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# *shinybeez*: A Shiny app for behavioral economic easy demand and discounting

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**Abstract**

This article introduces *shinybeez*, a free and open-source web application designed to streamline behavioral economic analyses of demand and discounting data. Although quantitative modeling of behavioral economic phenomena has increased in popularity and led to translational successes in clinical practice and policy, complex analyses have remained a barrier for many researchers and practitioners. The *shinybeez* application addresses this gap by providing an intuitive interface for conducting descriptive and inferential analyses without requiring programming expertise. The app integrates features previously scattered across multiple tools, allowing users to upload data, calculate empirical measures, identify systematic data sets, fit nonlinear models, and visualize results—all within a single platform. The *shinybeez* application supports various types of analysis for demand and discounting data, including indifference point data and the 27-Item Monetary Choice Questionnaire. Built on R Shiny and leveraging existing R packages, the app ensures reproducibility and consistency with underlying analytical methods while remaining flexible for future enhancements. The advantages of *shinybeez* include its accessibility through web browsers or local installation, ability to handle large data sets, and customizable data visualization options. By consolidating behavioral economic tools into a user-friendly interface, *shinybeez* is intended to broaden the reach of these analytical techniques and facilitate their application in addressing societal issues.

**KEYWORDS**
behavioral economics, demand, discounting, free and open-source software, R Shiny

Operant behavioral economics is an umbrella term that subsumes various approaches to studying organisms' allocation of behavior amidst varying dimensional manipulations of rewards (DeLeon et al., 2021; Hursh, 1984; Hursh et al., 2013; Kagel & Winkler, 1972; Reed et al., 2013; Vuchinich et al., 2023). The two most prominent concepts within the operant behavioral economics literature are demand and discounting. Simply put, demand is the extent to which an organism defends its reinforcement blisspoint (Hursh & Silberberg, 2008), whereas discounting is the subjective devaluation of a reinforcer due to its dimensional thinning (e.g., increasing delays, decreasing odds of receipt; Madden & Johnson, 2010; McKerchar & Renda, 2012; Odum, 2011). The success of demand and discounting in extending the reach of the experimental analysis of behavior outside behavior analysis cannot be overstated (Bickel et al., 2014; Hursh et al., 2013; Reed et al., 2022; Strickland & Lacy, 2020).

Quantitative modeling of demand and discounting phenomena has evolved over the past several decades. Demand and discounting are well-studied phenomena, with substantial attention in the literature dedicated to quantifying these processes and response patterns (Franck et al., 2015; McKerchar et al., 2009, 2010; Mitchell et al., 2015; Strickland et al., 2016). Myriad approaches and nonlinear models of these processes have subsequently been proposed (Borges et al., 2016; Gilroy et al., 2021; Hursh & Schwartz, 2023; Hursh & Silberberg, 2008; Kaplan et al., 2021; Koffarnus et al., 2015; Myerson & Green, 1995; Myerson et al., 2001; Newman & Ferrario, 2020; Yoon & Higgins, 2008). The precise and objective descriptions of environment–behavior relations

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afforded by these models give way to readily translatable metrics. For example, demand curve modeling can inform excise taxation policies (MacKillop et al., 2012; Reed et al., 2016) or unit price considerations for reinforcers selected for clinical interventions (Delmendo et al., 2009). Likewise, discounting metrics can inform public policies that involve extreme weather warning delays (Gelino & Reed, 2020) or token exchange delays in classroom interventions (Reed & Martens, 2011). Thus, quantitative models of demand and discounting—if made accessible to researchers and policy makers—have significant promise in addressing issues of societal concern.

Despite the quantitative modeling of demand and discounting being a primary reason for the success of behavioral economics, the complexity involved with these calculations and curve fitting remains a substantial barrier to many researchers and clinicians. These barriers are unfortunate given the translational success of these analyses in informing clinical practices and public policy interventions. Although these translational successes are well known, researchers and clinicians may have insufficient training or resources to conduct the relevant analyses (see discussions by Madden, 2013; Young, 2018). For example, nonlinear modeling requires access to advanced statistical software programs and adequate training to execute such analyses. Researchers have attempted to address these gaps by developing open-source tools that are freely accessible to the public, with some degree of automated analytic workflows to model or score data sets (Gilroy et al., 2017, 2018; Kaplan et al., 2019).

The current landscape of accessible operant behavioral economic tools presents its own challenges, however. Many of the early tools were based in Microsoft Excel (e.g., Kaplan et al., 2016; Reed et al., 2012; Stein et al., 2015), which has computational limits in terms of the types of analyses that the software is capable doing as well as the computer resources necessary for it to analyze large data sets. An additional issue with Excel-based tools is the risk of obsolescence when updates to Excel are pushed out to its users. The pivot toward open-source platforms (Gilroy & Kaplan, 2019; Gilroy, Kaplan, Bullock, et al., 2020) circumvents the Excel issues by creating opportunities for the software to have updates when corrections or additions are made by the creators. Unfortunately, many of these tools require the user to seek the updates themselves once the software is installed. Moreover, the programming languages used in these open-source tools often require some degree of user sophistication to execute their desired analyses.

This manuscript presents an overview of an open-source web app specifically designed to address the many issues and limitations of existing software, with the target audience being behavioral economic demand and discounting researchers with or without software programming prerequisites to conduct their analyses. We have designed the app to be flexible and customizable to meet the needs of various researchers as well as scalable and able to handle *very* large data sets that other software (e.g., Microsoft Excel) simply cannot accommodate. In addition, the app is capable of running on a variety of operating systems and devices, including desktop computers, laptops, tablets, and smartphones running Windows, MacOS, Linux, or ChromeOS.

This web app relies heavily on *beezdemand* (Kaplan et al., 2019; Kaplan, 2023) and *beezdiscounting* (Kaplan, 2025), which are existing R packages used to perform behavioral economic demand and discounting analyses and other tasks. The web app is developed using R Shiny (an R-based framework that facilitates the creation of dynamic, interactive web applications directly from R code; Chang et al., 2024). Thus, we have aptly named this web app *shinybeez* for its reliance on R Shiny to interface with the *beezdemand* and *beezdiscounting* R packages (Figure A1). We will first describe some of the overall features of *shinybeez*. Then, we will discuss specific features and capabilities related to behavioral economic demand data, followed by discussing specific features and capabilities related to behavioral economic discounting data. We will conclude with a discussion about how best to use *shinybeez* and what features we plan to integrate in future releases. We will not make any comparisons to other software available because *shinybeez* relies almost exclusively on existing R packages for conducting analyses "under the hood." The source code for those packages is readily available elsewhere (both on Github and on the Comprehensive R Archive Network [CRAN]). We note that although the specific user interface may change in the future, our goal is for *shinybeez* to always have the primary functionality outlined in this article, specifically, the ability to conduct quintessential demand and discounting analyses. We expect over time that the feature set will grow considerably while always maintaining the core goals (e.g., easily accessible, open-source, reproducible, user friendly, extensible, integrating best practices) discussed in this article. As mentioned later, the user guide will always remain up to date with added features or changes to the user interface and app in general.

One of our main goals while developing *shinybeez* was ensuring that an end user may always access the app in an efficient manner (whether via a web browser or a local installation). Toward that end, *shinybeez* will always be free and open-source and its source code will always be readily available for inspection and reproducibility. To accomplish this goal, there are at least two (current) locations to access *shinybeez*. The first location is https://github.com/brentkaplan/shinybeez, where the source code lives (hopefully indefinitely). This Github repository contains the code required to run the app locally, if desired (for more on Github in general, see Gilroy & Kaplan, 2019). To run the app locally, the user can first download the repository and open a new R session in the downloaded folder. Leveraging the *renv*

(Ushey & Wickham, 2024) package to keep track of the required package and fostering a reproducible environment, users should install all packages required in renv.lock file. Once all the required packages are installed, users should be able to run the command shiny::runApp(), thereby starting a local instance of the app. The Github repository will always have current URLs to access the web app,[1] so users are encouraged to check there. The second location is https://brentkaplan.shinyapps.io/shinybeez/. Shinyapps.io provides a straightforward platform for hosting and running Shiny applications. While on the topic of the *shinybeez* Github repository, we wish to bring attention to the reader that the current article is also located in the repository under the manuscript folder. Here, you will find the *Quarto* (Allaire et al., 2024) document along with any additional assets required to generate the manuscript (e.g., *renv* package, images).[2]

Before overviewing the features of *shinybeez*, we want to highlight that although the barrier to entry for *shinybeez* is quite low, and therefore *accessible* (by design), we spent considerable time and effort in balancing what a user can and *cannot* do with the app and for what kinds of analyses. Certainly, individuals who are not well versed with the intricacies of behavioral economic quantitative modeling could do more harm than good with this app, but we believe that as much, if not more, harm can be done using other existing (and quite commonly used) software (e.g., GraphPad Prism). Other software allows users to "try" a wider variety of options (e.g., constraining certain parameters, comparing curves, automatically excluding outliers, choosing different weighting methods) that may not be appropriate for the vast majority of use cases in behavioral economic modeling. In contrast, we designed *shinybeez* so that users (of different levels of proficiency) can perform a wide variety of analyses (both descriptive and inferential) in a manner that is consistent with the broader behavioral economic literature. In a Bayesian and behavioral economic sense, we have used our priors to inform the choice architecture of *shinybeez*. With that said, we *strongly* encourage users to have familiarity with the underlying concepts and processes of behavioral economic demand and discounting analyses. In addition to the several references to important publications and resources to help users gain this familiarity in the user guide of the app, we encourage readers to see the plethora of outstanding work in quantitative modeling, statistics, and behavioral economics (both demand and discounting and in no highly specific order): Critchfield and Reed (2009), Young (2018), Allison (1979), Reed et al. (2025), DeLeon et al. (2021), Reed et al. (2013), Koffarnus and Kaplan (2018), Koffarnus et al. (2022), Hursh and Silberberg (2008), Roma et al. (2017), Kaplan et al. (2021), Gilroy, Kaplan, and Reed (2020), Gilroy et al. (2019), Acuff et al. (2020), Strickland et al. (2020), Odum (2011), Reed et al. (2012), Young (2017), Odum et al. (2020), and Rung and Madden (2018).

The rest of this article is an overview of the features of *shinybeez* and is organized under the broad categories of demand and discounting. We have organized the article like this so that if you are primarily a demand researcher, you can focus on the demand section and, likewise, the discounting section if you are primarily a discounting researcher. Expansive discussion of specific demand and discounting concepts, tasks, and analyses are beyond the scope of this article, so we encourage readers to consult the resources provided above and in the user guide of the app.

# SHINYBEEZ

## Welcome page and documentation

We developed *shinybeez* to be intuitive for the user, no matter their familiarity with behavioral economic tasks, data, and analysis. Upon starting the app, users will find a welcome page that also serves to provide documentation about the app (Figure A2). We believe this feature sets it apart from other apps and tools that do not have such thorough documentation integrated directly into the interface. First-time users, as well as users who want to reference certain features of the app, should consult the welcome page. The welcome page, importantly, contains several downloadable template files that users can use to make sure their data are in the correct format. Users can upload data in either "wide form" (e.g., data collected from survey softwares like Qualtrics are typically in this format) or "long form" (i.e., each row is a single observation) for demand and discounting data, and *shinybeez* is typically intelligent enough to determine in which format data are provided. Specific formats are required for analyzing the data from the Monetary Choice Questionnaire (Kirby et al., 1999) and 5-trial discounting task (i.e., minute task; Koffarnus and Bickel, 2014; Koffarnus et al., 2021). If data are uploaded in an incorrect format, *shinybeez* will display a notification and users should modify the spreadsheet accordingly.

As new features are added, the welcome page will contain new documentation. At the top of the app are (currently) two tabs, depending on whether the user has demand or discounting data.[3] Users may also click the sun icon in the upper-left corner of the app to toggle dark mode. We discuss features for the demand (Figures 1–4) and discounting tabs (Figures 5–8) in the following sections.

[1]We plan to have additional ways to access the app in the future so that there is always an accessible web version.

[2]We would like to acknowledge the developers of the apaquarto extension (Schneider, n.d.) for allowing such a seamless process for creating documents in accordance with American Psychological Association's 7th Edition style requirements. We also want to acknowledge the various R packages that make *shinybeez* possible. Among others, these packages include *shiny* (Chang et al., 2024), *rhino* (Zyla et al., 2024), *bslib* (Sievert et al., 2024), *esquisse* (Meyer & Perrier, 2024), and *DT* (Xie et al., 2024).

[3]The app also supports dark mode theme (Figure A3), with a toggle option on the top right-hand side of the app.

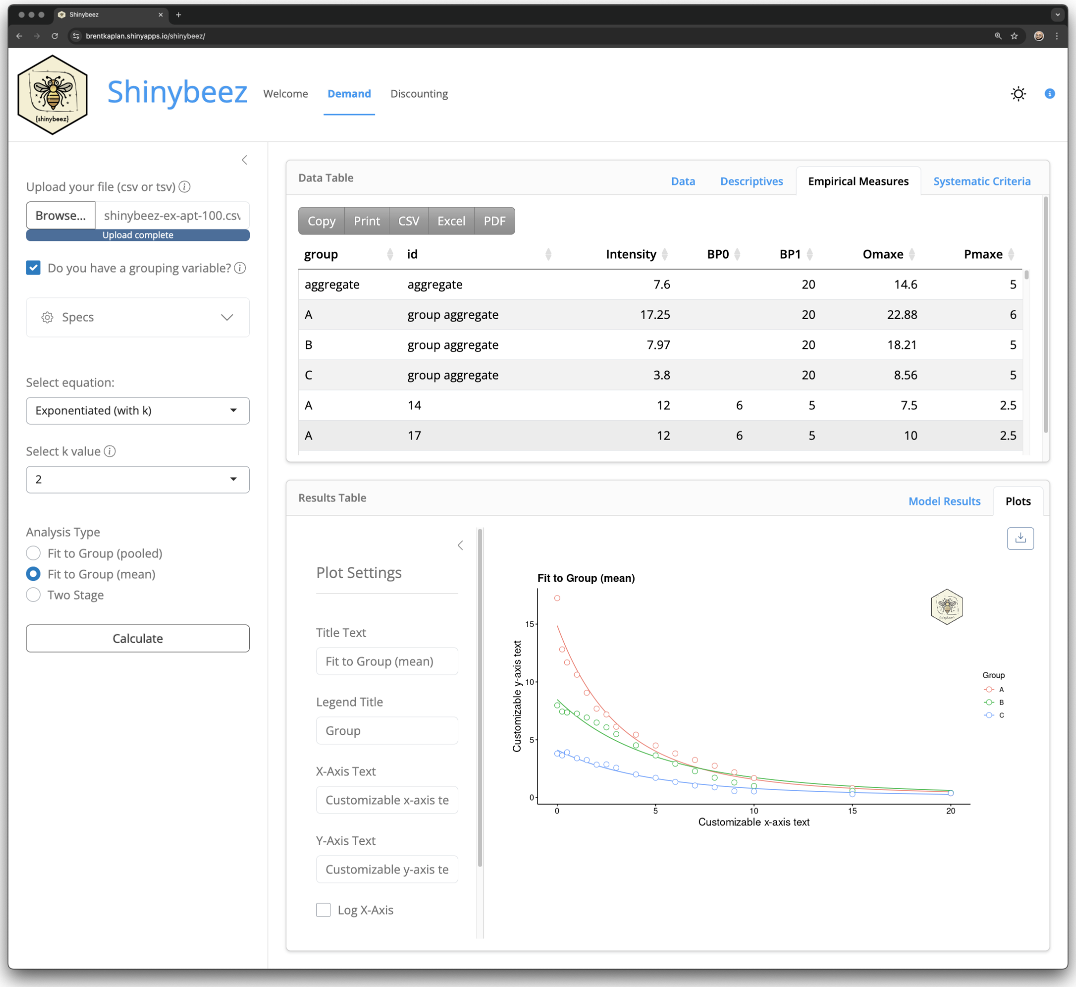


**FIGURE 1** Demand plot settings. Top box shows the exportable table of empirical demand measures. Bottom box shows visualization of the fit to group (mean) with group specified and the customizable settings for demand plots.

# Demand

Upon clicking the demand tab, users will see a collapsable sidebar where a data file is selected for upload as well as additional specifications related to analyzing the data. Currently, the available options to select are whether a grouping variable should be integrated into the results, whether $Q_0$ (i.e., consumption when price is free) should be constrained to a specific value, whether to use the exponentiated (Koffarnus et al., 2015) or exponential (Hursh & Silberberg, 2008) demand equation, what $k$ value method should be used, and the analysis type (discussed below). In the main panel of the app are two boxes with embedded tabs. The box at the top contains information related to the data (i.e., information that does not require any curve fitting), and the box at the bottom contains information related to the results of the curve fitting. Once data are uploaded, the top box is populated with information (by default, the uploaded data are displayed) and results in the bottom box are populated after the user clicks the “Calculate” button.

An important feature to note is that each of the tables displayed in the demand page can be exported in the following ways: “Copy” will copy the contents of the table to the clipboard; “Print” will open an option to print the table through the device print interface; “CSV” will prompt saving the table as a comma-separated text file; “Excel” will prompt saving the table as a Microsoft Excel file with a. xslx extension; “PDF” will prompt to download the table as a file with a .pdf extension.

## Descriptive statistics

The second tab contains a table of descriptive values for the entire sample. For each price, the table lists the mean, median, standard deviation (*SD*), proportion of zero values (PropZeros), number of missing values (NAs), minimum value (Min), and maximum value (Max). When a grouping variable is present and indicated, these values are calculated for each distinct group in the data set.

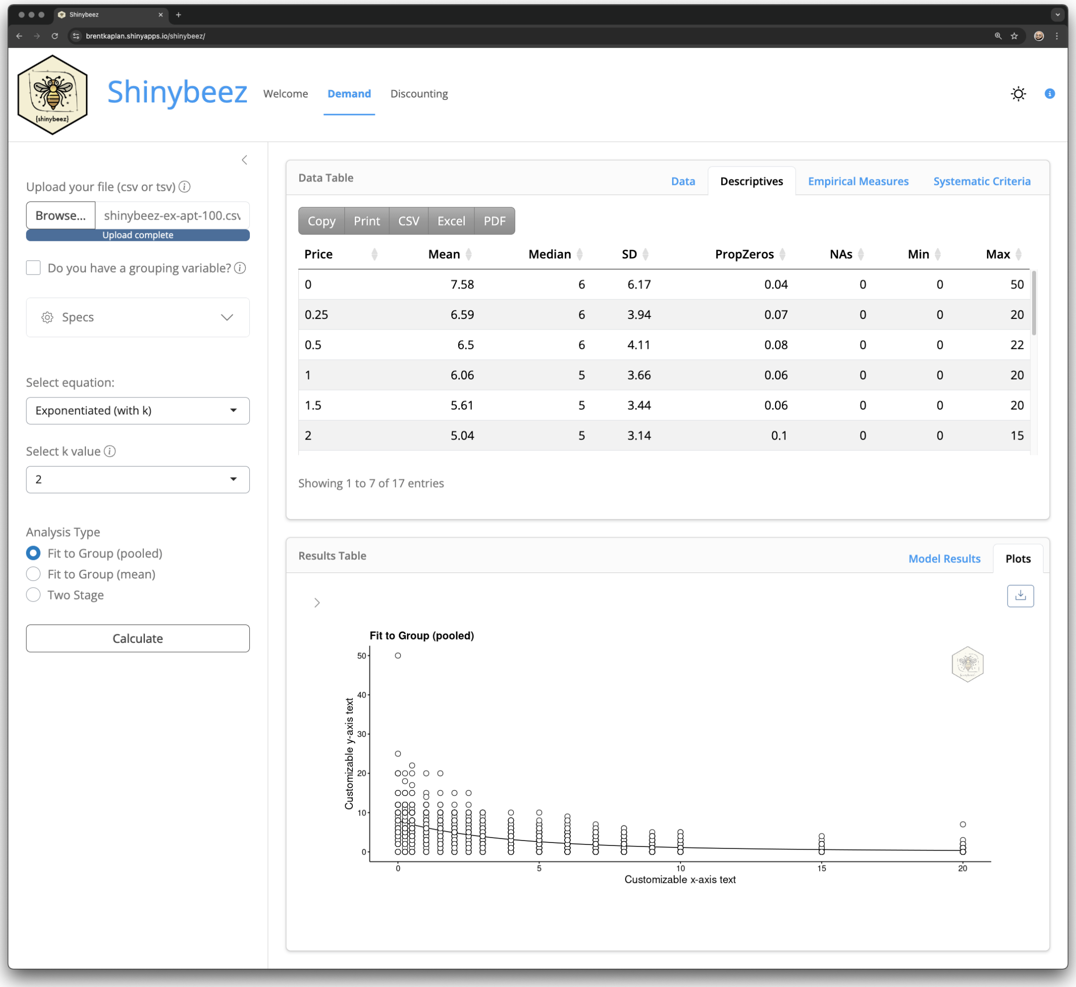


**FIGURE 2** Demand Fit to Group (pooled). Top box shows the exportable table of descriptive results. Bottom box shows visualization of the Fit to Group (pooled) with no group specified.

## Empirical measures

The third tab contains a table of empirical demand measures (see top of Figure 1). Empirical measures include intensity (observed $y$ value at the lowest $x$ value), Break point$_1$ ($BP_1$; the highest $x$ value associated with a nonzero $y$ value), Break point$_0$[4] ($BP_0$; the lowest $x$ value associated with a zero $y$ value), $O_{max}$ (observed highest value of multiplying each $x$ by $y$), and $P_{max}$ (the $x$ value associated with $O_{max}$). When no grouping variable is selected, these values are calculated for the entire sample and for each unique identifier. When a grouping variable is present and indicated, these values are calculated for the entire sample, for each distinct group, as well as for each unique identifier.

[4]Cells associated with $BP_0$ and $BP_1$ will sometimes be blank because the response set had all zeros (in the case of $BP_0$) or all nonzeros (in the case of $BP_1$). The latter is especially prevalent when data are aggregated.

## Systematic criteria

The fourth and final tab contains a table of criteria used for *identifying* systematic data sets according to the Stein et al. (2015) algorithm (Figure 4, top panel). The reported values include the number of total criteria passed and whether each criterion was met (passed) or not (fail). For each criterion, the value is provided. Finally, the number of total positive values is included in the final column. Note that this tab has additional features. When a user clicks to open the collapsable sidebar *within this tab*, they are presented with adjustments that can be made to the criterion values outlined in Stein et al. (2015). These values are set at the defaults outlined in Stein et al. (2015), and changing these values will update the table. When a grouping variable is specified, a group identification column is added but the results do not change, as these criteria are only applied at the individual level.

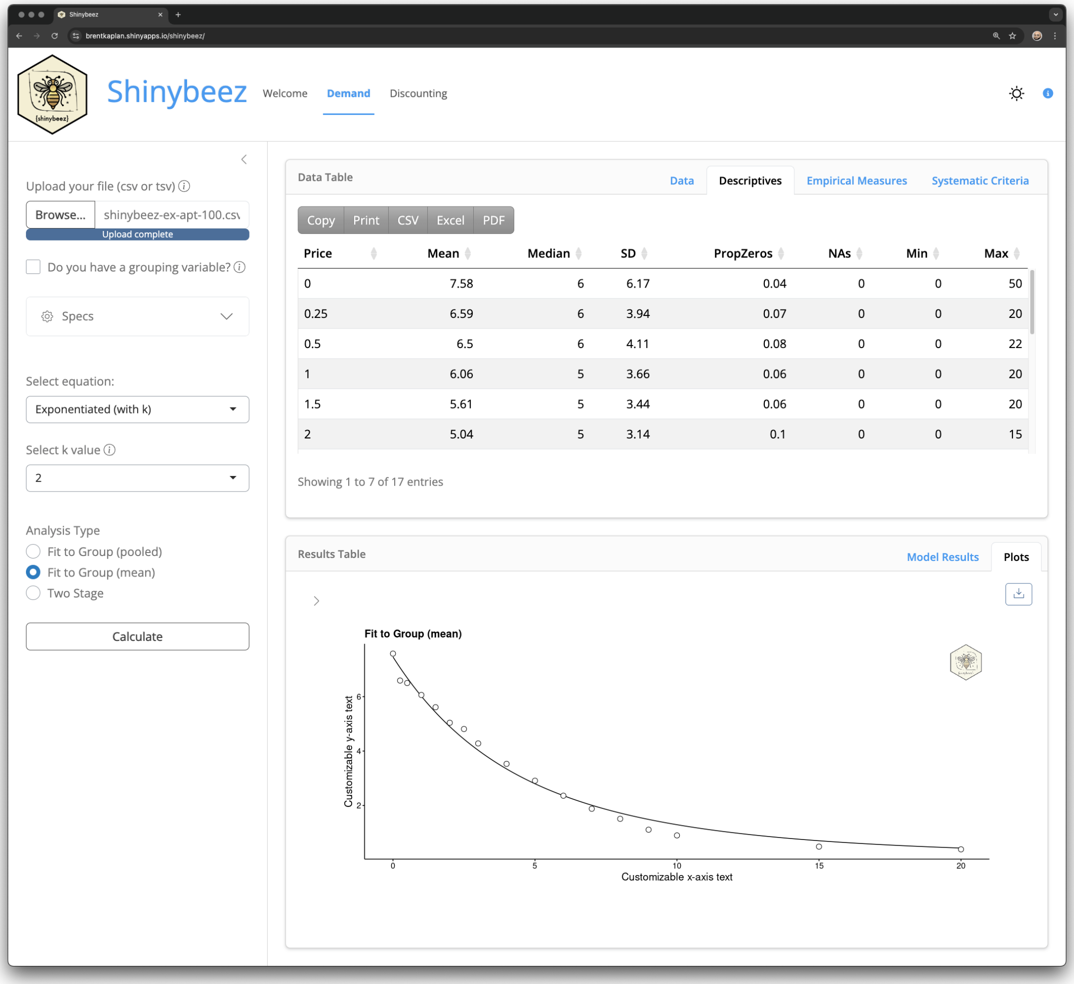


**FIGURE 3** Demand Fit to Group (mean). Top box shows the exportable table of descriptive results. Bottom box shows visualization of the Fit to Group (mean) with no group specified.

## Nonlinear model fitting

The bottom box on the demand page has two tabs and displays the results of the nonlinear curve-fitting process in a tabular format (Model Results tab) and graphical format (Plots tab). In the Model Results tab, a table is displayed with the following information: equation, estimated $Q_0$ (including standard error and confidence intervals), $k$ value, estimated $\alpha$ (including standard error and confidence intervals), $R^2$, model absolute sum of squares, standard deviation of the residuals, essential value, derived $O_{max}$, derived $P_{max}$, and analytic $O_{max}$ and analytic $P_{max}$ (see Gilroy et al., 2019). The last column of the table provides a note on whether the model converged, because the results for a model that does not converge should be interpreted cautiously. Note that these results *are identical to the results provided by the underlying R package beezdemand.*

The aforementioned model results are applied to the data depending on the analysis type chosen in the sidebar of the demand page. When the Fit to Group (pooled) analysis type is chosen, a single regression model is fit to the entire sample (all data points) and any dependence or clustering is ignored. When the Fit to Group (mean) analysis type is chosen, data are first aggregated by taking the mean of the $y$ values at each $x$ value and a regression line is then fit to those points. When the Two Stage analysis type is chosen, a regression model is fit to each subject separately. When a grouping variable is specified, the analysis types Fit to Group (pooled) and Fit to Group (mean) will fit curves as just described but *within* each group. There is no effect on whether a grouping variable is specified when the Two Stage analysis type is selected.

The second tab in the results box contains a plot of the results based on the settings specified in the sidebar, especially Analysis Type. Before describing and showing what these plots look like, we describe some plot customization settings in the collapsible side bar in the plot tab. Users may customize the plot title, the $x$-axis title, the $y$-axis title, and (when applicable) the group legend title. In addition, users can specify whether to (pseudo)log

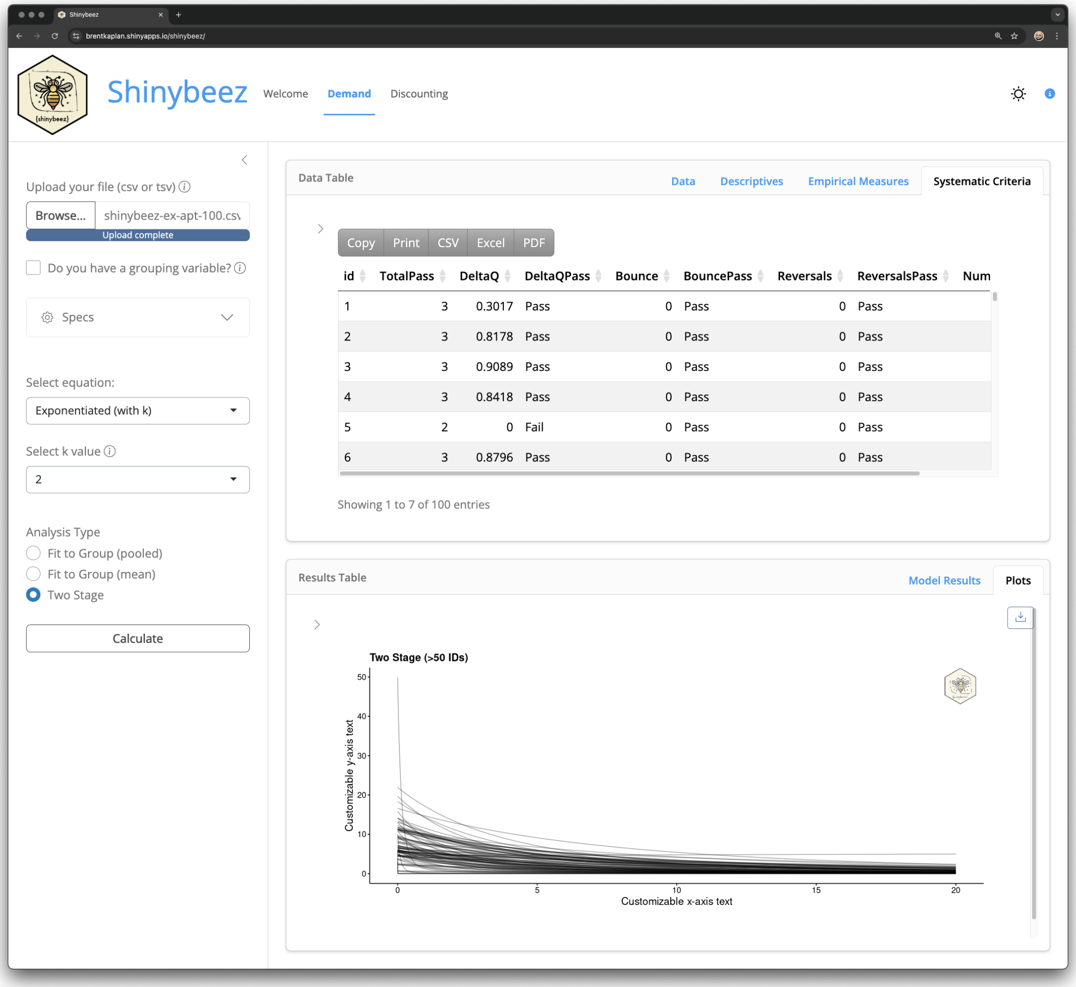


**FIGURE 4** Demand Two Stage analysis (>50 IDs). Top box shows the exportable and customizable systematic criteria table. Bottom box shows visualization of the Two Stage analysis option with more than 50 IDs.

transform[5] either the *x*- or *y*-axes (Figure 1). Then, the user may output the plot directly as a .png, .svg, or .jpeg file or display the plot in the viewer window and choose additional formats such as .pdf, .bmp, .eps, or .tiff. In this plot viewer, the user may specify specific height and width values as well as file name.

When the Fit to Group (pooled) analysis type is selected, all data points will display with the best-fit line (Figure 2). Similarly, when a group is specified the points and lines will be colored according to the groups (Figure A4). When the Fit to Group (mean) analysis type is specified, the preprocessed average data points are displayed with the best-fit line (Figure 3) and when a group is specified, the points and lines will be colored according to the groups (Figure 1). Finally, when the Two Stage analysis type is selected, plots will be displayed in one of two ways. When there are 50 or fewer IDs (e.g., respondents), each ID will get their own subplot (Figure A5), and all curves will be shown on a single plot when there are more than 50 IDs (Figure 4).

[5]The (pseudo)log transformation approximates a log scale while accommodating zero and negative values by smoothly transitioning to a linear scale around zero, making it suitable for a broader range of data. It is for visualization purposes only and does not affect the underlying data.

## Discounting

When users click on the Discounting tab, they are presented with a page similar to that on the Demand tab. The sidebar allows the user to choose their file for upload and also choose which discounting task they wish to score. Currently, *shinybeez* provides support for fitting regression models to indifference point data, scoring the 27-Item Monetary Choice Questionnaire (MCQ; Kaplan et al., 2016; Kirby et al., 1999), and analyzing two variants of the 5-trial (i.e., minute) discounting task (delay and probability discounting; see Koffarnus and Bickel, 2014; Koffarnus et al., 2017; Koffarnus et al., 2021).

## Indifference point regression

Uploading a file containing indifference point data will result in a table of data shown in long format (Data tab) and a tab for Systematic Criteria. A Results Table also appears at the bottom of the page. In the sidebar, users are prompted to choose the equation to be fit to the data. The default equation is Mazur's hyperbolic equation (Mazur, 1987), and the (current) alternative is the simple exponential equation (see Frederick et al., 2002). Then, akin to the demand page, users will choose which analysis type they would like to use. The default analysis type is Fit to Group (pooled), and the alternatives are Fit to Group (mean) and Two Stage.

### *Systematic criteria*

The Systematic Criteria tab contains a table of criteria used for *identifying* systematic data sets according to Johnson and Bickel (2008; see top panel of Figure 5). The two criteria are that (1) any subsequent indifference point that exceeds the previous value by more than a specified proportion of the larger later reward (0.2 by default) and (2) the last indifference point is not at least a specified proportion less than the first indifference point (0.1 by default). The table shows each response set's ID and whether that response set passes each criterion. Note that this tab has additional features. When a user clicks to open the collapsable sidebar *within this tab*, they are presented with adjustments that can be made to the criterion values outlined by Johnson and Bickel (2008). These values are set at the defaults, and changing them will update the table (see Figure A6).

### *Nonlinear model fitting*

The bottom box on the discounting page has two tabs and displays the results of the nonlinear curve fitting process in a tabular format (Results tab) and graphical format (Plots tab). In the Results tab, a table is displayed with the following information: method (i.e., analysis type: pooled, mean, or two stage), the $k$ estimate, standard error, high

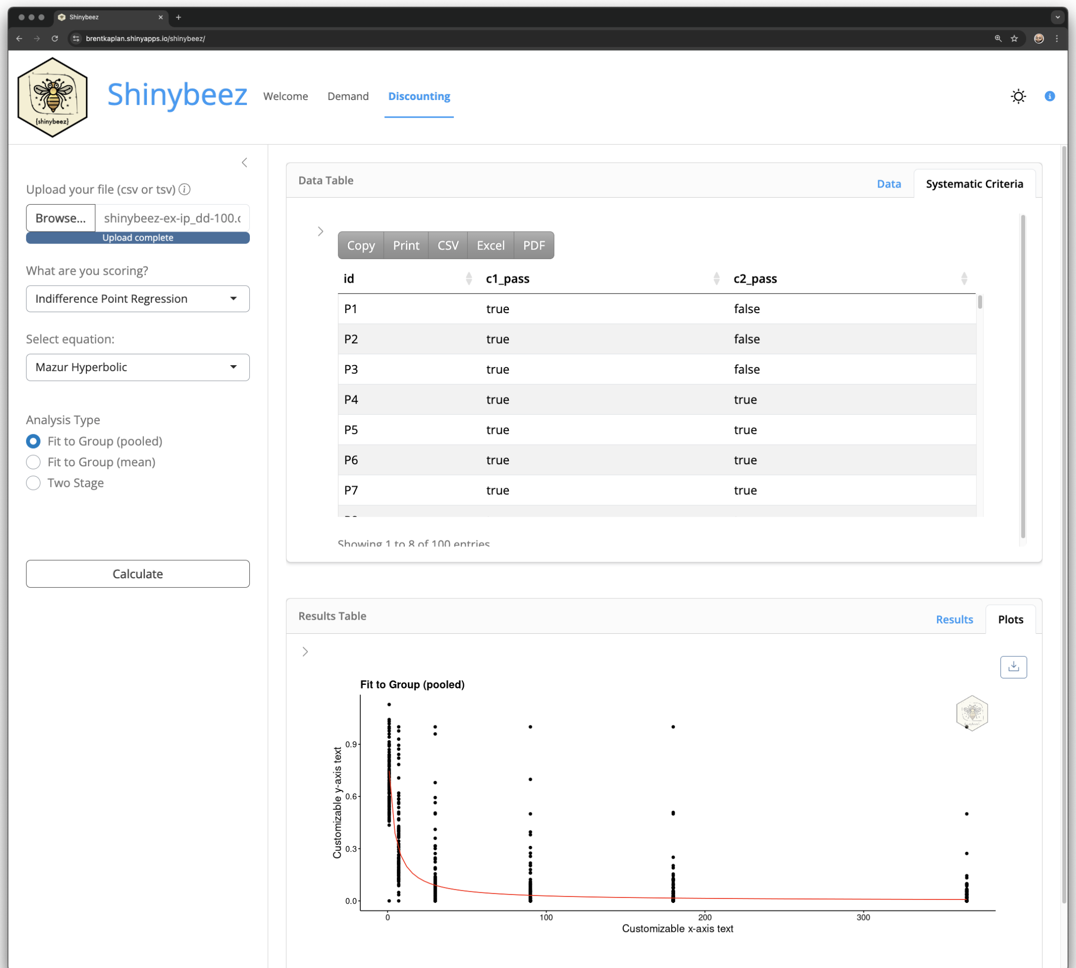


**FIGURE 5** Discounting Fit to Group (pooled). Top box shows the exportable table of customizable systematic criteria. Bottom box shows visualization of the Fit to Group (pooled).

and low confidence interval, the coefficient statistic and *p* value, model error (sigma), whether the model converged (isConv), and several other model statistics: log likelihood, Akaike information criterion, Bayesian information criterion, deviance, and residual degrees of freedom. The table also reports $R^2$ and three different variations of area under the curve (AUC), a model-free estimate of discounting. The three variations of AUC include traditional AUC (with no alteration to the $x$ values), log10 AUC (all $x$ values undergo a log10 transformation after one is added to accommodate zero delay), and ordinal AUC (all $x$ values are ranked resulting in equidistant $x$ values). These transformations are described by Borges et al. (2016) as well as in Kaplan (2025). Note that these results *are identical to the results provided by the underlying R package beezdiscounting*.

The second tab in the results box contains a plot of the results based on the settings specified in the sidebar, especially Analysis Type, similar to what is found in the demand page of *shinybeez*. Users may customize the plot title, the $x$-axis title, the $y$-axis title, and whether to log transform the $x$-axis (Koffarnus & Kaplan, 2018). Then, the user may output the plot directly as a .png, .svg, or .jpeg file or display the plot in the viewer window and choose additional formats such as .pdf, .bmp, .eps, or .tiff. In this plot viewer, the user may specify specific height and width values as well as a file name.

When the Fit to Group (pooled) analysis type is selected, all data points will display with the best-fit line (Figure 5). When the Fit to Group (mean) analysis type is specified, the preprocessed average data points are displayed with the best-fit line (Figure 6). Finally, when the Two Stage analysis type is selected, plots will be displayed in one of two ways. When there are 50 or fewer IDs (e.g., respondents), each ID will get their own subplot, and when there are more than 50 IDs, all curves will be shown on a single plot (Figure 7).

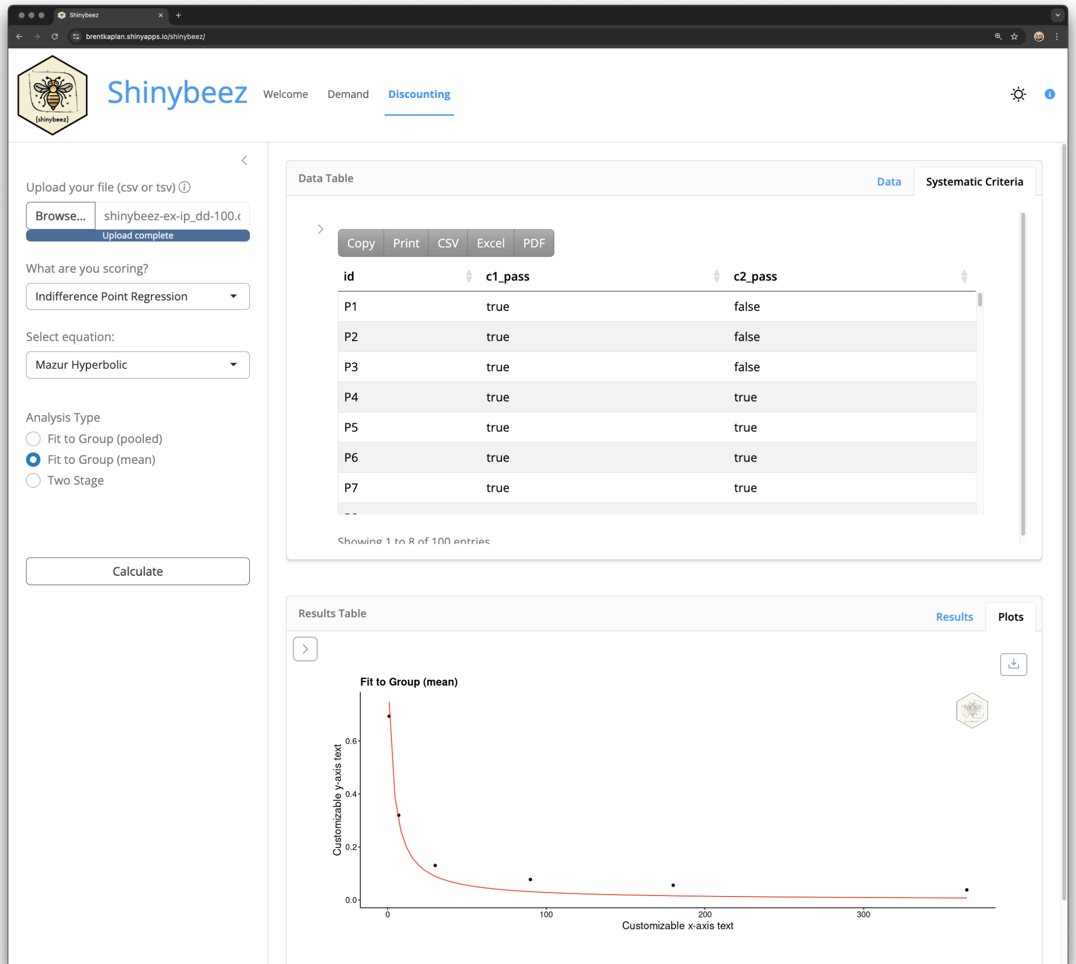


**FIGURE 6** Discounting fit to group (mean). Top box shows the exportable table of customizable systematic criteria. Bottom box shows visualization of the Fit to Group (mean).

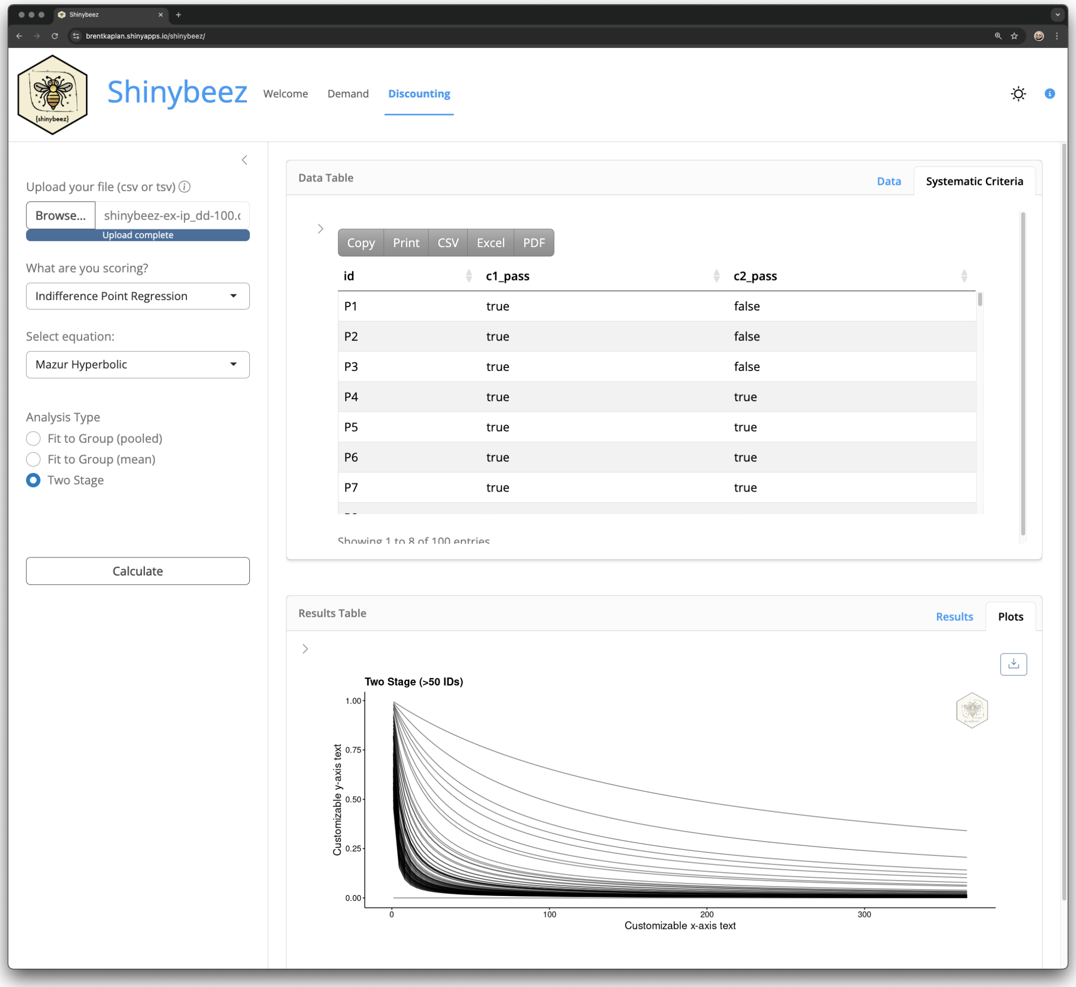


**FIGURE 7** Discounting Two Stage analysis (>50 IDs). Top box shows the exportable and customizable systematic criteria table. Bottom box shows visualization of the Two Stage analysis option with more than 50 IDs.

## 27-Item Monetary Choice Questionnaire

The 27-Item MCQ is a well-established tool used to assess an individual's subjective preference for delayed versus immediate rewards by presenting them with a series of dichotomous hypothetical choice scenarios and calculating a discount rate ($k$) based on their responses. The analyses and outputs for scoring the 27-Item MCQ are nearly identical to those of the popular 21- and 27-Item Monetary Choice Questionnaire Automated Scorer developed in Microsoft Excel (Kaplan et al., 2016; Kaplan et al., 2014). When a user uploads a spreadsheet in the specified format, two additional settings will appear in the sidebar. The first is a selector for imputing missing values (described next), and the second is a selector for transforming resulting $k$ values by "none" (no transformation), "log" (log base 10), or "ln" (log base e or natural log). These selectors will have a result on the output in the bottom box of the Discounting page but will have no effect on the top box of the discounting page that displays the uploaded data and the proportion of missing values for each subject ID.

**Treatment of missing values.** Missing values can be dealt with according to the methods outlined by Yeh et al. (2023): "none" (no imputation), "GGM" (group geometric mean), "INN (no random)" (item nearest neighbor), and "INN (random)" (item nearest neighbor with a random component). We will briefly discuss these methods but direct readers to Yeh et al. (2023) for a full treatment of the approaches. After calculating the small, medium, and large $k$ values for each person, the "GGM" option calculates the geometric (i.e., composite) $k$ value of the three amount sets *so long as one of the amount sets has been calculated*. For the "INN (no random)," the missing value will be imputed as the value from the adjacent small, medium, or large response(s) so long as the nonmissing responses are the same. For the "INN (random)," the same procedure is used except that in the case of nonidentical responses, the missing response will be replaced by either a 0 (i.e., SIR/SS) or 1 (i.e., LDR/

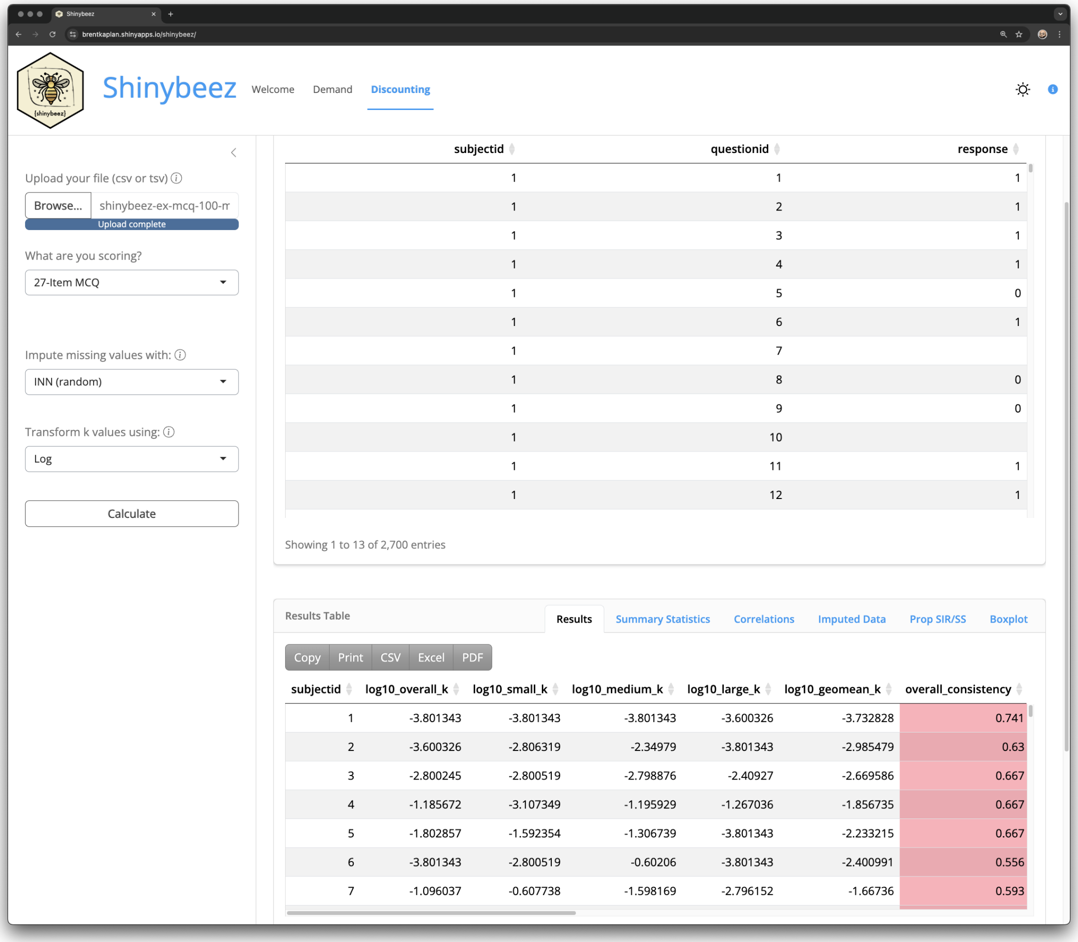


**FIGURE 8** Results table of scoring the 27-item Monetary Choice Questionnaire consistent with the Excel automated scorer.

LL) chosen from a binomial distribution with equal probabilities. Given the randomness of this latter approach, a table of the provided data along with an additional column with the new, imputed response is provided in the bottom box of the Discounting page.

**Results.** Once the user clicks the "Calculate" button on the sidebar, the bottom box of the Discounting page will populate with results. The following tabs are present: Results, Summary Statistics, Correlations, Imputed Data, Prop SIR/SS, and Boxplot. The Results tab displays an exportable table of the results[6] including overall, small, medium, large, and geomean (i.e., composite) $k$ values; overall, small, medium, large, and composite consistency; overall, small, medium, and large proportion of LDR/LL chosen; and the imputation method (Figure 8). As is the case in the Microsoft Excel Automated Scorer (Kaplan et al., 2016), consistency scores less than .75 (75%) are highlighted. The Summary Statistics tab displays an exportable table providing the mean, standard deviation, and standard error of the mean for the aforementioned $k$ values and consistency scores (Figure A7). The Correlations tab displays an exportable table with a Pearson correlation matrix between small, medium, and large $k$ values. The Imputed Data tab will populate an exportable table with the original data and imputed new response if either "INN" imputation method (random, no random) is selected in the sidebar. The Prop SIR/SS tab displays an exportable plot showing the proportion of SIR/SS choices at each $k$ value rank. Finally, the Boxplot tab displays an exportable plot that provides boxplots of the five different $k$ values (Figure A8). An important reminder is that choosing a different transformation in the sidebar will alter the content of all the tabs, except for the Prop SIR/SS tab.

[6]Even though the app will provide a notification to the user warning that missing data were detected when a file is uploaded, the results table will display blank cells when a metric cannot be calculated with the most likely reason being due to missing values.

## Scoring 5-trial (minute) discounting tasks

The *shinybeez* app also has the ability to automatically score results from the 5-trial delay and probability discounting tasks *provided in the Qualtrics Minute Discounting Task template* (Koffarnus et al., 2017; Koffarnus et al., 2021). The 5-trial (or minute discounting task) leverages a concise adjusting procedure—generally completed in under 1 min—to derive accurate discounting rates by systematically varying delays or probabilities across a small set of trials. The Results box displays an exportable table of the results including ResponseId, question index, ordered question number, page timing metadata, response (SS or LL) for each question index, whether the respondent's responses were flagged by the attention question (see Koffarnus et al., 2021, for additional information about this specific task), $k$ value, and Effective Delay 50 value (see Yoon & Higgins, 2008). In the case of the probability minute task, the $h$ value (instead of the $k$ value), Effective θ 50 value (instead of Effective Delay 50 value), and Effective Probability 50 value are displayed.

## DISCUSSION AND FUTURE DIRECTIONS

In this article, we have introduced a free and open-source app designed for behavioral economic demand and discounting researchers to conduct descriptive and inferential analyses on their data. We have provided an overview of the features and capabilities of *shinybeez* so that users may be able to quickly start using the app. The *shinybeez* app seamlessly consolidates features that heretofore were disparate. For example, there is now no need to enter demand data into a spreadsheet tool to identify potentially unsystematic response sets (Stein et al., 2015), then enter the same data into a tool to calculate observed metrics (Foster & Reed, 2020), then enter the same data (again) into a program capable of curve fitting (e.g., GraphPad Prism, Microsoft Excel), and then take the derived model outputs and enter those into another spreadsheet tool (Kaplan & Reed, 2014). Now nearly all of these steps can be accomplished by using *shinybeez*.

Our decision for *shinybeez*'s reliance on existing, open-source R packages is by design. As with any decision, this reliance has implications—both benefits and drawbacks. One drawback of this design choice is that the feature set in *shinybeez* is limited by the provided feature sets in *beezdemand* and *beezdiscounting*. However, we believe the current version of *shinybeez* not only has the foundational features necessary to conduct much of the current requirements of researchers but also that these features encompass nearly all of the features available in other user-friendly (i.e., those not requiring coding experience) tools. Contrasted with this drawback, we see advantages as a result of the reliance on existing R packages. First, *shinybeez* will provide output *consistent* with that of the underlying R packages. This means that results derived from *beezdemand* or *beezdiscounting* functions are *identical* to results derived from *shinybeez* (apart from occasional rounding for formatting). We want to stress this advantage because it is an important feature of *shinybeez*: whether a researcher uses *shinybeez* or the underlying R packages through the R scripting language, the results will be identical. We feel this serves as a tremendous benefit to the scientific landscape directed at improving replicability and reproducibility. Second, *shinybeez* is efficient and extensible such that additional features implemented into the underlying packages do not need to be replicated into *shinybeez*; instead, a minimal amount of added code is needed for *shinybeez* to interface with new features. Third, *shinybeez* is highly transparent given the open-source nature of the app; anyone can inspect how the app interfaces with the underlying R packages to present the results to the user.

### Data security

The *shinybeez* app is configured to operate under an ephemeral model, meaning that user-submitted data and results are retained only during each session, with no persistent storage on the server's disk or external databases. Any given instance of a *shinybeez* session will end if the user stops interacting with the app for some specified period (approximately 10 minutes of no activity). Once a session ends or is refreshed, any data in that session's memory is discarded, thereby reducing the likelihood of unauthorized access or unintended retention. This approach aligns with privacy-oriented design principles by limiting the lifespan of sensitive information and eliminating the need for secure data-wiping procedures. As a result, researchers can upload and analyze data in *shinybeez* without concern for long-term data management while also maintaining compliance with institutional or regulatory guidelines that discourage or prohibit prolonged storage of sensitive data.

With those benefits elucidated, we appreciate that the current feature set will not cover every single use case. With the ever-changing landscape of the field, we foresee valuable additions for future versions of *shinybeez*, as ultimately implemented in *beezdemand* and *beezdiscounting* (Figure A1). For example, readers can expect the following features to be included in future releases including but not limited to additional behavioral economic demand and discounting models, additional customizations for data visualization, more complex specifications of groupings reflecting different experimental designs for both demand and discounting models, modeling cross-price elasticity data (Bickel et al., 2018), and mixed-effects models (Kaplan et al., 2021; Young, 2017). We are also planning to implement the ability to view, run, and save R code directly in the app as well as improve performance via webR integration (Stagg et al., 2023).

We encourage all those who are interested in contributing to the development of *shinybeez* to make a pull request on Github (Gilroy & Kaplan, 2019). Users may also bring issues or feature requests to our attention through Github's "Issue" tab in the repository or by emailing the corresponding author.

## AUTHOR CONTRIBUTIONS

Author roles were classified using the Contributor Role Taxonomy (CRediT; https://credit.niso.org/) as follows: *Brent A. Kaplan*: conceptualization, data curation, software, validation, writing—original draft writing, review, and revisions. *Derek D. Reed*: conceptualization, writing—original draft writing, review, and revisions.

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## CONFLICT OF INTEREST STATEMENT

We declare that there are no conflicts of interest relevant to this research for any of the authors involved in this study.

## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in shinybeez at https://github.com/brentkaplan/shinybeez. The code to recreate this manuscript, the source code for *shinybeez*, and the most current URLs to access *shinybeez* are located at https://github.com/brentkaplan/shinybeez and https://codedbx.com/. The URLs (at the time of publication) to access the *shinybeez* app are https://shinybeez.app and https://brentkaplan.shinyapps.io/shinybeez/.

## ETHICS APPROVAL

No subjects were recruited for this technical report.

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# APPENDIX A

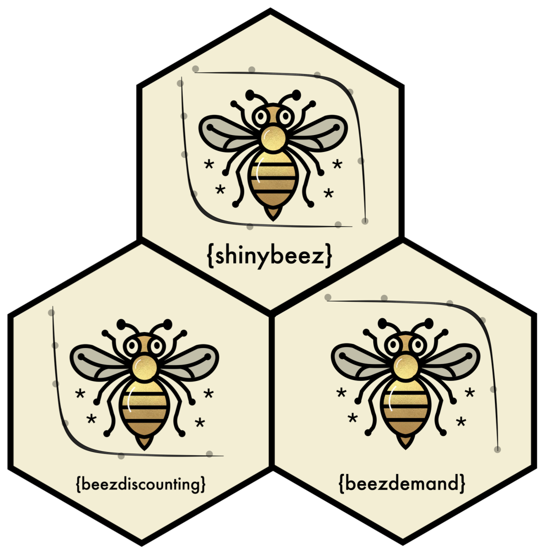


**FIGURE A1** The beezhive. The *beez*hive where *shinybeez* neatly uses tested software to fill the void of behavioral economic tools.

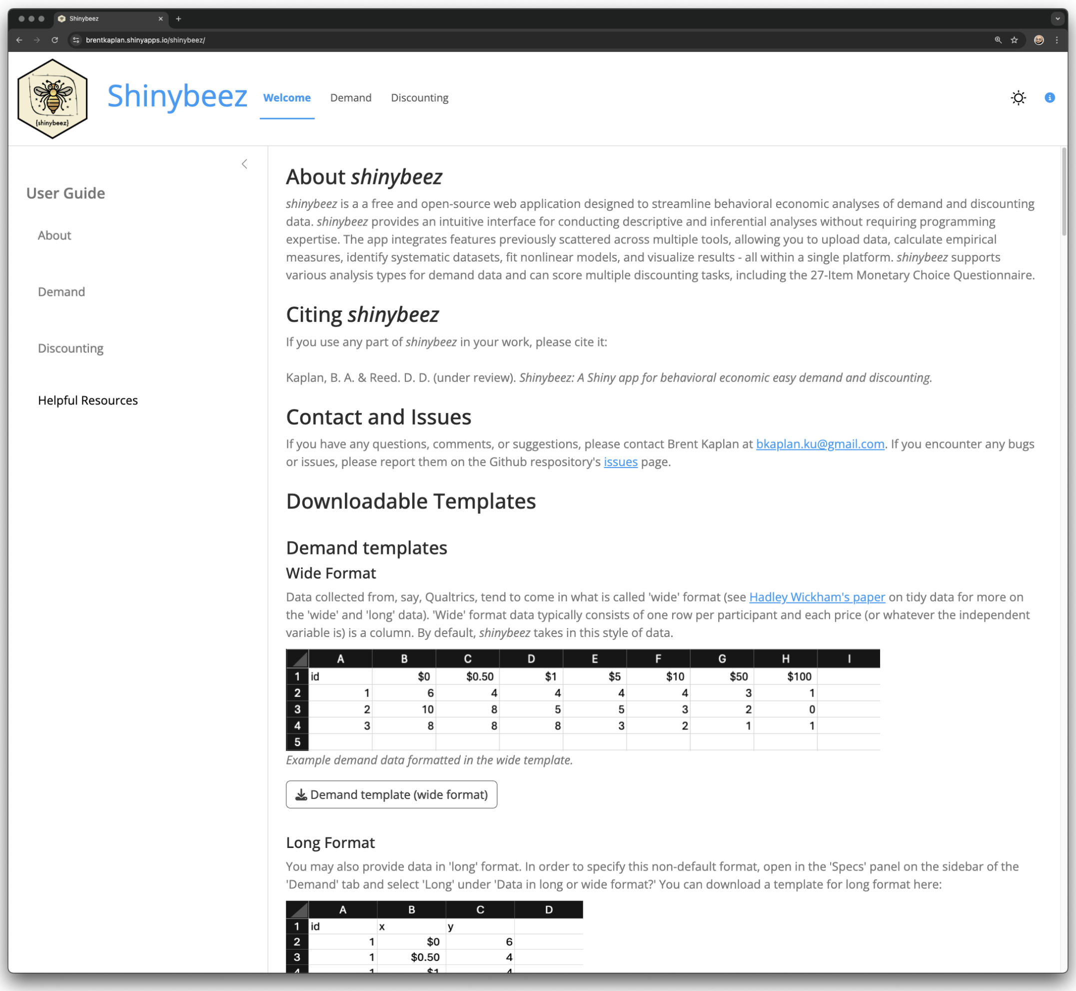


**FIGURE A2** Welcome page with instructions about how to use the app along with template files.

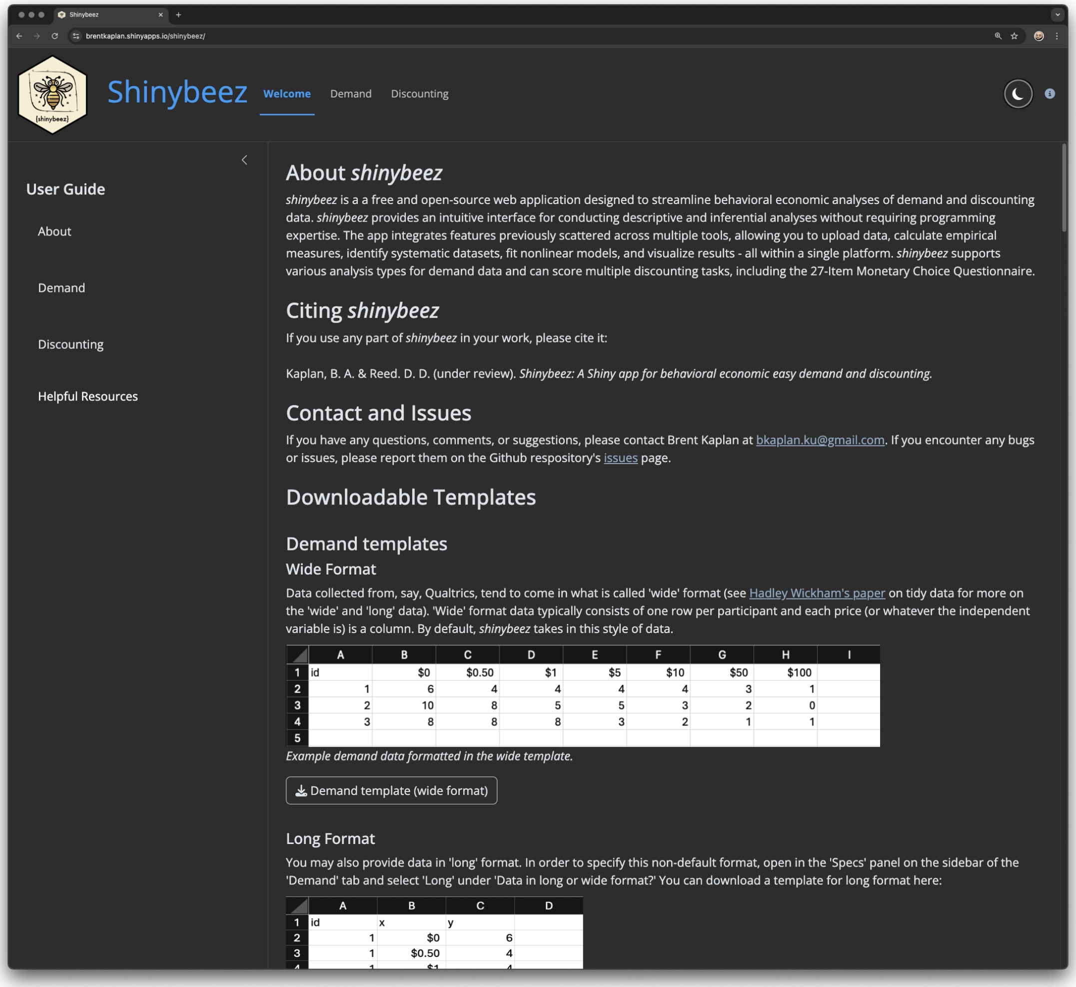


**FIGURE A3** Welcome page (dark mode). Welcome page (with dark mode option selected) with instructions about how to use the app along with template files.

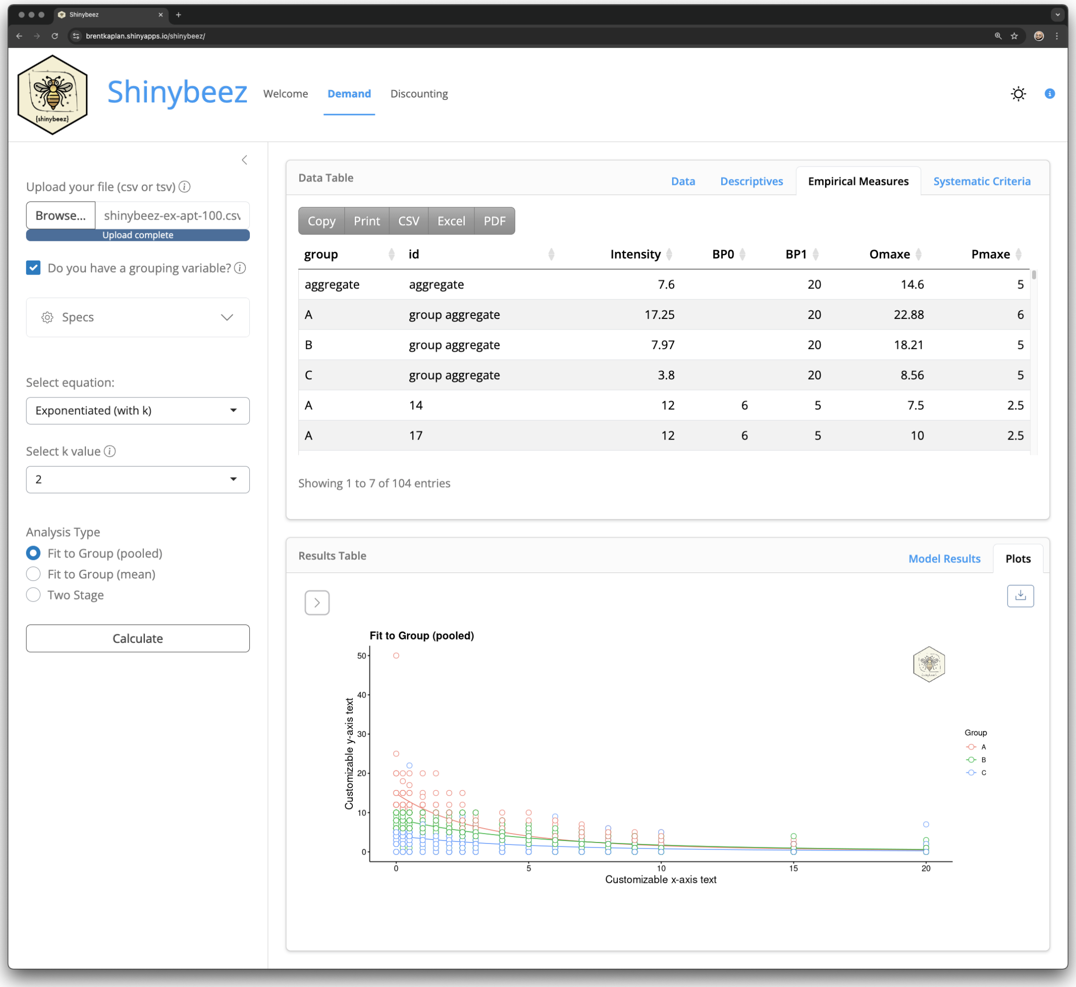


**FIGURE A4** Fit to Group (Pooled) with group. Top box shows the exportable table of empirical demand measures. Bottom box shows visualization of the Fit to Group (pooled) with group specified.

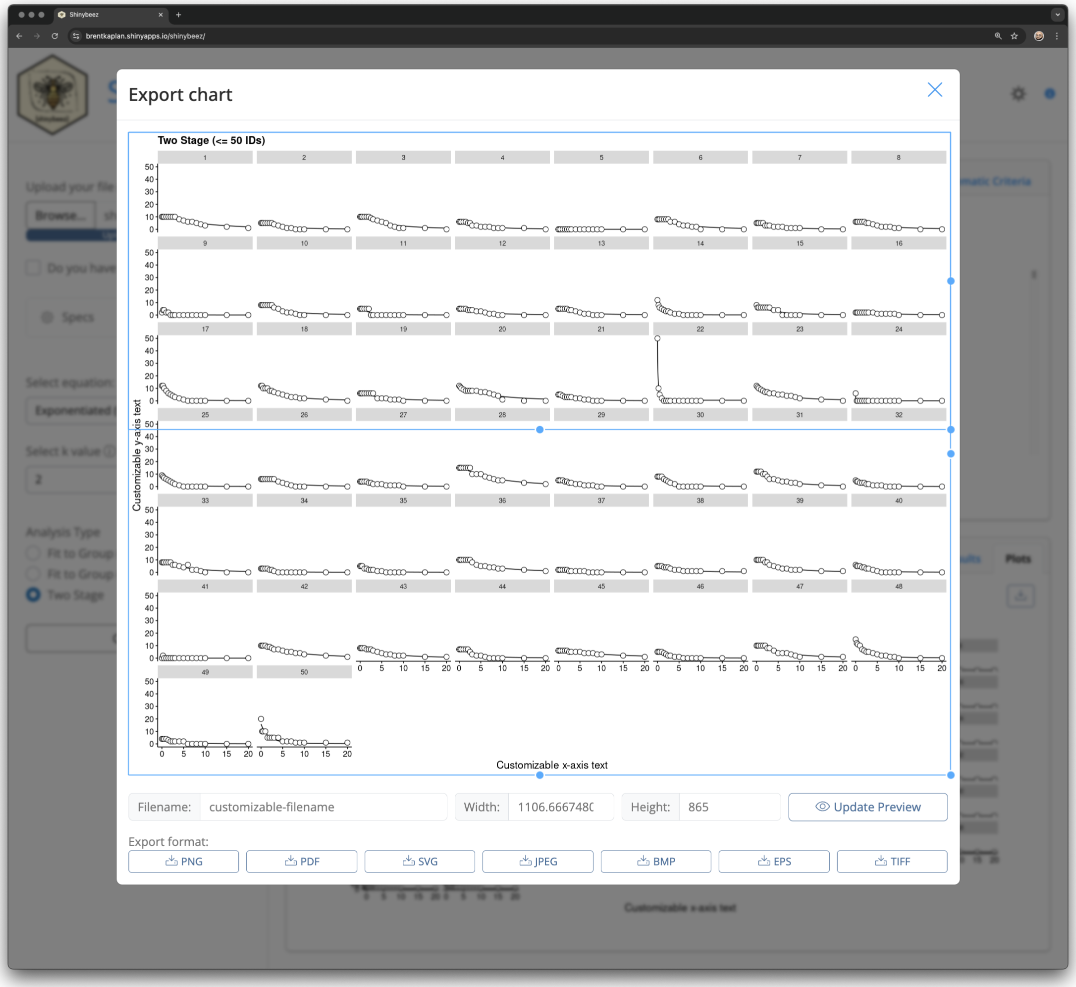


**FIGURE A5** Two Stage (50 or fewer IDs) and associated export options.

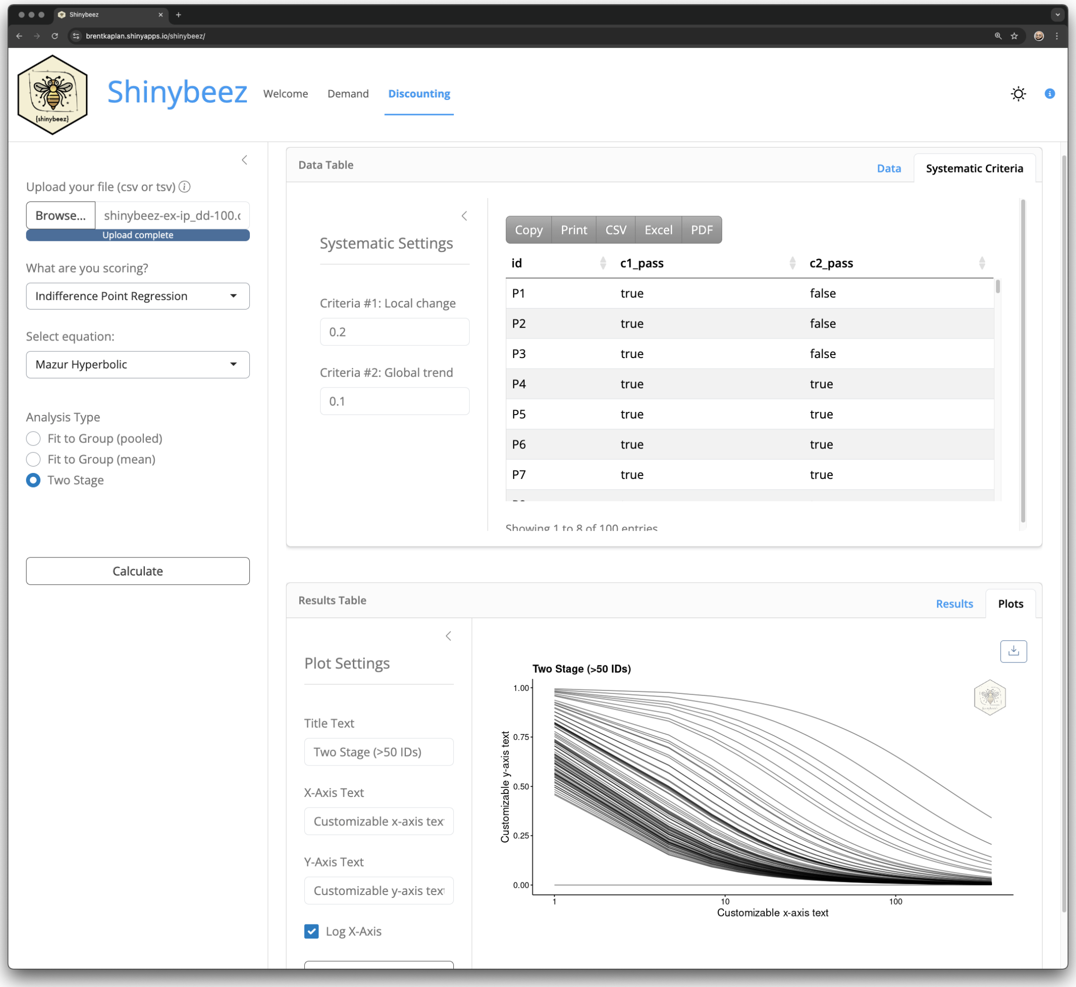


**FIGURE A6** Discounting customizable criteria and plot settings. Top box shows the customizable criteria options for discounting. Bottom box shows customizable plot settings for discounting.

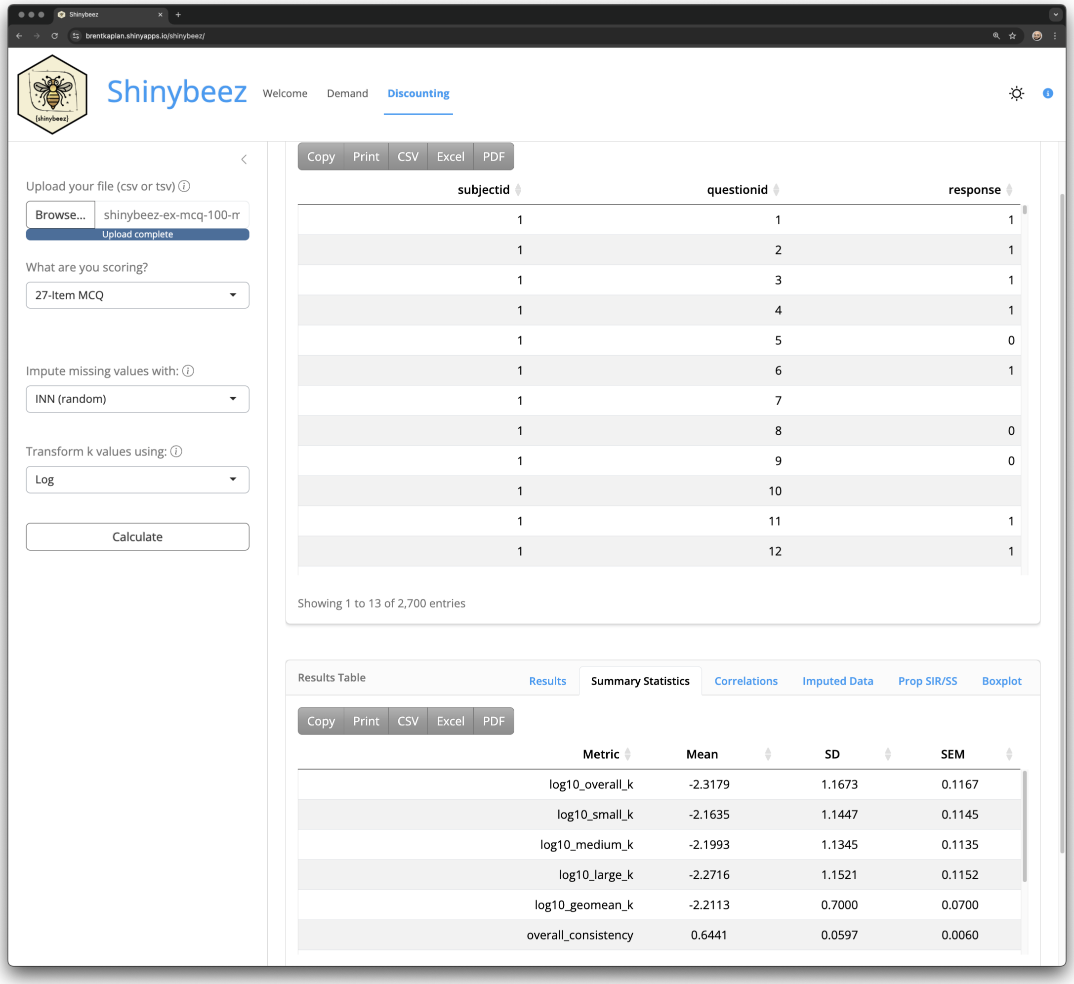


**FIGURE A7** 27-Item MCQ summary.

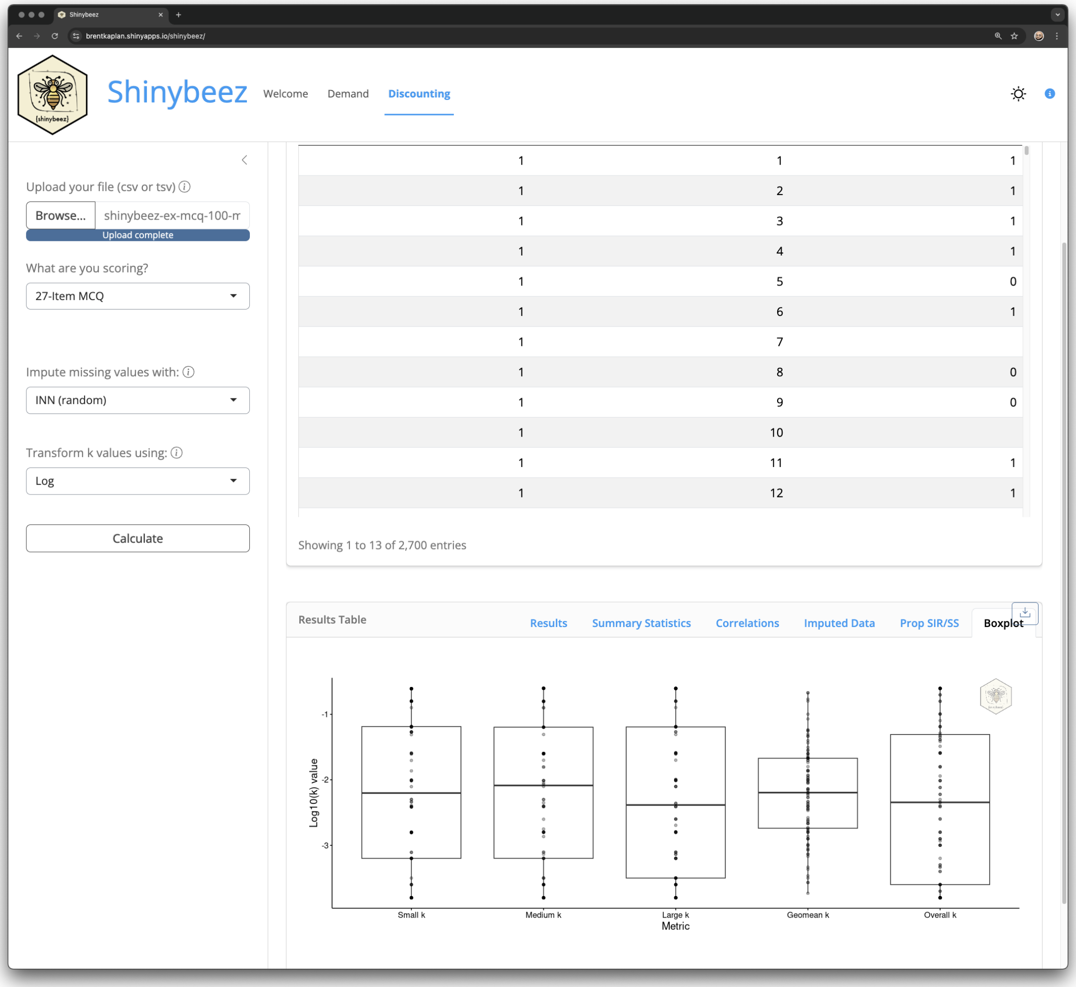


**FIGURE A8** 27-Item MCQ boxplots. Boxplots of $k$ values generated from scoring the 27-Item Monetary Choice Questionnaire.