, Green, Kagel, & Battalio, 1976).

Operant behavioral economics (Foxall, 2016), a subset of behavioral economics in keeping with its behavior analytic roots, was initially developed from basic experiments that evaluated the competing assumptions between behavior science and traditional economic theory (Hursh & Bauman, 1987; Hursh & Winger, 1995; Kagel, Battalio, Rachlin, & Green, 1981). Economic terms and conventions have since been adapted for use in experimental procedures to evaluate the complex relationship between reinforcers and the patterns of behavior individual organisms demonstrate to access them (Hursh, 1980, 1984). Since its introduction, operant behavioral economics has expanded traditional economic conventions, such as the open and closed economies (Hursh, 1980, 1984; Imam, 1993), demand for reinforcers across varying costs (Hursh et al., 1988; Kagel et al., 1981), the substitutability of reinforcers (Bickel et al., 2018; Green & Freed, 1993; M. W. Johnson, Bickel, & Kirshenbaum, 2004; M. W. Johnson, Johnson, Rass, & Pacek, 2017; Madden, Smethells, Ewan, & Hursh, 2007b), and reinforcer complements (Madden, Smethells,

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Ewan, & Hursh, 2007a; Spiga, Martinetti, Meisch, Cowan, & Hursh, 2005).

Continuing from research on the cost–reinforcer relationship, or the demand for reinforcers, subsequent research has expanded to include various aspects of human and nonhuman consumption. For example, this methodology has been applied to patterns of consumption such as those demonstrated by heavy users of cigarettes (M. W. Johnson et al., 2004; M. W. Johnson et al., 2017; MacKillop et al., 2008) and alcohol (Kaplan, Foster, et al., 2018; MacKillop et al., 2010; Murphy & MacKillop, 2006) as well as consumption of illegal substances, such as marijuana (Aston, Metrik, Amlung, Kahler, & MacKillop, 2016; Aston, Metrik, & MacKillop, 2015), "bath salts" (P. S. Johnson & M. W. Johnson, 2014), heroin (Jacobs & Bickel, 1999), and cocaine (Bruner & Johnson, 2014). Beyond the study of substance abuse, specifically, the cost–reinforcer framework has also been applied to more "every-day" patterns of consumption. For example, researchers have used these methods to evaluate food choices related to obesity (Epstein, Paluch, et al., 2018; Rasmussen, Robertson, & Rodriguez, 2016; Saelens & Epstein, 1996; Smith & Epstein, 1991), the demand for "green" and reusable goods (Kaplan, Gelino, & Reed, 2018), workplace attrition (Henley, DiGennaro Reed, Reed, & Kaplan, 2016), and the use of indoor tanning services (Reed, Kaplan, Becirevic, Roma, & Hursh, 2016). Further, many elements of this approach have also been adapted to better understand preference and choice for individuals with developmental disabilities (Gilroy, Kaplan, & Leader, 2018; Reed, Niileksela, & Kaplan, 2013). Beyond choices at the individual level, others have also applied these methods to group-level behavior to better inform the development of public policy (Hursh & Roma, 2013; MacKillop et al., 2012; Reed, Kaplan, Roma, & Hursh, 2014).

Behavioral Economics and Relative Reinforcer Efficacy

In earlier studies using behavioral economics to evaluate the potency of drugs as reinforcers, the strength of these reinforcers was inferred by inspecting one or more aspects of responding as the costs to produce them varied (Katz, 1990). Among the methods used to evaluate reinforcers over a range of costs, many studies have used some derivative of the Progressive Ratio (PR) schedule of reinforcement (Findley, 1958; Hodos, 1961; Jarmolowicz & Lattal, 2017). In this arrangement, the strength of a reinforcing relation can be inferred by inspecting various aspects of responding, such as the peak levels of responding, the highest schedule requirements reached (i.e., breakpoint), or some other trend in responding as costs progressively increase.

Among the methods available to assess the relative efficacy of reinforcers, the strength of the response–reinforcer relation is most often inferred from its breakpoint. Breakpoint represents some cost, or schedule or reinforcement (e.g., FR10), wherein the cost becomes insufficient to maintain the levels of responding necessary to produce access to the reinforcer.[1] That is, breakpoint (BP_0) identifies a cost where the demands of the schedule of reinforcement, and theoretically any response requirements beyond it, yield levels of responding insufficient to produce access to the reinforcer. Using BP_0 as an indicator of reinforcer efficacy, stimuli with higher BP_0 are generally more efficacious up until higher costs while stimuli with a lower BP_0 are considered less efficacious and are likely to be effective only at relatively lower costs. While BP_0 is easily determined through visual inspection, inferring the strength of a reinforcing relation based on this measure alone presents several limitations. First, BP_0 is a measure that references a single schedule of reinforcement (Hursh & Silberberg, 2008). That is, BP_0 is a reference to a schedule of reinforcement where responding was insufficient to produce the reinforcer—it provides no information on how the reinforcer performed at any other cost. For example, two reinforcers may share the same BP_0 but differ substantially in levels and patterns of responding on other schedules of reinforcement. Second, BP_0 is highly dependent on the way it is assessed. For example, a reinforcer evaluated using PR schedule

[1]We note that the term 'breakpoint' has been used to describe the cost–reinforcer relationship in multiple ways. Whereas most have used this term to describe the schedule of reinforcement where responding no longer produces access to the reinforcer (BP_0), others have used this term to refer to the leanest schedule of reinforcement that produced some access to the reinforcer (BP_1).

A (1, 2, 4, 8, 16, 32, 64, 128 responses) may yield a BP_0 of 64 but result in a BP_0 of 41 on PR schedule B (1, 11, 21, 31, 41, 51, 61, 71, 81, 91, 101, 111, 121 responses). As such, BP_0 is influenced by both the number of schedules assessed and the magnitude of changes between them. As a result, PR schedules that use larger progressions may result in larger BP_0 while PR schedules that use smaller progressions may result in smaller BP_0. Due to this variability, procedural differences in how BP_0 is assessed may obscure small, but relevant, differences in relative reinforcer efficacy (Jarmolowicz & Lattal, 2017).

Behavioral Economics and Operant Demand Curves

More recent research on the effectiveness of reinforcers has incorporated economic methods to assist in quantifying the relationship between reinforcers and the cost to produce them (Allison, 1983; Bickel et al., 1993; Foxall, Olivera-Castro, Schrezenmaier, & James, 2007; Hursh, 1984). Rather than assessing the relative efficacy of reinforcers based on a single aspect of responding (e.g., BP_0, peak responding), the *demand* for a reinforcer can be assessed over a domain of increasing costs. In this way, the strength of a reinforcer is represented as a curve rather than a single point (e.g., BP_0, peak responding).

As illustrated in Figure 1, the domain of the demand curve is characterized by two separate regions—one *inelastic* and the other *elastic*. These two regions are distinct in how changes in cost, or price, differentially affect the demand for a reinforcer. The left portion of the demand curve, the inelastic range, is characterized by relatively small changes in demand as prices increase. In contrast, the right portion of the demand curve, the elastic range, is characterized by increasingly larger changes in demand as prices increase. That is, even small increases in price can substantially impact the demand for a reinforcer within the elastic range. The point at which demand switches from inelastic to elastic is termed P_{MAX}. P_{MAX} represents a point where a one-unit increase in the cost is associated with a one-unit decrease in consumption.[2] In addition to revealing the change from inelastic to elastic demand, a larger P_{MAX} value would indicate that the demand for some reinforcer was not impacted substantially until *higher prices* were reached and a smaller P_{MAX} value would indicate that the demand for some reinforcer decreased substantially earlier on when increases at *lower prices* were observed.

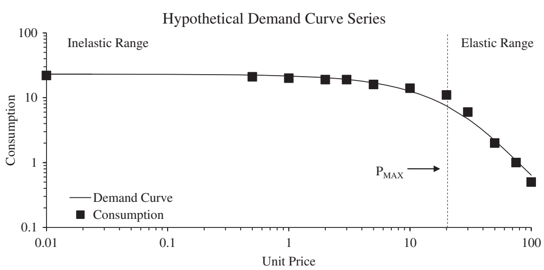

Fig. 1. Prototypical demand curve. This figure illustrates the form and composition of the demand curve. The inelastic range represents a portion of the demand curve characterized by relatively slight changes in consumption as price increases. In contrast, the elastic range is characterized by larger changes in consumption as prices increase.

When representing the strength of reinforcers as a curve, various aspects of the cost–reinforcer relationship can be represented in a single, unified approach using a *demand curve analysis* (Bickel, Marsch, & Carroll, 2000; M. W. Johnson & Bickel, 2006). In modeling demand for a reinforcer, the form of the demand curve provides information related to the intensity of demand at a free, or low, cost (i.e., Q_0) as well as its sensitivity to changes in price (i.e., α). For this reason, among others, researchers have called for an increased use of demand methods in lieu of individual measures of relative reinforcer efficacy, such as BP_0 (Bickel & Madden, 1999; Bickel et al., 2000; Reed et al., 2009). For a broader overview of behavioral economics, especially demand curve analysis, readers are encouraged to consult Reed, Kaplan, and Becirevic (2015). Additionally, a review of behavioral economics as applied in applied behavior analytic work is provided in Gilroy et al. (2018).

[2] We note that P_{MAX} refers to a point where the slope of a demand function equals -1. This can be determined using the first order derivative or the slope of a tangent line, though alternative calculations for determining this value have also been provided (Hursh & Roma, 2013).

Supporting Behavioral Economics in Applied Research Using Technology

Given that there are increased challenges associated with the cost, complexity, and accessibility of the tools necessary for applying more advanced behavioral economic analyses, such as demand curve analysis, additional tools were necessary to support the recommended use of these newer methods by a wide range of researchers. To address these challenges, software was designed to perform many of the tasks required when conducting operant demand curve analyses. This program, the Demand Curve Analyzer (DCA), enables users to easily apply systematic screening measures, to select from one of several conventional methods for determining the scaling parameter *k*, to apply nonlinear model fitting from several models of operant demand, to select from one of several optimization algorithms, and to display the resulting demand curves. The program was developed to openly source and to function across all current major platforms (i.e., Windows, macOS, Linux). The user interface was constructed using the Qt Framework and the underlying computations were performed using the ALGLIB linear algebra library (Bochkanov & Bystritsky, 1999). Both tools were selected based on their maturity as stable, well-documented open-source components that function across multiple platforms. The entire program was written in C++ to maximize the performance, portability, and compatibility of the program on various systems and architectures.

To explore the accuracy and utility of this novel software, evaluations were necessary to determine whether this tool provided results commensurate with existing options. Comparisons of the DCA and GraphPad Prism™ (GP) were drawn using computer simulation and reanalysis of existing peer-reviewed works. To evaluate this new software, the following questions were posed: 1) Does the DCA computer program perform demand curve analyses and produce results that are commensurate with existing tools (i.e., GP) for fitting the Exponential and Exponentiated models (i.e., two contemporary models) of demand using simulated data; 2) Does the DCA computer program model operant demand and provide results that are consistent with existing tools when using data extracted from peer-reviewed studies?

Method

Statistical Programs for Quantifying Operant Demand

The DCA was constructed to address a range of barriers specific to the use of demand curve analyses in research. Specifically, the software was constructed to assist researchers in consistently determining scaling parameters (i.e., *k*), preparing data for analysis with demand models, applying one of several models of operant demand, and deriving several behavioral economic indices using a streamlined interface (e.g., P_{MAX}). A list of the models of demand featured in the DCA, as well as their structure, is provided in Table 1. The DCA was designed to mirror familiar interactions with spreadsheet software (i.e., Microsoft Excel™) and all options for modeling were provided using a guided graphical user interface (GUI; e.g., handling of zeros, optimization). The GUI of the DCA, along with the relevant fitting options, is depicted in Figure 2. A customized GUI was constructed following observations that these features improved the clarity and usability of statistical methods for behavior analysts (Fisher & Lerman, 2014). In addition to providing a user-friendly GUI for statistical methods, the DCA was also designed to operate identically across all multiple platforms (i.e., Windows, macOS, Linux), to provide seamless updates and bug fixes, and to accommodate future releases with additional modeling options and enhancements.

Table 1

Behavioral economic models of operant demand included in the DCA

Model	Form	Source
Linear-Elasticity	$logC = log\,L + b(log\,P) - a\,P$	Hursh et al. (1988)
Exponential	$log_{10}C = log_{10}Q_0 + k\left(e^{-\alpha Q_0 P} - 1\right)$	Hursh & Silberberg (2008)
Exponentiated	$C = Q_0 * 10^{k\left(e^{-\alpha Q0P} - 1\right)}$	Koffarnus et al. (2015)

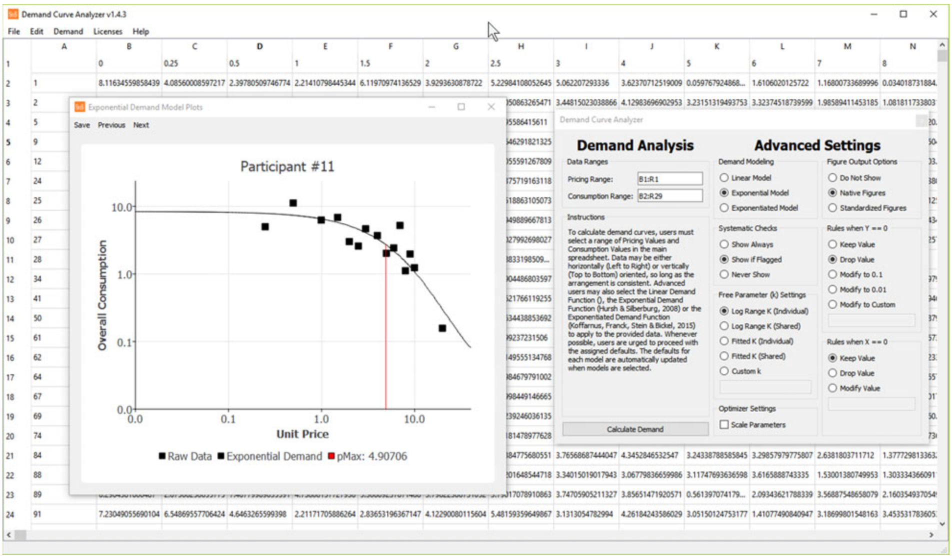

Fig. 2. This figure depicts the GUI of the DCA and associated options. Among the options for fitting, the DCA assists users in performing screening criteria, fitting one of several models of demand, handling scaling parameters, and managing data options (i.e., handling zero values). In this way, the DCA supports the application of demand curve modeling while providing functionality that no other software currently performs (e.g., scaling parameter *k*, handling zero values, screening data).

Importing Consumption and Price Data

The GUI for the DCA was designed to mirror existing conventions used in spreadsheet-based software to aid researchers in transitioning from the use of basic spreadsheets to more robust software that offered a range of relevant features. For example, the DCA was designed so that researchers could import existing spreadsheet files and/or paste existing data (i.e., unit prices, consumption) directly into the program. Once entered, relevant data are selected using "point-and-click" interactions that do not require programming to perform. For an R-based package (requiring programming) for conducting behavioral economic demand curve analyses, we encourage the readers to consult Kaplan, Gilroy, Reed, Koffarnus, and Hursh (in press).

Preparation of Demand Data for Modeling

Models of demand can have limitations with respect to the values they can accommodate. For example, the Linear (Hursh et al., 1988) and Exponential (Hursh & Silberberg, 2008) models of demand require that certain data be transformed into logarithmic space prior to fitting the model. In the cases of zero values (i.e., consumption is zero), the logarithm of these values is naturally undefined and further analysis cannot proceed. There are cases in which no zeros exist in the dataset; however, when zeros are present they have conventionally been transformed to some other real number (e.g., 0.1, 0.01) or dropped from consideration entirely (Kaplan, Foster, et al., 2018). The DCA was designed to streamline this process, where such issues are handled automatically, and researchers may select whether the software should replace these data (e.g., 0.1, 0.01, lowest real consumption value) or drop them from consideration. Currently, there is no consensus on a "superior" model. Users may want to use the Exponential model when data are aggregated or when there are few zero values. However, if there are a relatively large proportion of zero values in the data, users may prefer the Exponentiated equation given that replacing zero values may bias parameter estimates (Koffarnus, Franck, Stein, & Bickel, 2015; Yu, Liu, Collins, Vincent, & Epstein, 2014).

Application of Criteria for Systematic Demand Data

The DCA provides methods to screen consumption data prior to applying models of demand (Stein, Koffarnus, Snider, Quisenberry, & Bickel, 2015). The Stein et al. (2015)

algorithm for determining nonsystematic responding uses three criteria to quantify several patterns of responding: 1) trend (i.e., ΔQ), 2) bounce, and 3) reversals from zero. The first criterion, trend, is calculated by dividing the difference from the first and last consumption values (i.e., levels of responding) in $\log_{10}$ units by the difference between final and first price values (i.e., schedule requirements) in $\log_{10}$ units. The trend criterion limit was set to 0.025 ($\log_{10}$ units) by default (as recommended by Stein et al.) and this measure was designed to identify instances where demand does not change significantly as prices increased.

The second criterion from Stein et al. (2015), bounce, was designed to check for local (i.e., sequential) fluctuations in responding as prices increase. That is, the bounce criterion provided a measure that assessed sequential decreases in responding as a function of sequential increases in price. A "bounce" was considered an instance where responding increased by 25% (or more) of the levels of responding at the lowest (or free) price point and systematic purchase data are thought to include very few, often none, of these instances. An overall bounce measure was constructed by dividing the number of bounces by the number of price increments. Consistent with the recommendations from Stein et al., individual patterns of responding with a bounce value of 0.1 or greater were flagged as nonsystematic.

The third and final criterion from Stein et al. (2015) was specific to reversals from zero (i.e., BP_0). In analyses of demand, it is generally assumed that price points where there are zero rates of reported consumption should not be followed by nonzero rates of reported consumption (i.e., should not reverse from zero consumption). That is, it is atypical to demonstrate zero rates of reported consumption at some price (e.g., FR 30) and then demonstrate some level of responding at a higher price (e.g., FR 50). Per the Stein et al. criterion, a reversal from a single zero was tolerable but reversals from two consecutive zeroes at consecutive prices were indicative of nonsystematic responding.

Using the three Stein et al. (2015) screening (but not necessarily exclusion) criteria, the DCA provides information relevant to any potentially nonsystematic sets of data prior to beginning demand analyses. This information was provided in this manner to make the user aware of potential issues that could complicate the application and interpretation of subsequent modeling. That is, the user is provided with information regarding the nature of the data supplied and is offered the opportunity to choose to continue with analysis or, as we recommend, revisit the data supplied prior to interpreting results. For example, series flagged as not meeting certain assumptions may prompt the researcher to use an alternative analysis or exclude such data entirely. A thorough review of these criteria, along with guidelines for handling of nonsystematic data, can be found in Stein et al.

Determination of Scaling Parameter *k*

Both the Exponential and Exponentiated models of operant demand require the determination of parameter k to fit parameters Q_0 and α. Briefly, this parameter generally specifies the range of consumption values in $\log_{10}$ units. That is, this parameter jointly represents sensitivity to changes in prices through the interaction of k with other model parameters. As such, direct comparisons of α should not be made when ks differ. This parameter can be determined empirically (i.e., by referencing the observed range of the data) or through fitting it along with the other model parameters. Both approaches can be used either individually or in aggregate (i.e., across all participants).

The calculation of parameter k is a topic of some debate and researchers have accommodated the complexity of this parameter in several ways. First, the empirical approach for determining k is calculated by determining the difference (in $\log_{10}$ units) between the minimum and maximum levels of consumption (e.g., Koffarnus et al., 2015). While seemingly straightforward, this approach is driven by the *observed* minimum and maximum levels of consumption. That is, the maximum *observed* level of consumption may not necessarily be representative of the highest *modeled* consumption. For example, the empirical k calculated at prices between a unit price of 1 and 1000 would not completely represent the range of modeled demand as a higher level of demand might well be assumed at prices less than what was measured (i.e., at 0.5 or 0.0). For this reason, researchers have added a constant (e.g., 0.5) to the range of consumption observed to minimize the likelihood that this parameter underestimates the true *maximum* level of demand (Kaplan, Foster, et al., 2018). Additionally, the addition of a small constant also limits the likelihood that k becomes so small that other parameters become increasingly inflated as a result (Gentile, Librizzi, & Martinetti, 2012).

Similarly, the fitting of parameter k as a model parameter also presents challenges. Aside from challenges associated with fitting parameters on multiple orders, a challenge in gradient-based optimization, fitting parameter k without known bounds introduces additional complexities. Namely, this parameter can become theoretically much larger or much smaller than the empirical method—if it even successfully converges at all. As such, fitting this parameter without known constraints may introduce greater levels of variability than the empirical approach. To facilitate a range of modeling scenarios, the DCA was constructed to provide both these options at the individual and group levels. In this way, researchers are supplied with a range of potential comparisons without the need to manually determine these values for each data set.[3] A fitted k parameter with aggregated data is performed using a single shared k value across all individual data series (i.e., one k with many Q_0/α pairs).

Nonlinear Model Fitting

The ALGLIB linear algebra library was used to perform nonlinear model fitting for all included models in this study[4] (Bochkanov & Bystritsky, 1999). The underlying Levenberg–Marquardt (LM) optimizer was used to perform gradient-based optimization of model parameters (Marquardt, 1963). Within the DCA, the LM optimizer was set to perform optimization using both the gradient and hessian. Maximum iterations for individual fittings was 1000 and change in error sum of squares to indicate convergence was set to 0.0001. The fitted Q_0 parameter had a lower bound of 0.001 and all other parameters were unbounded ($-\infty < p < +\infty$). Individual starting parameters were dynamically generated using a brute-force grid search based on a range of probable, proximal values, given the data. These settings were identical for both the Exponential (Hursh & Silberberg, 2008) and Exponentiated (Koffarnus et al., 2015) models of demand.

Study Aim 1: Simulation Study and Statistical Validation

A simulation study was conducted to investigate the accuracy and replicability of the DCA with respect to GP. Formal evaluation of the DCA against existing commercial products was necessary to determine whether the DCA accurately and reliably provided results consistent with current methods and practices. To explore the accuracy and reliability of the DCA 1,000 series were simulated. Simulation series were constructed using the consumption values of 1,104 participants in an Amazon Mechanical Turk (www.mturk.com) decision-making experiment (Kaplan & Reed, 2018). Participants in this study completed a hypothetical Alcohol Purchase Task (Kaplan, Foster, et al., 2018) in which they were asked how much alcohol they would consume at various prices and the specific price points included in this study were: \$0.00 (free), \$0.25, \$0.50, \$1.00, \$1.50, \$2.00, \$2.50, \$3.00, \$4.00, \$5.00, \$6.00, \$7.00, \$8.00, \$9.00, \$10.00, \$15.00, and \$20.00. From these data, the means and standard deviations of each price point were extracted and used to simulate hypothetical consumption data across various price points. Simulated data series were included if they passed all indicators of systematic demand, as measured by existing screening methods (Stein et al., 2015). To support transparency and replicability of these simulations, all data and seed values have been open-sourced and can be found in the Appendix of this article.

Both the DCA and GP were used to fit the Exponential and Exponentiated models of demand. The k scaling parameter was determined by taking the difference between the base 10 logarithm of the highest and lowest

[3] We make note that the DCA calculates an empirical parameter k using the $\log_{10}$ range method and adds a constant of 0.5 to the result. This added value is provided to mitigate risks associated with modeling using a very small k value.

[4] Optimization was performed using the LM algorithm, as most commercial packages employ a gradient descent-based approach to parameter estimation. The DCA also provides derivative-free optimization using Genetic Algorithms for challenging datasets, though this was not compared to the results from GP.

nonzero consumption values and adding 0.5. A single k value was constructed using the log range plus 0.5 method (Gentile et al., 2012; Kaplan, Foster, et al., 2018). Model fitting was performed in GP using program defaults, as indicated in the Nonlinear Model Fitting section. The DCA performed analyses for both models of demand with the LM optimizer using both the gradient and hessian. A maximum of 1,000 iterations was set and the error sum of squares to indicate convergence was set to 0.0001. To address the limitations of the GP software (i.e., fitting a maximum of 255 series at once), simulation series were grouped into batches of 200 and subsequently analyzed in GraphPad Prism. The results from these analyses were later combined to provide a total of 1,000 fitted demand curves for the GP analyses.

Study Aim 2: Replicating Existing Study Results

Reported consumption was extracted from peer-reviewed publications to compare the results from the DCA to GP using real data. Three publications were selected for reanalysis to sample a range of demand-based applications. These included consumption of cigarettes among smokers with and without schizophrenia (MacKillop & Tidey, 2011), and consumption of nicotine products in humans (M. W. Johnson et al., 2017) and rats (Smethells, Harris, Burroughs, Hursh, & LeSage, 2018). Observed consumption data were extracted from published study figures by pairs of independent observers using the WebPlotDigitizer program (Rohatgi & Stanojevic, 2017). Once extracted by observers, data were compared to evaluate the accuracy and reliability of the data collected. Data were considered reliable if there was no more than a 5% difference in the values extracted by observers. Once considered reliable, the final extracted values were computed using the arithmetic mean of the two extracted values.

Extracted study data were reanalyzed using both the DCA and GP with both the Exponential and Exponentiated models of demand. Individual k values were constructed for each series, derived from respective consumption values. Results were compared across fitted parameters as well as indices of model fitness.[5]

Results

Study Aim 1: Simulated Data

A simulation study was conducted to evaluate potential differences in how the two statistical softwares modeled demand for the Exponential and Exponentiated models. Descriptive statistics from both software programs are listed in Table 2. Individual Wilcoxon rank sum tests were performed for the Q_0, α, and R^2 values resulting from each of the programs for both the Exponential and Exponentiated models. For the Exponential model, individual Wilcoxon rank sum tests revealed no significant differences between the two software programs for fitted α, $W = 4.997 \times 10^5$, $p = .972$, $r = .817$, Q_0, $W = 4.999 \times 10^5$, $p = .999$, $r = .756$, or R^2 values, $W = 5.000 \times 10^5$, $p = .999$, $r = .813$. The same analyses were repeated for the Exponentiated model for both software programs and no significant differences found for α, $W = 4.997 \times 10^5$, $p = .979$, Q_0, $W = 4.999 \times 10^5$, $p = .998$, or R^2 values, $W = 4.999 \times 10^5$, $p = .999$, $r = .999$.

Study Aim 2: Real Data

Published study data were extracted and reanalyzed using both GP and the DCA. The results from demand curve analyses for both software programs are presented in Table 3. With respect to the original analyses in the source work, the results of demand curve analysis with extracted data produced results that matched closely with original results in the source works. With respect to comparisons across software programs and models, results in all combinations produced nearly identical results. As illustrated in Table 3, the results from demand curve analysis with both software programs produced results identical to the fourth decimal place across all parameters.

Discussion

Behavioral economics has provided a significantly expanded framework to understand

[5]We note that while the R^2 value was used as a measure to compare results across software packages, this metric has questionable utility in nonlinear applications. For this reason, measures such as the Root Mean Square Error (RMSE) are provided in the DCA.

Table 2

Results of simulation study

Model	**GraphPad**			**Demand Curve Analyzer**		
	Mean α(Q1-Q3)	Mean Q_0(Q1-Q3)	Mean R-Squared (Q1-Q3)	Mean α(Q1-Q3)	Mean Q_0(Q1-Q3)	Mean R-Squared (Q1-Q3)
Exponential	0.0026(0.0022-0.0029)	5.866(5.028-6.536)	0.686(0.592-0.796)	0.0026(0.0022-0.0029)	5.866(5.028-6.536)	0.686(0.592-0.796)
Exponentiated	0.0026(0.0022-0.0029)	6.637(5.899-7.319)	0.726(0.660-0.809)	0.0026(0.0022-0.0029)	6.637(5.899-7.319)	0.726(0.661-0.809)

Note. An overall k value was determined by the aggregate log range plus 0.5 method, resulting in a k value of 5.312 that was used in both approaches and with both modeling options. Parameter estimation was performed using the Levenberg–Marquardt algorithm.

individual choice and decision-making. Despite offering robust methods for quantifying the strength of reinforcers, various areas of the applied research have yet to adopt formal demand curve analyses in lieu of individual assessments of relative reinforcer efficacy (Gilroy et al., 2018). Presumably, the increased complexity and cost of suitable tools are barriers to researchers widely adopting and using more advanced methods. The purpose of this study was to evaluate the accuracy and reliability of a free and open-source computer program that assists researchers in performing demand curve analyses. Specifically, this study sought to answer the following questions: 1) Does the DCA software program perform demand curve analyses and produce results that are commensurate with existing tools (i.e., GP) for fitting the Exponential and Exponentiated models of demand using simulated data; 2) Does the DCA software model operant demand and provide results that are consistent with existing tools when using data extracted from peer-reviewed studies? Based on the results of this study, the DCA provides results that are commensurate with those from the GP program but also offers additional functionality that supports the recommended use of demand curve analyses through a streamlined GUI.

Although this study found that the DCA provides results that are consistent with GP, the DCA software offers several notable advantages. First and foremost, the DCA is a free and open-source statistical program. This program will run free of charge on all modern versions of Windows (95+), MacOS (10.6+), and Linux. The program source code has been openly shared and affords the possibilities of being expanded as advances in demand curve modeling are proposed and evaluated, and best-practice recommendations are established. The DCA includes several demand models (as shown in Table 1) but can be expanded to accommodate newer models as they are developed.

Second, the DCA facilitates the a priori use of data inspection methods using recommended screening criteria (Stein et al., 2015). Historically, this type of procedure would have to be designed by the user with separate spreadsheet software or programming. Users, therefore, required multiple

Table 3

Fitting comparisons with extracted data

		GraphPad Prism		Demand Curve Analyzer	
Hursh & Silberburg Model (2008) – Exponential	*k*	*Q0*	*α*	*Q0*	*α*
Smethells et al. (2018) – Electronic Cigarette Liquid	2.90292	2.5759	0.0004	2.5759	0.0004
Smethells et al. (2018) – Nicotine Liquid	2.83988	4.1812	0.0005	4.1812	0.0005
Johnson et al. (2017) – Tobacco Cigarettes	4.50478	52.449	0.0118	52.449	0.0118
Johnson et al. (2017) – Electronic Cigarettes	4.50120	76.173	0.0068	76.173	0.0068
MacKillop & Tidey (2011) – Schizoaffective Smokers	4.09596	67.539	0.0015	67.539	0.0015
MacKillop & Tidey (2011) – Control Smokers	3.90741	35.847	0.0025	35.847	0.0025
Koffarnus et al. (2015) Model – Exponentiated					
Smethells et al. (2018) – Electronic Cigarette Liquid	2.90292	2.6020	0.0004	2.6020	0.0004
Smethells et al. (2018) – Nicotine Liquid	2.83988	2.6717	0.0008	2.6717	0.0008
Johnson et al. (2017) – Tobacco Cigarettes	4.50478	148.97	0.0275	148.93	0.0275
Johnson et al. (2017) – Electronic Cigarettes	4.50120	110.26	0.0120	110.26	0.0120
MacKillop & Tidey (2011) - Schizoaffective Smokers	4.09596	37.208	0.0033	37.208	0.0033
MacKillop & Tidey (2011) - Control Smokers	3.90741	25.279	0.0060	25.279	0.0060

Note: An overall *k* value was determined by the aggregate log range plus 0.5 method. Given that *k* was derived empirically, the same *k* value was retained across both modeling options.

tools in addition to the GP templates to perform this recommended step. As a result, this automation of systematically screening may also limit the possibility of human error in the design and use of supplemental tools.

Third, the DCA supports several recommended methods for determining the parameter *k*. Through the DCA, users can determine a *k* value based on several options commonly observed in the literature. Previously, *k* would have to be determined a priori before modeling or fitted along with other parameters. Like the application screening criteria, attempts to determine *k* a priori without the DCA would require the use of separate spreadsheet software, programming, or changing more advanced features in GP. Through providing options for dynamically determining *k*, the DCA may limit the degree to which novice users inaccurately prepare this parameter or defer to some existing or arbitrary default. These options also allow for comprehensive and transparent reporting of how demand analyses are carried out (Kaplan, Foster, et al., 2018).

Fourth, the DCA provides functionality that supports a broader range of demand applications. The GP program has known limits that may be a barrier to performing certain analyses. For example, users of the DCA can fit a shared, global regression *k* parameter to data sets of any size while GP is limited by the number of data sets that can be fitted in this way (i.e., 255). Presently, GP does not offer the possibility to lift this restriction and no workaround has yet been presented. For example, Kaplan and Reed (2018) conducted a study with more than 1,000 participant datasets and the DCA software would allow for the fitting of a global regression *k* while the GP templates would not. As such, the DCA may prove to be a tool that supports a wider range of experiments and demand curve analyses.

Lastly, the DCA provides additional functionality while also simplifying the modeling of demand. That is, the DCA displays information using spreadsheet-based controls and provides options for modeling using a simplified GUI. Through supporting a range of modeling options in an easily accessible format, the DCA and tools like it may encourage users to consider using more advanced and contemporary analyses rather than defaulting to simpler methods, such as those in assessments of relative reinforcer efficacy. In this way, user-focused tools such as the DCA may further support a growing movement towards increasing the use of modern statistics and quantitative techniques in behavior analytic research (Fisher & Lerman, 2014; Young, 2018).

Limitations

Although the results from the DCA mirror those obtained from existing commercial products and support the use of a wide range of demand curve analyses, these new possibilities are not without new risks of improper use. For example, researchers using assessments of relative reinforcer efficacy have traditionally used methods that did not require mathematical modeling or statistical consultation. Tools such as the DCA and others like it are not a replacement for formal training in statistics or proper consultation with trained statisticians. The DCA should be viewed as one means to support the use of statistics while encouraging the use of recommended screening criteria, standardized handling of parameter *k*, and calculations of demand elasticity.

Furthermore, careful consideration should be taken in choosing demand curve analysis options (e.g., model type, handling of zero values).

Although the DCA performs most of the quantitative methods that are used in contemporary studies of operant demand, there are some advanced techniques that it does not yet perform. For example, the DCA does not provide some of the more complex calculations referenced in the literature. For example, the DCA has yet to include methods such as the Extra Sum-of-Squares F-test (Roma, Hursh, & Hudja, 2016), analyses of substitutability (Hursh & Roma, 2013), and mixed-effects demand curve modeling (Zhao et al., 2016). Even further, model selection procedures do not yet exist for recommending one model of demand over another. As such, the DCA will require ongoing development and expansion to ensure that researchers with a range of backgrounds can reliably and accurately perform modern demand curve analyses. Future developments in the study of operant demand should capitalize on the open-source nature of this project and researchers are encouraged to evaluate the source code and methods, as well as propose enhancements using the source repository identified in the Appendix of this work.

Conclusions

The DCA is free and open source software (FOSS) to analyze data from operant behavioral economic studies of demand. Its performance matches that of commercial products, and it provides additional analyses that are not provided in these other programs. The software is GUI-based and user-friendly. Marr (2017) identified a lack of quantitative expertise and application as a major impediment to further development in behavior analysis and behavior science. As quantitative methods become more complex, the response and economic costs associated with their use rise commensurately. With the introduction of the DCA and other behaviorally relevant FOSS applications such as BDataPro (Bullock, Fisher, & Hagopian, 2017) and Discounting Model Selector (Gilroy, Franck, & Hantula, 2017; Gilroy & Hantula, 2018), perhaps barriers may be lessened and quantitative tools may be more readily used in basic, translational and applied research.

More quantitatively sophisticated research in operant behavioral economics has great promise to break new ground in diverse areas including effort-based choice (Salamone, Correa, Yang, Rotolo, & Presby, 2018), consumer behavior analysis (Foxall, Wells, Chang, & Oliveira-Castro, 2010; Oliveira-Castro & Foxall, 2016; Oliveira-Castro, Foxall, & Wells, 2010; Wells & Foxall, 2011), and interventions for individuals with disabilities (Gilroy et al., 2018). Perhaps some of the most important are those related to health behavior change (Bickel, Moody, & Higgins, 2016). Indeed, enduring challenges such as alcohol use and sexual risk (Lemley, Fleming, & Jarmolowicz, 2017; MacKillop et al., 2015), food choice and obesity (Epstein, Stein, Paluch, MacKillop, & Bickel, 2018; Rasmussen et al., 2016), including applications to nutrition education (Guthrie, 2017) and improving the USA SNAP program (Ammerman, Hartman, & DeMarco, 2017) may be informed by such work. Further, innovative practical and policy approaches for emerging health issues such as nonmedical use of prescription drugs (Pickover, Messina, Correia, Garza, & Murphy, 2016), indoor tanning (Reed et al., 2016), cannabis use (Strickland, Lile, & Stoops, 2017), and substitution between conventional cigarettes and e-cigarettes (Snider, Cummings, & Bickel, 2017) may well arise from this work.

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Appendix

The source code necessary to simulate and systematically compare the accuracy of the Demand Curve Analyzer to other statistical tools has been open-sourced and publicly shared. All simulations and analyses were performed using the R computer program and all R scripts and supplemental files can be found on the corresponding author's public Git (https://github.com/miyamot0), located in the repository named "DemandSimulations." The source code necessary to build the Demand Curve Analyzer is available in the repository named "DemandCalculatorQT" and installation files are available under the "Releases" tab.