
GLIMPSE User Manual



Version 2.1.0

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1. Introduction

1.1. Version Information and Licensing

This manual describes version 2.1.0 of the GLIMMPSE software. The manual applies to all 2.1.x versions of GLIMMPSE (e.g. 2.1.0, 2.1.1, 2.1.2, etc.).

GLIMMPSE is released under the [GNU Public License version 2.0](#).

The GLIMMPSE program is free software. Users can redistribute it and/or modify it under the terms of the GNU General Public License as published by the Free Software Foundation, using either version 2 of the License, or any later version. This program is distributed in the hope that it will be useful, but WITHOUT ANY WARRANTY—without even the implied warranty of MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE. See the GNU General Public License for more details.

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1.2. Welcome to GLIMMPSE 2.1.0

GLIMMPSE 2.1.0 is an open-source online tool for calculating power and sample size. GLIMMPSE has been designed so that researchers and scientists with a varying levels of statistical training can have access to reliable power and sample size calculations. For optimum usability, GLIMMPSE provides two different modes. In *Guided Mode* users receive step-by-step guided instructions for entering data in order to obtain power and sample size outputs. In *Matrix Mode* users receive less guidance, and are assumed to possess in-depth statistical training.

GLIMMPSE can compute power or sample size for univariate and multivariate linear models with Gaussian errors [Muller and Stewart \(2006\)](#). GLIMMPSE supports two main types of study design models: designs with only fixed predictors, and designs with fixed predictors and a single Gaussian covariate. The values of a fixed predictor are set as part of the study design, and are known without appreciable error. In contrast, Gaussian covariates are not observed until data is collected. Common designs with only fixed predictors include t-tests, analysis of variance (ANOVA), and multivariate analysis of variance (MANOVA). Common designs that control for a covariate include analysis of covariance (ANCOVA) and multivariate analysis of covariance (MANCOVA).

Details about power calculations for the general linear multivariate model with Gaussian data and fixed predictors can be found in ([Muller and Peterson 1984](#)), ([Muller and Barton 1989](#)), ([Muller, Lavange, Ramey, and Ramey 1992](#)), ([Muller, Edwards, Simpson, and Taylor 2007](#)), ([Muller and Stewart 2006](#)), and ([Muller et al. 2007](#)). Details for fixed predictors with a single Gaussian covariate can be found in ([Glueck and Muller 2003](#)).

GLIMMPSE utilizes a Java web services architecture ([McGovern, Tyagi, Stevens, and Mathew 2003](#)), designed to facilitate future support of additional statistical models. The tool is hosted at .

1.3. Why GLIMMPSE?

Other programs, such as POWERLIB, NQuery, and Pass, also calculate power and sample size. So why use GLIMMPSE?

GLIMMPSE has several advantages over these other programs, because GLIMMPSE:

1. **Is free.** GLIMMPSE provides free online power and sample size computing.
2. **Is user friendly.** In both *Guided Mode* and *Matrix Mode* GLIMMPSE provides a step-by-step interface to assist researchers in producing accurate power and sample size calculations.

3. Calculates power and sample size for any univariate or multivariate test for the general linear multivariate model, assuming fixed predictors.
4. Produces confidence intervals on power estimates for designs with fixed predictors.
5. Produces power and sample size calculations for designs with a single Gaussian covariate.
6. Supports designs with unequal group sizes, and complicated covariance structures.
7. Creates basic power curves.

2. Using GLIMMPSE

2.1. When to Use GLIMMPSE

GLIMMPSE is a tool researchers and scientists can use to calculate reliable values for power and sample size. GLIMMPSE calculates power or sample size for designs with normally distributed outcomes, and for a variety of multilevel and longitudinal studies. GLIMMPSE can calculate power and sample size for common statistical tests and models including:

- One sample t-test
- Paired t-test
- Two sample t-test
- Analysis of variance (ANOVA)
- Analysis of covariance (ANCOVA)
- Repeated measures analysis of variance
- Multivariate analysis of variance (MANOVA)
- Multivariate analysis of covariance (MANCOVA)

2.2. How to Use GLIMMPSE

2.2.1. Initiating the GLIMMPSE Wizard

GLIMMPSE can be accessed with a standard web browser at . The GLIMMPSE start screen is shown in Figure 1. GLIMMPSE has been tested in Internet Explorer 8 ([Microsoft 2010](#)), Mozilla Firefox 13.0.1 ([Mozilla 2011](#)), Google Chrome 23.0.1271.95 ([Google 2011](#)) and Safari 5.0.3 ([Apple 2010](#)).

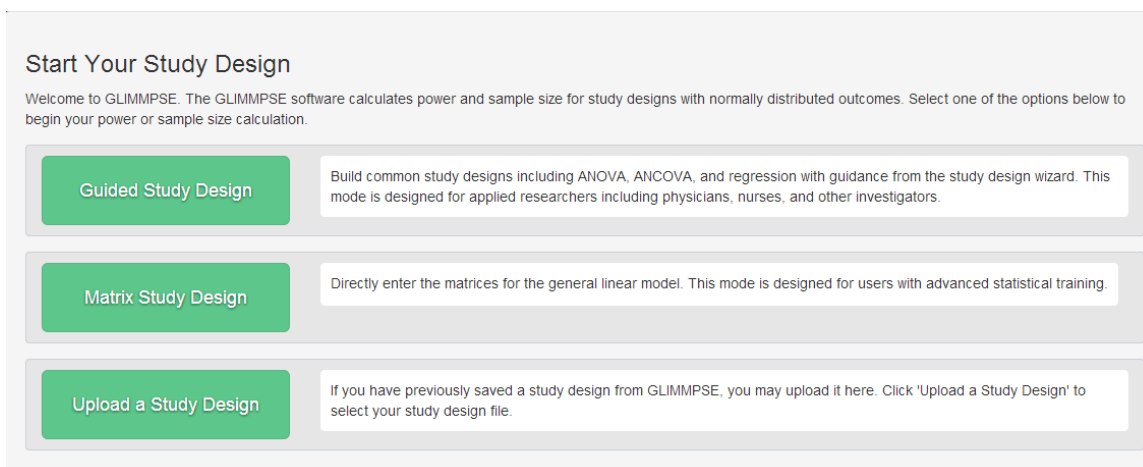


Figure 1: GLIMMPSE Start Screen

2.2.2. Choosing Between Guided Mode and Matrix Mode

The GLIMMPSE start screen presents three options: *Guided Mode*, *Matrix Mode*, and *Upload a Study Design*.




In *Guided Mode* users receive step-by-step guided instructions when entering inputs for power or sample size calculations. To choose Guided Mode, click the Guided Study Design box.

In *Matrix Mode* users receive less guidance, and are assumed to possess in-depth statistical training. *Matrix Mode* allows direct input of all matrices required for a power or sample size calculation. To choose Matrix Mode, click the Matrix Study Design box.

If the user has a study design saved from a previous GLIMMPSE session, the user may upload it by clicking the *Upload a Study Design* box. GLIMMPSE will open the saved study design and allow the user to continue the power or sample size analysis.

2.3. Basic Navigation for GLIMMPSE in Both *Guided Mode* and *Matrix Mode*

Once a mode of entry has been chosen, the steps required for GLIMMPSE to calculate power are listed as tabs on the left side of the *Introduction* screen. A white background indicates a tab as active, and a blue background designates a tab as inactive. Blue text designates a page within a tab as active, and gray designates a page as inactive. Only one page within one tab can be active at a time.

On the upper right of any screen in GLIMMPSE is a menu of options enabling users to save their study design by clicking  Save, consult the help library by clicking  Help, or cancel without saving and return to the *Start Your Study Design* screen by clicking .

Each section is broken into one or more sub-sections with the title in bold at the top of the page. Each screen contains instructions and/or areas for user inputs. Users navigate by clicking on the section titles and sub-sections in the left navigation panel.

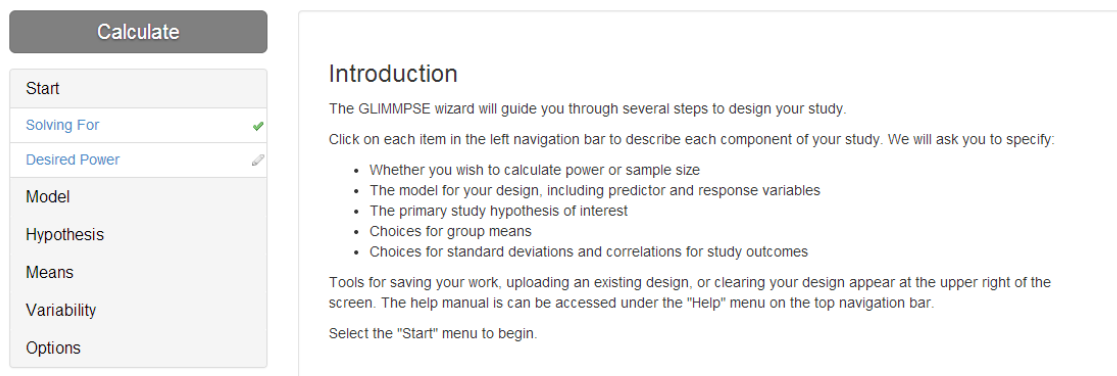

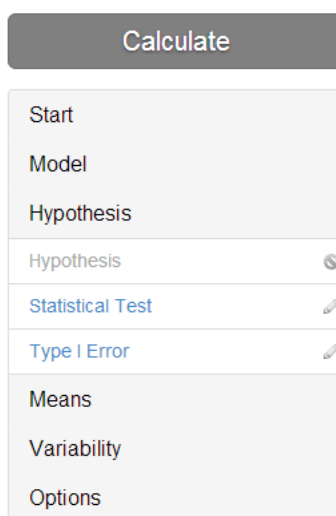
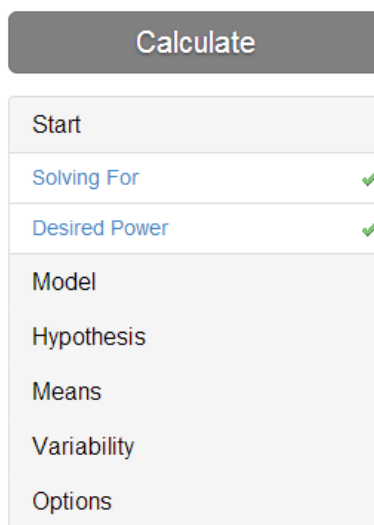


Figure 2: Example Start Screen

Following the *Introduction* screen (Figure 2), GLIMPSE will prompt the user to enter the details for the power or sample size calculation. The user may enter the details in any order. However, some screens cannot be accessed unless the user has completed information from previous screens. For example, if the user has not entered information in the *Response Variables* tab, then the user will not be able to enter information in the *Hypothesis* tab. If a tab is inaccessible due to missing information in an earlier screen, it will be indicated by a grey circle with a slash through it .

Figure 3: More information is required to access the *Hypothesis* screen.

Notice that in Figure 2 above there are pencil icons beside the *Desired Power* screen in the active *Start* tab. The pencil icons indicate screens which require additional information. Once the user have entered the required information, the pencil will turn into a green check mark, as shown in Figure 4.



Calculate	
Start	
Solving For	✓
Desired Power	✓
Model	
Hypothesis	
Means	
Variability	
Options	

Figure 4: Indication that the *Solving for* screen is complete.

Some screens are optional, and will already have a check mark beside them.

2.3.1. Typing Into a Text Box

Several screens in GLIMMPSE will ask you to specify information by typing into a text box. To input information in a text box, click in the text box and type the requested information. To complete the entry you may press **Enter** on your keyboard.

To delete entries in a list associated with the text box, click ✕ to delete the entry.

Figure 5 shows three examples of text box entries with the text boxes highlighted in blue.

Figure 5 shows three sections of the GLIMMPSE interface:

- A Desired Power:** A text box labeled "Enter a power value" with a dropdown arrow. Below it are two input fields containing "0.95" and "0.99", each with a clear button (X).
- B Response Variable Name:** A text box labeled "Enter a response variable". Below it is an input field containing "Expected Pain" with a clear button (X).
- C Scale Factor for Means:** A text box labeled "Scale Factors for Means" with a dropdown arrow. Below it are two input fields containing "2" and "4", each with a clear button (X).

Figure 5: Examples of text boxes that are used to A) list the desired power values; B) enter response variables name; and C) specify scale factors for means.

2.3.2. Using Drop Down Lists

When GLIMMPSE requires you to choose from a defined list of options, these options will be presented in a drop down list. Figure 6 shows an example of a drop down list. To choose an option from a drop down list, click on the down arrow (see [1]), then select your choice from the list of options (see [2]).

Figure 6 shows a table with two columns: "Gender" and "Relative Group Size".

Gender	Relative Group Size
Male	1 ▼
Female	1 ▼

An arrow labeled [1] points to the down arrow in the "Male" row. A second arrow labeled [2] points to the number "4" in the expanded dropdown list for the "Female" row. The expanded list shows numbers 1 through 10, with "4" highlighted in blue.

Figure 6: Example of a drop down menu.

2.3.3. Radio Buttons and Check Boxes

In some cases, you must choose from a list of options by selecting a radio button or checking a box. The radio buttons allow you to select only one option. The check boxes allow you to select more than one option. To select an option, click on the radio button or check the box next to that option. Figure 7 shows an example of a radio button (see A), and a check box (see B).

Select the assumptions for the confidence intervals:

☒ B is fixed, but Σ_e is estimated ← A. Choose one option
☐ Both B and Σ_e are estimated

Select one or more statistical tests

☒ Hotelling Lawley Trace ← B. Choose multiple options
☐ Pillai-Bartlett Trace
☐ Wilks Likelihood Ratio
☒ Univariate Approach to Repeated Measures with Box Correction
☐ Univariate Approach to Repeated Measures with Geisser-Greenhouse Correction
☐ Univariate Approach to Repeated Measures with Huynh-Feldt Correction
☐ Univariate Approach to Repeated Measures, uncorrected

Figure 7: Example of radio buttons and check boxes.

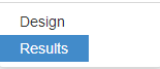

2.3.4. Results Report


Power results are displayed in a table with each row representing an individual power calculation. If multiple factors have been specified in the study design (for example, multiple Type I error rates, variability scale factors, etc.) then the results table will have multiple rows. See Table 1 below for an example of the information displayed for a given results report.

Every results report for power contains both calculated and desired power values. When solving for power, these two values are the same. When solving for sample size, it may not be possible to achieve the exact power value specified by the user. In this case, *Target Power* is the default power value (the power value specified by the user), and *Power* is the calculated power for the sample size that best matches the desired power.

A power curve may also be requested, with power on the vertical, or Y , axis and either the regression coefficient scale factor, covariance scale factor, or total sample size on the horizontal, or X , axis.

Power results can be saved to a comma delimited file so that users can import the data into other statistical

packages. To save the power results, click  from the  menu on the upper right corner of the screen. For transparency, the matrices used in the calculations are accessible on the results screen. This is most useful in *Guided Mode*, where matrix information is largely hidden from the user. To view the exact matrices used

in the calculations, click .

Column Name	Description
Power	Calculated power
Confidence Limits	Lower and Upper limits of the 95% confidence interval
Total Sample Size	Total number of research participants required to achieve the actual power
Target Power	The desired power
Type I Error Rate	The Type I error value
Test	Name of the statistical test
Means Scale Factor	Scale factor applied to the \mathbf{B} or \mathbf{B}_F matrix
Variability Scale Factor	Scale factor applied to the Σ_E matrix
Power Method	Indicates whether conditional, unconditional, or quantile power was used
Quantile	If the current power method is quantile power, this indicates the quantile of the distribution of possible powers. Otherwise, this field is empty.

Table 1: Information displayed for each power result.

2.4. Basic Navigation for *Guided Mode*

2.4.1. Entering Predictor Variables

In Guided Mode, GLIMPSE requires the user to enter labels for predictor variable(s) (also called independent variables) and outcome variable(s) (also called dependent variables). Figure 8 shows an example of entering variable labels. To enter a variable label, type the label into the text box provided (see [1] in Figure 8). After each entry, press **Enter** on the keyboard.

For the predictor variables, GLIMPSE also asks the user to specify the categories for each variable. For example, the predictor variable “gender” has two categories, “male” and “female.” To specify categories associated with a given predictor, select a predictor in the text box on the left (see [2]), then enter the category labels into the text box on the right (see [3] in Figure 8). After each entry, press **Enter** on the keyboard.

Only category labels associated with the highlighted predictor label are shown. To delete predictors or category labels, select the unwanted label and click **×**. This removes the label from the list. If the user removes a predictor, the associated categories are automatically deleted.

Figure 8: Example of entering labels

2.5. Basic Navigation for *Matrix Mode*

2.5.1. Resizing and Entering Values Into a Matrix

In Matrix Mode, GLIMMPSE requires the user to define the matrices for the power calculation. Figure 9 shows an example of a matrix template in *Matrix Mode*. Sometimes the matrix dimensions are pre-determined. If not, the user can set the matrix dimensions by typing the number of rows into the row text box (see [1] in Figure 9) and the number of columns into the column text box (see [2] in Figure 9). Fill in the elements of the matrix by entering values into the text boxes within the matrix template (see [3] in Figure 9).

[1] 3	×	3 [2]
1	0	0
0	1	0
0	0	1

Figure 9: Example of entering values into a matrix

3. Using *Guided Mode: A Screen-by-Screen Tour*

In *Guided Mode* users receive step-by-step guided instructions when entering inputs for calculating power and sample size for use in study design.

3.1. Start

3.1.1. Introduction

The *Introduction* screen contains a summary of the steps involved in the power or sample size analysis.

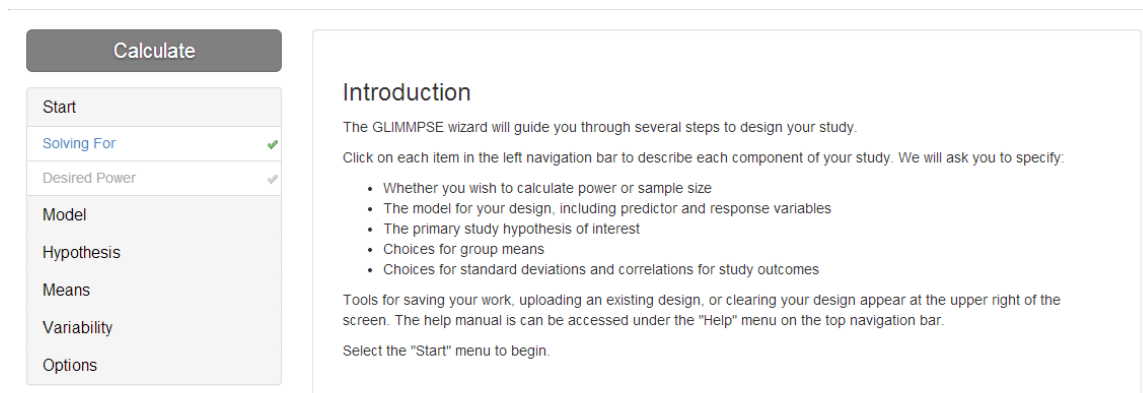


Figure 10: Introduction Screen

3.1.2. Solving For?

The *Solving For?* screen allows the user to select either a power or sample size calculation.

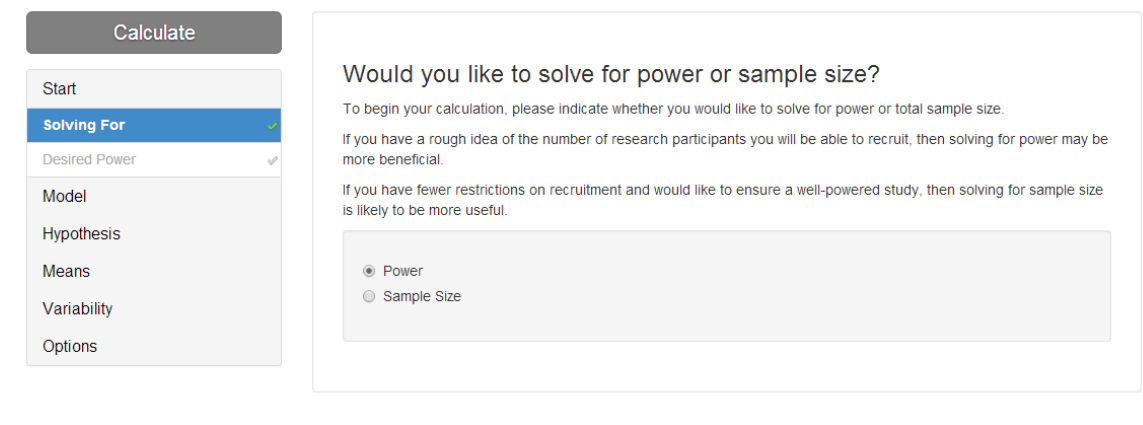


Figure 11: Solving For? Screen

When *power* is selected, the inputs will be used for a power analysis. The power analysis will produce a value(s) between 0 and 1, representing the probability the study will provide an answer to the question of interest. When *sample size* is selected, the inputs will be used to calculate the number of individual sampling units (also called participants, if referring specifically to people) needed for the study to achieve the desired power.

If the number of participants is not set, we recommend solving for sample size in order to obtain the appropriate sample size for achieving the goals of your study. However, if the sample size is set due to budgetary or other restrictions, a power calculation will indicate the probability that your study will provide a definitive answer to the question of interest.

On the screen, select *Power* or *Total Sample Size* by selecting the appropriate radio button.

3.1.3. Desired Power (if solving for Total Sample Size)

When solving for sample size, the user must enter the desired power for the study. Enter the target values as

decimals, i.e. 0.95, in the Power Values box and press **Enter** on the keyboard to add the value to the list.

Figure 12: Desired Power Screen

3.2. Model

3.2.1. Introduction

This screen provides an introduction to the *Model* section and defines the concept of an independent sampling unit. The sampling unit is typically the study participant. For multilevel designs and cluster randomized trials, the sampling unit may be a group of participants, such as schools or neighborhoods.

Figure 13: Sampling Units: Introduction Screen

3.2.2. Clustering

Clustering is present when research participants are organized into groups. Often, randomization in a study occurs at the group level rather than by individual research participants. The *Clustering* screen allows the user to enter up to three levels of clustering.

An example of clustering would be a study design in which the participants are students randomly selected from different schools in an area. In this case, each school would represent a cluster. An example of subgroups within a cluster would be each classroom within a given school.

Figure 14: Clustering Screen

If the study design does not include clustering, simply click on other sub-sections to proceed.

To add clustering, click the *Add clustering* button. Three text boxes will appear at the bottom of the screen:

Calculate

Start

Model

Clustering ✎

Predictors ✓

Covariate ✓

Response Variables ✎

Repeated Measures ✓

Relative Group Size ✓

Smallest Group Size ✓

Hypothesis

Means

Variability

Options

Clustering

In a clustered design, the independent sampling unit is a cluster, such as a community, school, or classroom. Observations within a cluster are correlated. The labels for observations within a cluster must be exchangeable. For example, child "id" within classroom can be reassigned arbitrarily. In contrast, observations across time cannot be reassigned and should not be considered clustered observations. Clustering, or repeated measures, or a combination, creates a multilevel design. The common correlation between any pair of cluster members is termed the intraclass correlation or intracluster correlation.

To include clustering in the study, click "Add clustering" and follow the prompts. Use the "Remove clustering" button to remove clustering information.

Cluster name (Level 1)

Number of observations or sub-clusters within clusters of this type

Intracluster correlation

Add Subgroup
Remove Subgroup
Clear All

Figure 15: Clustering Options

Enter the *Cluster name*, specify the *Number of observations or sub-clusters within each cluster of this type*, and specify the *Intra-cluster correlation*. The Intra-cluster correlation is the expected correlation between pairs of observations within the cluster.

To add a subgroup to the cluster, click *Add subgroup* and fill in the information for that subgroup. GLIMMPSE allows one primary cluster and two subgroups.

Calculate

Start

Model

Clustering ✓

Predictors ✓

Covariate ✓

Response Variables ✎

Repeated Measures ✓

Relative Group Size ✓

Smallest Group Size ✎

Hypothesis

Means

Variability

Options

Clustering

In a clustered design, the independent sampling unit is a cluster, such as a community, school, or classroom. Observations within a cluster are correlated. The labels for observations within a cluster must be exchangeable. For example, child "id" within classroom can be reassigned arbitrarily. In contrast, observations across time cannot be reassigned and should not be considered clustered observations. Clustering, or repeated measures, or a combination, creates a multilevel design. The common correlation between any pair of cluster members is termed the intraclass correlation or intracluster correlation.

To include clustering in the study, click "Add clustering" and follow the prompts. Use the "Remove clustering" button to remove clustering information.

Cluster name (Level 1)

Number of observations or sub-clusters within clusters of this type

Intracluster correlation

Cluster name (Level 2)

Number of observations or sub-clusters within clusters of this type

Intracluster correlation

Add Subgroup
Remove Subgroup
Clear All

Figure 16: Clustering Sub-Groups

Continuing with the above example, the subgroup *Cluster name* would be “classroom,” the *Number of observations* would be the number of students within each classroom, and the *Intra-cluster correlation* would be the expected agreement between students within each classroom.

To remove a subgroup or remove clustering, simply click *Remove subgroup* or *Clear All*.

3.2.3. Predictors

Independent sampling units may be randomized to different treatments, or be classified by characteristics such as gender. The characteristics divide the sampling units into study groups. The *Predictors* screen allows the user to define the study groups by specifying *fixed predictors*. Enter the fixed predictors as described in Section 2.4.1. For one-sample designs with no fixed predictors, leave the table blank.

Calculate

Start

Model

Clustering ✓

Predictors ✓

Covariate ✓

Response Variables ✎

Repeated Measures ✓

Relative Group Size ✓

Smallest Group Size ✎

Hypothesis

Means

Variability

Options

Predictors

Describe the predictors which assign independent sampling units into groups, such as gender or treatment. The choice of study design determines the values of fixed predictors (such as drug dose or gender). A common example of a fixed predictor is treatment group, for which the independent sampling unit is randomized to a placebo or an active drug group.

For a one sample design, leave the table blank.

To enter fixed predictors: Enter the name of each predictor into the list box and click "enter" on your keyboard. To remove an item, click the "x" next to the item. For example, one might enter "treatment" as a predictor. For example, one could select "treatment", then add the values "drug" and "placebo."

Predictor Name

Enter predictor name

treatment x

Category Names for 'treatment'

Enter category for 'treatment'

home based program x

delayed program control x

Figure 17: Predictors Screen

3.2.4. Covariate

The *Covariate* screen allows the user to control for a single, normally distributed predictor (also known as a normally distributed covariate). For example, a scientist may wish to examine the effect of a drug when controlling for age. In this case, age would be the covariate. If the study design does not include a normally distributed predictor, leave the checkbox blank. If the study design does include a covariate, check the checkbox.

Calculate

Start

Model

Clustering ✎

Predictors ✓

Covariate ✓

Response Variables ✎

Repeated Measures ✓

Relative Group Size ✓

Smallest Group Size ✓

Hypothesis

Means

Variability

Options

Controlling for a single, normally distributed predictor

A common experimental design is an analysis of covariance, which includes one or more fixed predictors and one or more continuous control variables, the "covariates." For example, one might run an experiment with 10 males and 10 females, with an indicator variable for gender as a fixed predictor and age as a covariate.

A common special case uses a series of repeated measurements on a continuous outcome. The first measurement, observed prior to treatment, is used as a baseline covariate. The other repeated measurements are outcomes in the general linear multivariate model.

GLIMMPSE can calculate power for hypotheses concerning the fixed predictors, optionally controlling for a single normally distributed predictor. If you plan to include a single normally distributed predictor in your model, click the checkbox below.

At present, the GLIMMPSE software does not calculate power for multiple normally distributed predictors nor non-normally distributed predictors.

☐ Control for a single, normally distributed predictor.

Figure 18: Gaussian Predictor Screen

3.2.5. Response Variables

The *Response Variables* screen allows the user to specify the response or dependent variables for the study. For example, if “expected pain” is the desired outcome, enter “expected pain” in the text box.

Figure 19: Response Variables

3.2.6. Repeated Measures

The *Repeated Measures* screen allows the user to describe repeated measures. Repeated measures are present in a study when multiple measurements are taken on each research participant. An example of repeated measures would be researchers taking a participant’s blood pressure once a month for six months.

If the design does not have repeated measures, simply click on other sub-sections to proceed. If the design includes repeated measures, click *Add repeated measures* and fill in the requested information.

Units is a user-specified description of the repeated measure. For example, if the repeated measures are taken once every month, the unit could be “month.” Enter a label for the units of the repeated measure.

Enter the *Type* of unit. For *Numeric* repeated measures, both the distance and ordering between measurements is meaningful. Measuring blood pressure every month for 6 months is a numeric repeated measure. GLIMPSE will auto-populate an equal distance between repeated numeric measures. You can change the distance between the measures by typing into the text boxes. For *Ordinal* repeated measures, the ordering of the measurements is meaningful, but the distance between measurements is assumed to be equal. For example, repeated measures of the participant’s heart rate taken in the morning, afternoon, and evening. For *Categorical* repeated measures, neither the ordering nor the distance between the measures is meaningful. For example, repeated measures of breast density using three different instruments, Device A, B, and C.

Number of Measurements allows you to specify the number of times the repeated measure will be taken. For the blood pressure example, the *Number of Measurements* would be 6 because blood pressure was measured every 6 months. For numeric repeated measures, GLIMPSE 2.0 auto-populates equidistant measurements. To change the distance between measures, type into the text boxes. For example, if blood pressure was measured every month for the first three months, then every other month for the next six months, the user would type 1, 2, 3, 5, 7, 9 into the text boxes.

Calculate

Start

Model

Clustering ✓

Predictors ✓

Covariate ✓

Response Variables ✓

Repeated Measures ✓

Relative Group Size ✓

Smallest Group Size ✎

Hypothesis

Means

Variability

Options

Repeated Measures

Repeated measures are present when a response variable is measured on each research participant on two or more occasions or under two or more conditions.

If the study includes repeated measurements, click "Add repeated measures" and follow the prompts. The text entered in the "Units" text box indicates the dimension over which measures were taken (ex. time, days, locations, etc.). The choice of "Type" indicates whether the repeated measures are numeric (ex. time), ordinal (ex. 1st, 2nd, 3rd), or categorical (ex. arm, leg, hand).

You may specify up to 3 factors of repeated measures.

Units (Level 1)

month

Type

Numeric ▼

Number of measurements

6 ▼

Spacing

1

2

3 ▲▼

4

5

6

Reset to Equal Spacing

Add Level
Remove Level
Clear All

Figure 20: Repeated Measures

Nested repeated measures are added via the *Add Level* button. For example, consider a design in which a participant's blood pressure is measured every month for six months, and at each visit in three different positions (for example, standing, sitting, and supine). The design would include doubly repeated measures with one level for "month" and a second nested level for "position." The user may add up to three levels of repeated measures.

To add a sub-level, click the *Add level* button. Three more text boxes will appear:

Calculate

Start

Model

Clustering ✓

Predictors ✓

Covariate ✓

Response Variables ✓

Repeated Measures ✓

Relative Group Size ✓

Smallest Group Size ✎

Hypothesis

Means

Variability

Options

Repeated Measures

Repeated measures are present when a response variable is measured on each research participant on two or more occasions or under two or more conditions.

If the study includes repeated measurements, click "Add repeated measures" and follow the prompts. The text entered in the "Units" text box indicates the dimension over which measures were taken (ex. time, days, locations, etc.). The choice of "Type" indicates whether the repeated measures are numeric (ex. time), ordinal (ex. 1st, 2nd, 3rd), or categorical (ex. arm, leg, hand).

You may specify up to 3 factors of repeated measures.

Units (Level 1)

Type

Numeric ▼

Number of measurements

6 ▼

Spacing

1

2

3

4

5

6

Reset to Equal Spacing

Units (Level 2)

Type

Ordinal ▼

Number of measurements

3 ▼

Add Level
Remove Level
Clear All

Figure 21: Repeated Measures: Add Level

3.2.7. Relative Group Sizes (if solving for Power)

For designs with multiple study groups (see Section 3.2.3), the user may specify equal or unequal group sizes. On the Relative Group Sizes screen, the user can select the relative sizes of each group by selecting a value from the drop down list.

For example, consider a design with males and females, randomized to receive either an active drug or a placebo. For equal group sizes, a "1" should be selected for each drop down list as shown in Figure 22. However, if there were twice as many males receiving the drug compared to females receiving the drug, the user would select a "2" for the male + drug group, and "1" for the remaining groups.

Calculate

Start

Model

Clustering ✓

Predictors ✓

Covariate ✓

Response Variables ✎

Repeated Measures ✓

Relative Group Size ✓

Smallest Group Size ✓

Hypothesis

Means

Variability

Options

Relative Group Sizes

Specify whether the study subgroups are of equal or unequal size.

For equal group sizes, select a "1" in the drop-down list next to each study subgroup. This is the default study design.

For unequal group sizes, specify the ratio of the group sizes. For example, consider a design with an active drug group and a placebo group. If twice as many study participants receive the placebo, a value of "2" would be selected for the placebo group, and a value of "1" would be selected for the active drug group.

treatment	Gender	Relative Group Size
drug	male	1 ▼
drug	female	1 ▼
placebo	male	1 ▼
placebo	female	1 ▼

Figure 22: Relative Group Sizes Screen

3.2.8. Smallest Group Size

When solving for power, the user specifies the total sample size for the design by the relative group sizes and the smallest group size. On the *Smallest Group Size* screen, the user may enter one or more values describing the number of participants in the smallest group.

For example, consider a design with a treatment and a placebo group, in which three times as many participants receive the treatment compared to the placebo. With a smallest group size of 20, 30, or 40, the total sample size for the design would be 80 (i.e. 60 treated participants, 20 with placebo), 120, and 160 participants respectively.

Calculate

Start

Model

Clustering ✓

Predictors ✓

Covariate ✓

Response Variables ✎

Repeated Measures ✓

Relative Group Size ✓

Smallest Group Size ✓

Hypothesis

Means

Variability

Options

Size of the Smallest Group

Enter the number of independent sampling units (participants, clusters) in the smallest group in the study. If your group sizes are equal, the value is the same for all groups. You may enter multiple values for the smallest group size in order to consider a range of total sample sizes.

Type each value into the list box and click "enter" on your keyboard. To remove an item, click the "x" next to the item.

Smallest Group Size

Enter a sample size value

20 ✕

30 ✕

40 ✕

Figure 23: Smallest Group Size Screen

3.3. Hypothesis

3.3.1. Introduction

This screen provides an introduction to the *Hypothesis* section.

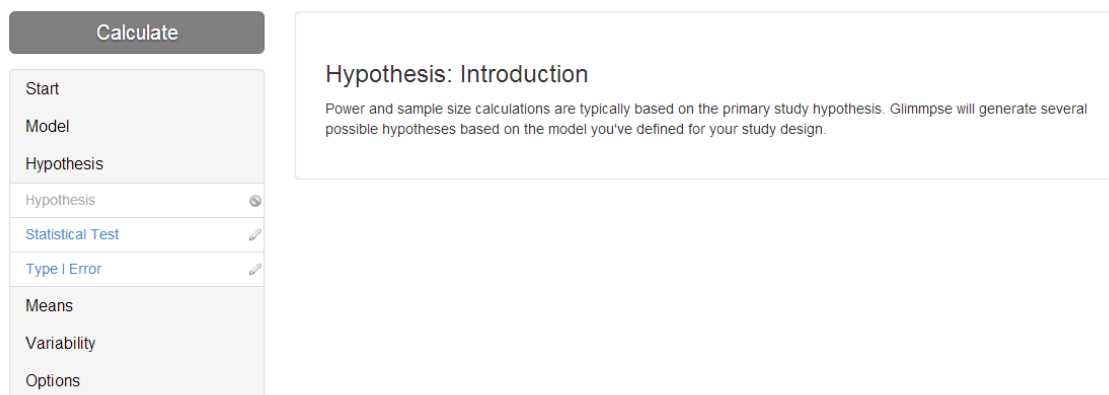


Figure 24: Hypothesis Introduction Screen

3.3.2. Hypothesis

The *Hypothesis* screen allows the user to select the primary hypothesis of interest. The user first selects the type of hypothesis by clicking the drop down list. Additional information will be requested depending on the type of hypothesis.

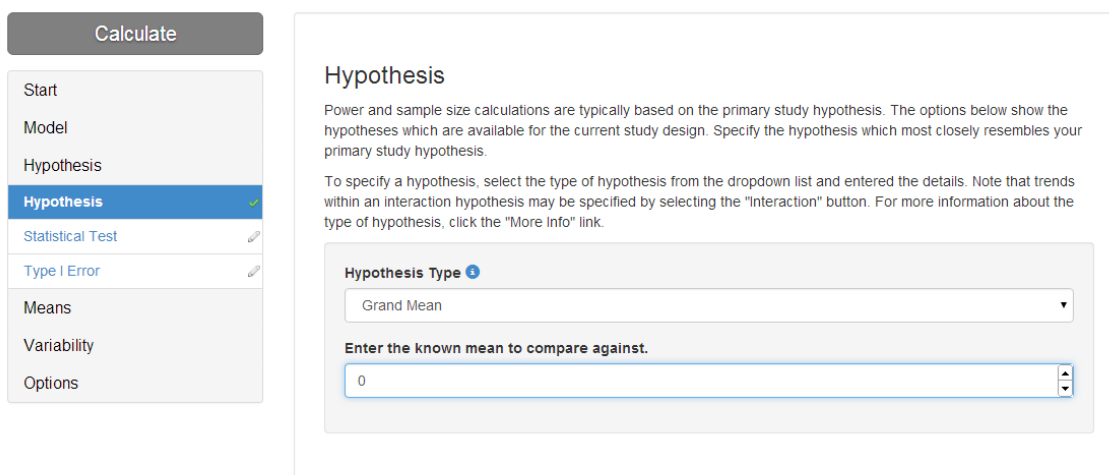


Figure 25: Hypothesis Screen

A *Grand Mean* hypothesis compares the overall mean response in a sample of participants against a known value. For example, an investigator may wish to determine if body mass index values for participants in a particular state

differs from the United States national average. After selecting the *Grand mean* radio button, the user will be prompted to enter the known mean value for each response variable.

A *Main effect* hypothesis tests for the effect of a single predictor variable averaged across all other factors. For example, testing whether responses of participants in the treatment group differ on average from participant responses in a placebo group is a common main effect hypothesis. After selecting the *Main effect* radio button, the user will be prompted to select one predictor of interest by selecting the appropriate radio button.

A *Trend* hypothesis tests whether the effect of a single predictor follows a particular polynomial pattern, such as a linear or quadratic trend, across different levels of the predictor. After selecting the *Trend* radio button, the user will be prompted to select one predictor of interest. In addition, the user may select from six possible trends: no trend, change from baseline, linear trend, quadratic trend, cubic trend, or all polynomial trends.

An *Interaction* hypothesis tests whether the effect of one predictor changes depending on the value of one or more additional predictors. An interaction test also can be interpreted as a test of differences, as well as a test of parallel trajectories of response. For example, testing whether the effect of a cholesterol lowering medication on total serum cholesterol differs depending on the participant's gender is an example of an interaction hypothesis. After selecting the *Interaction* radio button, the user will be prompted to select one or more factors of interest by clicking the appropriate check boxes. In addition, the user may specify a trend for given factor by clicking the *Edit trend* button.

3.3.3. Statistical Test

The *Statistical Test* screen allows the user to select one or more statistical tests for the power or sample size calculations. A tutorial providing guidelines for selecting a test is available from the GLIMPSE Tutorials page at <http://samplesizeshop.org/education/tutorials>. Select the statistical test(s) you wish to use by clicking one or more check boxes.

Calculate

Start

Model

Hypothesis

Hypothesis

Statistical Test

Type I Error

Means

Variability

Options

Statistical Tests

Select the statistical tests to include in your calculations. For study designs with a single outcome, power is the same regardless of the test selected. Note that only the Hotelling-Lawley Trace and the Univariate Approach to Repeated Measures are supported for designs which include a baseline covariate.

Note that only the Hotelling-Lawley Trace and the Univariate Approach to Repeated Measures are supported for designs which include a baseline covariate.

Click [here](#) to learn more about selecting an appropriate test.

Select one or more statistical tests

- ☒ Hotelling Lawley Trace
- ☐ Pillai-Bartlett Trace
- ☐ Wilks Likelihood Ratio
- ☐ Univariate Approach to Repeated Measures with Box Correction
- ☐ Univariate Approach to Repeated Measures with Geisser-Greenhouse Correction
- ☐ Univariate Approach to Repeated Measures with Huynh-Feldt Correction
- ☐ Univariate Approach to Repeated Measures, uncorrected

Figure 26: Statistical Tests

3.3.4. Type I Error

Enter the target values for Type I Error as decimals (i.e. 0.05) in the Type I Error Values box. The user may

specify up to five Type I Error values.

Calculate

- Start
- Model
- Hypothesis
- Statistical Test
- Type I Error**
- Means
- Variability
- Options

Type I Error Rates

A Type I error occurs when a scientist declares a difference when none is actually present. The Type I error rate is the probability of a Type I error occurring, and is often referred to as α . Type I error rates range from 0 to 1. The most commonly used values are 0.01, 0.05, and 0.1.

Type each value into the list box and click "enter" on your keyboard. To remove an item, click the "x" next to the item.

Type I Error Rate

Enter a Type I error value

- 0.01
- 0.05
- 0.1

Figure 27: Type I Error

3.4. Means

3.4.1. Introduction

This screen provides an introduction to the *Means* section.

Calculate

- Start
- Model
- Hypothesis
- Means**
- Means
- Scale Factors
- Variability
- Options

Means: Introduction

In power analysis, it is necessary to choose mean values for the outcomes before running the study. The means are often obtained from published results or pilot data. Larger mean differences are easier to detect, and so have greater power. To detect smaller differences, the investigator will typically need a larger sample size.

To detect a difference between the groups, at least two subgroups should have means which differ by a scientifically meaningful amount. For example, in a study of cholesterol-lowering medication, we would expect the mean cholesterol level in the active drug group to be lower than the placebo group.

Figure 28: Means Introduction Screen

3.4.2. Means

The *Means* screen allows the user to enter the expected mean value for the experiment. Expected mean values are typically drawn from the literature or from pilot data. Differences between the entered means typically represent the smallest clinically relevant difference. The table should contain at least one value that is non-zero.

Calculate

- Start
- Model
- Hypothesis
- Means
- Means** ✓
- Scale Factors ✓
- Variability
- Options

Means

The table below shows the mean values for each outcome within each study subgroup. The study subgroups are listed along the left hand side of the table, and the outcomes are listed across the top.

Enter the mean values you expect to observe for each outcome within each study subgroup. The table should contain at least one value that is non-zero. Also, at least two subgroups should have means which differ by a scientifically meaningful amount.


month	1	2	3
Response	Expected Pain	Expected Pain	Expected Pain
Sample Mean	0.0	0.0	0.0

Figure 29: Means Screen

For designs with repeated measures, the user may enter means at each time (place, etc.).

3.4.3. Scale Factors

The *Scale Factors* screen for Means allows the user to compute power or sample size for the means as specified. For example, entering the scale factors 0.5, 1, and 2 would compute power for the the mean values divided by 2, the mean values as specified, and the mean values multiplied by 2. Type each value into the text box and press

Enter on your keyboard. To remove an item, click the  next to the item.

Calculate

- Start
- Model
- Hypothesis
- Means
- Means ✓
- Scale Factors** ✎
- Variability
- Options

Scale Factors for Means

In power analysis, it is not possible to know the exact values of means before the experiment is observed. Scale factors allow you to consider alternative values for the means by scaling the values entered on the previous screen. For example, entering the scale factors 0.5, 1, and 2 would compute power for the the mean values divided by 2, the mean values as specified, and the mean values multiplied by 2.

Type each value into the text box and click "enter" on your keyboard. To remove an item, click the "x" next to the item.

Scale Factor for Means

Figure 30: Scale Factors for Means Screen

3.5. Variability

3.5.1. Introduction

This screen provides an introduction to the *Variability* section.

Calculate

Start

Model

Hypothesis

Means

Variability

Within Participant

Covariate

Scale Factors

Options

Variability: Introduction

Power analysis requires information about the variability in the study outcomes, and the correlation among measurements on a given independent sampling unit.

In this section, you will provide standard deviations and correlations for the study outcomes and the covariate (if specified).

Figure 31: Variability Introduction Screen

3.5.2. Within Participant Variability

For a given participant, responses may vary across repeated measurements and for different response variables. The amount of variability can dramatically impact power and sample size. The *Within Participant Variability* screen allows the user to describe the variability he or she expects to observe for each within participant factor and response variable.

Separate tabs are presented for each “source” of correlation in the design. The *Responses* tab allows the user to specify the standard deviations of the response variables and any correlation between them. If repeated measures are present, a single tab will be presented for each level of repeated measures. Figure 32 shows an example design in which blood pressure is measured once a month for six months. GLIMMPSE will automatically combine the sources of correlation into a final covariance matrix.

Calculate

Start

Model

Hypothesis

Means

Variability

Within Participant ✓

Covariate ✎

Scale Factors ✎

Options

Within Participant Variability

For a given research participant, responses vary across response variables and across repeated measurements. The amount of variability can dramatically impact power and sample size.

Click on each of the tabs below to describe the variability you expect to observe for the response variables and each within-participant factor.

month

responses

Variability across month

Enter the correlations you expect to observe among the responses.

Correlation

	month 1	month 2	month 3	month 4	month 5	month 6
month 1	1	0.7	0.6968ℰ	0.6937ℰ	0.6906ℰ	0.6876ℰ
month 2	0.7	1	0.7	0.6968ℰ	0.6937ℰ	0.6906ℰ
month 3	0.6968ℰ	0.7	1	0.7	0.6968ℰ	0.6937ℰ
month 4	0.6937ℰ	0.6968ℰ	0.7	1	0.7	0.6968ℰ
month 5	0.6906ℰ	0.6937ℰ	0.6968ℰ	0.7	1	0.7
month 6	0.6876ℰ	0.6906ℰ	0.6937ℰ	0.6968ℰ	0.7	1

Unstructured correlation

Lear correlation

Figure 32: Within Participant Variability

3.5.3. Scale Factors

While GLIMMPSE requests standard deviations, it actually computes variances when it conducts the power or sample size calculations. There may be considerable uncertainty about what standard deviation or variance value to use. To account for this uncertainty, it is common to calculate power or sample size using alternative values for variability. Scale factors allow you to consider alternative values for variability by scaling the calculated covariance matrix. For example, entering the scale factors 0.5, 1, and 2 would compute power for the covariance matrix divided by 2, the covariance matrix as entered, and the covariance matrix multiplied by 2. Type each value into the text box and press **Enter** on your keyboard. To remove an item, click the ✕ next to the item.

Calculate

- Start
- Model
- Hypothesis
- Means
- Variability
- Within Participant
- Covariate
- Scale Factors**
- Options

Scale Factors for Variability

On the previous screens, you entered standard deviations and correlations. Glimpse will use these values to calculate a covariance matrix which describes the overall variability in the design.

Changes in variability can dramatically affect power and sample size results. It is not possible to know the variability until the experiment is observed. Scale factors allow you to consider alternative values for variability by scaling the calculated covariance matrix. For example, entering the scale factors 0.5, 1, and 2 would compute power for the covariance matrix divided by 2, the covariance matrix as entered, and the covariance matrix multiplied by 2.

Type each value into the text box and click "enter" on your keyboard. To remove an item, click the "x" next to the item.

Scale Factors for Variance

Scale Factors for Variability

2

Figure 33: Scale Factors for Variability Screen

3.6. Options

This screen provides an introduction to the Options section.

Calculate

- Start
- Model
- Hypothesis
- Means
- Variability
- Options**
- Power Method
- Confidence Intervals
- Power Curve

Options: Introduction

In this selection, you may optionally request confidence intervals for power, and power plots. For designs with a baseline covariate, you may select from different power methods.

Options: Introduction

Options: Introduction

Figure 34: Options

3.6.1. Power Calculation Method

For designs with a baseline covariate, two different methods are available to calculate power: quantile and unconditional power. For theoretical details, please see [Glueck and Muller \(2003\)](#). Select the power methods by clicking the check boxes. If quantile power is selected, the user must also specify one or more quantile values. For example, median power would be obtained by selecting *Quantile* power and entering "0.5" in the quantile list box.

Calculate

Start

Model

Hypothesis

Means

Variability

Options

Power Method ✓

Confidence Intervals ✓

Power Curve ✓

Power Calculation Method

For designs including a baseline covariate, two methods are available to calculate power: unconditional power and quantile power. One can think of the random covariate values as having been sampled from a normal distribution. Thus there are many possible realizations of the same experiment, and each realization may have a different power. The unconditional power is defined as the average of the possible power values (Gatsonis and Sampson, 1989; Glueck and Muller, 2003). The $100 \times v$ th quantile power is the power value chosen so that power as small or smaller occurs in $100 \times v$ percent of all possible realizations of the experiment.

For a detailed description of unconditional and quantile power, please see [Gatsonis and Sampson \(1989\)](#) and [Glueck and Muller \(2003\)](#).

Select one or more power methods below

☐ Unconditional

☒ Quantile

Enter one or more quantiles in the list below

Enter a quantile

0.5 ✕

Figure 35: Statistical Tests

3.6.2. Confidence Intervals

Power analysis involves some uncertainty in the choices for means and variability. Therefore, the *Confidence Intervals* screen allows the user to request confidence intervals on the power results. To include confidence intervals, uncheck the checkbox. The information on the confidence interval screen describes the data set (or publication) from which the choices for means and variances were obtained. For example, if a scientist were calculating power based on the means and variances obtained from pilot data, the scientist would enter information describing the pilot data set. The following information is required:

The *Assumptions* section allows the user to indicate if he or she is uncertain about the variance, but reasonably certain of the mean values, or uncertain of both the means and variance.

The *Upper and lower tail probabilities* define the width of the confidence interval. For example, a centered 95% confidence interval would have both upper and lower tail probabilities of 0.025.

The *Total sample size* value indicates the number of independent sampling units in the pilot data set (or publication).

The *Rank of the design matrix* describes a property of the predictor matrix used in the pilot data set. Please see [Muller and Stewart \(2006\)](#) for details about matrix rank.

Calculate

Start

Model

Hypothesis

Means

Variability

Options

Power Method ✓

Confidence Intervals ✓

Power Curve ✓

Confidence Interval Options

If the means (B) or the error covariance (Σ_e) are sample estimates, then the power values produced from these matrices will be random quantities. To account for this randomness, GLIMMPSE can calculate confidence intervals for power values using the techniques described by Taylor and Muller (1995), Gribbin (2007), and Park (2007).

☐ Don't include confidence intervals for power

Select the assumptions for the confidence intervals:

☒ B is fixed, but Σ_e is estimated

☐ Both B and Σ_e are estimated

Enter the upper and lower tail probabilities for the confidence intervals.
 We typically recommend the value 0.05 for the lower tail probability and 0 for the upper tail probability.

Lower Tail Probability

Upper Tail Probability

Describe the data from which you obtained the values for B and Σ_e .

Total sample size

Rank of the design matrix

Figure 36: Confidence Intervals

3.6.3. Power Curve Options

The *Power Curve Options* screen allows the user to create a power curve. A power curve describes the change in power (Y axis of the power curve) relative to the total sample size, regression coefficient scale factor, or the variability scale factor (all options for the X axis of the power curve).

To create a power curve, the user must 1) uncheck the check box, 2) select the value to appear on the horizontal axis, and 3) add one or more data series.

Depending on the study design, the user may request a large number of power or sample size values in a single request. A data series is defined by selecting a subset of the power or sample size values. The user creates a data series by selecting values for several study design variables and clicking the checkbox. A data series will be displayed as a single line on the power curve plot, as shown in Figure .

Results

- Table
- Plot
- Matrices

Start

- Design
- Coefficients
- Hypothesis
- Variability
- Options

Power Method ✓

Confidence Intervals ✓

Power Curve ✓

Power Curve Options

To create a power curve, uncheck the box below. Follow the prompts to define the curve.

☐ Don't create a power curve

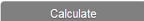
Select the quantity to display on the horizontal axis of the power curve.
The vertical axis will display the power value.

Total Sample Size

Select one or more data series by clicking the checkboxes
Double click the label to edit the legend label for the data series

<input type="checkbox"/> Label	Type I Error Rate	Means Scale	Variability Scale
<input checked="" type="checkbox"/> Series 1	0.05	3	5

Figure 37: Power Curve

Note that the *Power Curve Options* screen is the final screen in the GLIMMPSE wizard. If the study design is not complete, the Calculate button will be disabled . If you click on the Calculate button while it is disabled, a modal will appear on the screen and list the missing inputs, as shown in Figure 38.

SampleSizeSh

Save

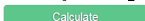
The following items are incomplete

- Hypothesis > Type I Error
- Means > Scale Factors
- Variability > Scale Factors
- Options > Power Curve

OK

Figure 38: Incomplete Study Design Modal

3.7. Calculate

When sufficient information for your power or sample size calculation has been entered, the *Calculate* button will be highlighted green. Click  to receive the results of your power analysis. Example results are shown in

Figures 39 and 41. For detailed information regarding the Power Results table, refer to Table 1. When calculating sample size for a clustered design, Power Results provide total sample size, with a breakdown of sample size per unit, as shown in Figure 40.

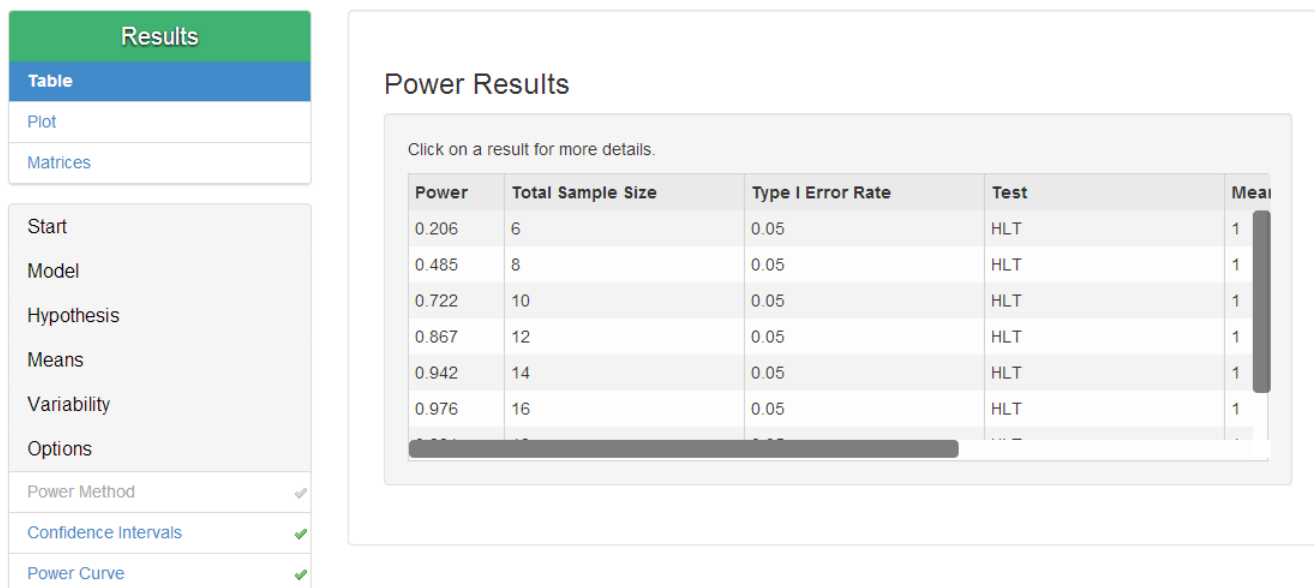


Figure 39: Results Table

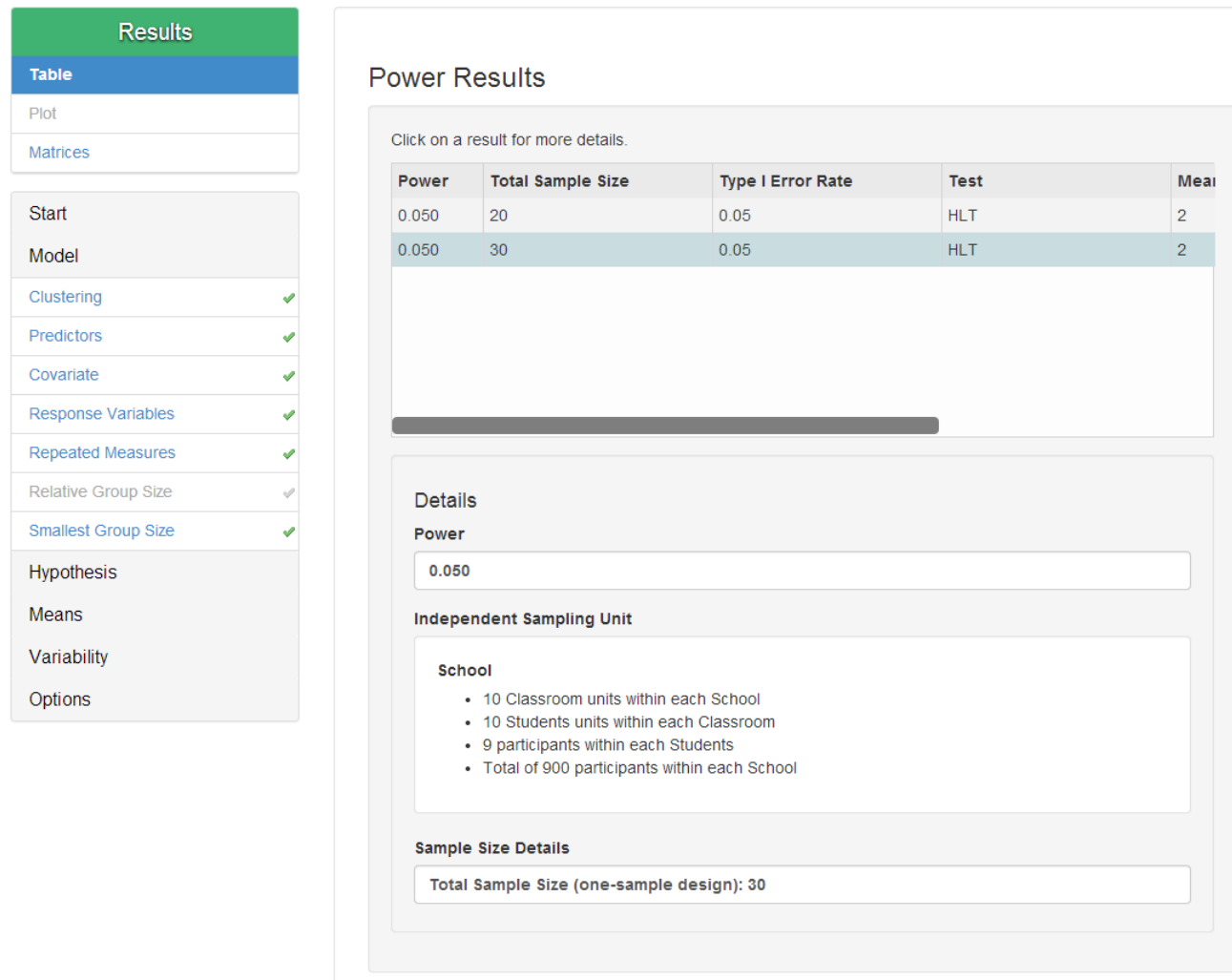


Figure 40: Total Sample Size for Clustered Design

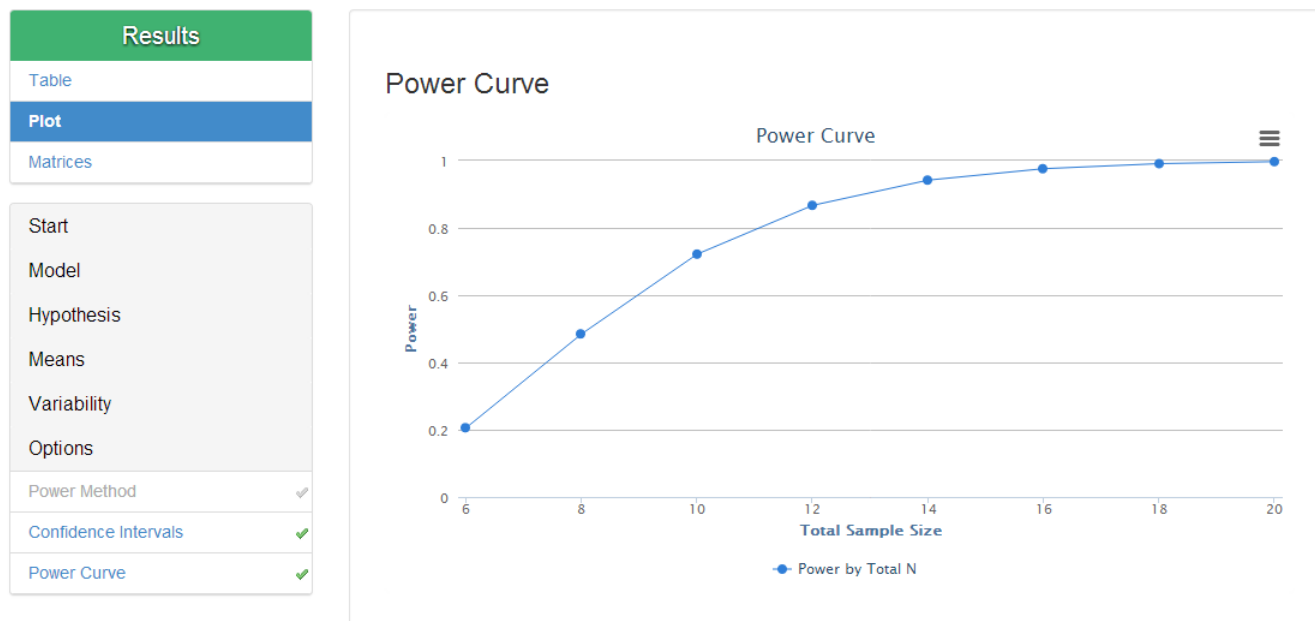


Figure 41: Results Plot

4. *Matrix Mode* Screen-by-Screen Tour

Matrix Mode allows direct input of all matrices required for a power calculation. In *Matrix Mode* users receive less guidance than in *Guided Mode*, and are assumed to possess in-depth statistical training.

4.1. Start

4.1.1. Introduction

The *Introduction* screen shown in Figure 42 briefly describes the required matrix inputs for the power or sample size calculation.

Calculate

Start

Solving For ✓

Desired Power ✓

Design

Coefficients

Hypothesis

Variability

Options

Introduction

The GLIMPSE wizard will guide you through several steps to design your study.

Click on each item in the left navigation bar to describe each component of your study. We will ask you to specify:

- Whether you wish to calculate power or sample size
- The model for your design, including predictor and response variables
- The primary study hypothesis of interest
- Choices for group means
- Choices for standard deviations and correlations for study outcomes

Tools for saving your work, uploading an existing design, or clearing your design appear at the upper right of the screen. The help manual is can be accessed under the "Help" menu on the top navigation bar.

Select the "Start" menu to begin.

Figure 42: Introduction Screen for *Matrix Mode*

4.1.2. Solving For?

The *Solving For?* screen shown in Figure 43 allows the user to select either a power or sample size calculation.

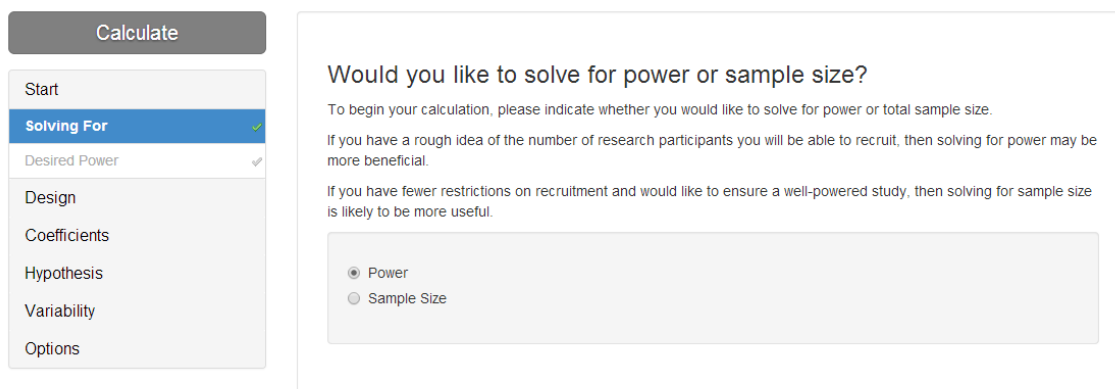


Figure 43: Solving For? Screen

When *Power* is selected, the inputs will be used for a power analysis. The power analysis will produce a value(s) between 0 and 1, representing the probability the study will answer the question of interest. When *Total Sample Size* is selected, the inputs will be used to calculate the number of individual sampling units (also called participants, if referring specifically to people) needed for the study to achieve the desired power.

If the number of participants is not set, we recommend solving for sample size in order to obtain the appropriate sample size for achieving the goals of your study. However, if sample size is set due to budgetary or other restrictions, a power calculation will indicate the probability that the study will provide a definitive answer to the question of interest.

On the screen, select *Power* or *Total Sample Size* by selecting the appropriate radio button.

4.1.3. Desired Power (if solving for Total Sample Size)

When solving for sample size, the user must enter the desired power for the study. Enter the target values as decimals (i.e. 0.95) in the Power Values box shown in Figure 44 and press **Enter** on your keyboard to add the value to the list.

Figure 44: Desired Power Screen

4.2. Design

4.2.1. Design Essence

In the *Design* section, the user will define the composition of the study by specifying the number of groups, how subjects are divided into groups, the size of each group, and whether the design will include a Gaussian covariate.

The Design Essence Matrix

In the general linear multivariate model with fixed predictors, $\mathbf{Y} = \mathbf{XB} + \mathbf{E}$, the \mathbf{X} matrix represents the study design. The same is true for \mathbf{F} in the general linear multivariate model with fixed predictors and a Gaussian predictor (Glueck and Muller 2003). For simplicity, we will only discuss \mathbf{X} (since the instructions do not change for \mathbf{F}). In data analysis, the \mathbf{X} matrix would contain a single row for each subject. Since power analysis does not include actual data, the design “essence” matrix (Muller and Stewart 2006) is a version of the \mathbf{X} matrix that contains a single row for each unique combination of predictors in the study design. Note that the essence matrix specifies only the fixed, or categorical, predictors in the study design.

For example, consider a 2-factor ANOVA design with 2 levels per factor, 3 subjects per group, and a cell means coding. In data analysis, the design matrix and corresponding essence matrix would be:

$$\mathbf{X} = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 \end{bmatrix} \Rightarrow \text{Es}(\mathbf{X}) = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 \end{bmatrix}$$

GLIMMPSE requires that the design coding is full rank. Unequal group sizes may be coded by replicating a row

to reflect the relative sizes of the groups.

After entering the desired dimensions for the matrix in the row and column dimension text boxes, click anywhere on the screen for the matrix to be resized. Type in the matrix text boxes shown in Figure 45 to enter the matrix information.

Calculate

- Start
- Design
- Design Essence** ✓
- Covariate ✓
- Smallest Group Size ✎
- Coefficients
- Hypothesis
- Variability
- Options

The Design Essence Matrix

In the general linear model, $Y = XB + E$, the X matrix contains predictor and covariate information. For power analysis, please specify a design essence matrix, $Es(X)$. The $Es(X)$ matrix contains one and only one copy of each unique row in the full design matrix. This allows separation of the study design information from overall and relative sample size.

Enter the $Es(X)$ matrix below. To change the row dimension of the matrix, enter the updated number of rows in the left-most textbox above the matrix data. To change the column dimension, enter the desired number of columns in the right-most textbox above the matrix data. Please use a full rank coding for this matrix.

3	×	3
1	0	0
0	1	0
0	0	1

Figure 45: Type I Error

4.2.2. Covariate

Currently, GLIMPSE only performs power calculations for hypotheses about fixed predictor variables. However, a single, continuous, normally distributed predictor variable may be included in the analysis.

To include such a predictor, click the checkbox next to *Control for a single, normally distributed Gaussian predictor* at the bottom of the screen, shown in Figure 46.

Calculate

- Start
- Design
- Design Essence ✓
- Covariate** ✓
- Smallest Group Size ✓
- Coefficients
- Hypothesis
- Variability
- Options

Controlling for a single, normally distributed predictor

A common experimental design is an analysis of covariance, which includes one or more fixed predictors and one or more continuous control variables, the "covariates." For example, one might run an experiment with 10 males and 10 females, with an indicator variable for gender as a fixed predictor and age as a covariate.

A common special case uses a series of repeated measurements on a continuous outcome. The first measurement, observed prior to treatment, is used as a baseline covariate. The other repeated measurements are outcomes in the general linear multivariate model.

GLIMPSE can calculate power for hypotheses concerning the fixed predictors, optionally controlling for a single normally distributed predictor. If you plan to include a single normally distributed predictor in your model, click the checkbox below.

At present, the GLIMPSE software does not calculate power for multiple normally distributed predictors nor non-normally distributed predictors.

☐ Control for a single, normally distributed predictor.

Figure 46: Gaussian Predictor Screen

4.2.3. Smallest Group Size

When solving for power, the user specifies the total sample size for the design by the relative number of repeated rows in the design essence matrix, and the smallest group size. On the *Smallest Group Size* screen, the user may enter one or more values describing the number of participants in the smallest group.

To enter one or more per group sample size, type the sample size in the *Per Group Sample Size* box, shown in Figure 47. After each entry, press **Enter** on your keyboard. To delete a value, select the unwanted value and click **x** to remove the value from the list.

Figure 47: Smallest Group Size Screen

4.3. Coefficients

4.3.1. Beta Coefficients: *B* Matrix

This section requires the user to enter choices for values for the hypothesis test, $\Theta = CBU$.

In the general linear multivariate model with fixed predictors, $\mathbf{Y} = \mathbf{X}\mathbf{B} + \mathbf{E}$, the \mathbf{B} matrix represents the proposed relationship between the predictor variables, \mathbf{X} , and the outcome variables, \mathbf{Y} . The same is true for \mathbf{B}_F in the General Linear Multivariate Model with Fixed Predictors and a Gaussian Predictor. For simplicity, we will only discuss \mathbf{B} (since the instructions do not change for \mathbf{B}_F). To calculate power, enter values for the regression coefficients for each unique combination of predictors in the study design. The row dimension of \mathbf{B} is determined by the number of columns in the essence matrix. Change the column dimension of \mathbf{B} to match the intended number of outcomes in the study, or the columns of \mathbf{Y} in the general linear multivariate model with fixed predictors regression equation.

For example, an investigator may want to compare vitamin D and calcium levels of children who live in three different regions: urban, suburban, and rural. The \mathbf{B} matrix would have three pre-specified rows, one for each region, and two columns, one for vitamin D and one for calcium. To calculate power, the investigator must enter the expected mean vitamin D (column 1) and calcium (column 2) levels of the children in the rural (row 1), suburban

(row 2), and urban (row 3) regions. The investigator may choose $\mathbf{B} = \begin{bmatrix} 120 & 4 \\ 60 & 8 \\ 45 & 10 \end{bmatrix}$ as shown below:

Calculate

Start

Design

Coefficients

Beta Coefficients ✓

Beta Scale Factors ✎

Hypothesis

Variability

Options

Regression Coefficients: B Matrix

The B matrix contains regression coefficients. Specify the values you expect to see for these coefficients. These values may be determined from pilot data or previous studies. We recommend selecting values which represent scientifically meaningful differences. At least one of the values in the B matrix should be non-zero. Otherwise, power will equal the test size.

The number of columns in B indicates the number of outcomes in your study (i.e. the number of columns in Y). To adjust the number of outcomes in your study, change the column dimension in the text box above the matrix data. The number of rows in B must equal the number of columns in $Es(X)$, so it cannot be adjusted on this screen.

Enter values for the regression coefficients in the matrix below.

3

×

2

12	4
60	8
45	10

Figure 48: Beta Matrix

Enter the number of columns, or the number of outcomes in the study, in the column text box (right) in the matrix, as shown in Figure 48. Enter proposed values of the B coefficients in their corresponding text boxes in the matrix.

4.3.2. Beta Scale Factors

GLIMMPSE allows users to specify scale factors for the B matrix in order to generate power or sample size values for different coefficient values. Since power is based on proposed regression coefficients, it is common to calculate power for the proposed value, as well as alternative values such as half and twice the proposed value.

One or more scale factors for the B matrix may be specified for inclusion in the power calculation. For example, to calculate power for regression coefficients that are half the values in your B matrix, enter 0.5. To use the exact B matrix specified, enter 1. To delete a value, select the unwanted value and click ✕ to remove the value from the list, as shown in Figure 49.

Calculate

- Start
- Design
- Coefficients
- Beta Coefficients
- Beta Scale Factors**
- Hypothesis
- Variability
- Options

Scale Factors for Regression Coefficients

In power analysis, it is not possible to know the exact values of regression coefficients before the experiment is observed. Scale factors allow you to consider alternative values for the regression coefficients by scaling the \mathbf{B} matrix. For example, entering the scale factors 0.5, 1, and 2 would compute power for the \mathbf{B} matrix divided by 2, the \mathbf{B} as entered, and the \mathbf{B} matrix multiplied by 2.

Type each value into the text box and click "enter" on your keyboard. To remove an item, click the "x" next to the item.

Scale Factor for Means

Scale Factors for Means

- 0.5
- 1
- 2

Figure 49: Beta Scale Factors

4.4. Hypothesis

In this section, the user defines the contrast matrices in the study. The contrast matrices, \mathbf{C} and \mathbf{U} , consist of the hypotheses to be tested. They are used to calculate the expected hypothesis matrix, $\mathbf{\Theta} = \mathbf{C}\mathbf{B}\mathbf{U}$.

4.4.1. Between-Participant Contrast

The \mathbf{C} matrix consists of the between-participant contrasts. The between-participant contrasts test hypotheses between independent sampling units. The number of rows in the \mathbf{C} matrix represent the degrees of freedom for the hypothesis test. For example, suppose an investigator wants to compare the average final exam test scores of students in class A and class B. The contrast matrix would be $\mathbf{C} = [1 \quad -1]$. When multiplied by \mathbf{B} , this becomes the difference in the proposed average test scores between class A and class B.

Enter the number of rows/number of contrasts in the study, in the row text box (left) under \mathbf{C} Matrix to resize the blank matrix. Fill in the contrasts you wish to test in the matrix, as shown in Figure 50.

The number of rows in the \mathbf{C} matrix cannot exceed the number of rows in the essence matrix minus 1. In addition, the \mathbf{C} matrix must conform to the \mathbf{B} matrix, so the number of columns cannot be adjusted on this screen.

Calculate

Start

Design

Coefficients

Hypothesis

Between Participant Contrast ✓

Within Participant Contrast ✓

Null Hypothesis Matrix ✓

Statistical Test ✎

Type I Error ✎

Variability

Options

Between-Participant Contrast: \mathbf{C} Matrix

The \mathbf{C} matrix defines the contrasts for between-participant effects. The number of rows in the \mathbf{C} matrix is at most one fewer than the number of rows in $\mathbf{Es}(\mathbf{X})$. The number of columns in \mathbf{C} must equal the number of columns in \mathbf{B} . To ensure conforming matrices, the number of columns of \mathbf{C} cannot be adjusted on this screen.

Enter your between-subject contrast matrix below.

1	×	2
1		-1

Figure 50: Between-participant Contrast Matrix

4.4.2. Within-Participant Contrast

The \mathbf{U} matrix consists of the within-participants contrasts. The within-participants contrasts are the hypotheses that compare measurements on the same independent sampling unit.

The \mathbf{U} matrix is most useful for multivariate designs and repeated measures. For example, suppose an investigator wants to examine whether student test scores improve from their midterm exams to their final exams. The investigator would have two measurements per student, one for the midterm and one for the final. The within-participant contrast matrix would be $\mathbf{U} = \begin{bmatrix} 1 & -1 \end{bmatrix}$. The matrix contrasts two different test scores, the midterm and the final, for the same student.

Enter the number of columns, or the number of within-subject contrasts, in the study, in the column text box (right). Fill in the contrasts in the matrix, as shown in Figure 51.

The \mathbf{U} matrix must conform to the \mathbf{B} matrix, so the number of rows cannot be adjusted on this screen.

Calculate

Start

Design

Coefficients

Hypothesis

Between Participant Contrast ✓

Within Participant Contrast ✓

Null Hypothesis Matrix ✓

Statistical Test ✎

Type I Error ✎

Variability

Options

Within-Subject Contrast: \mathbf{U} Matrix

The \mathbf{U} matrix defines the contrasts for within-subject effects. The matrix is necessary for multivariate and repeated measures designs. The number of rows in \mathbf{U} must equal the number of columns in \mathbf{B} . To ensure conforming matrices, the row dimension of \mathbf{U} cannot be adjusted on this screen.

Enter your within-subject contrast matrix below.

2	×	1
1		
-1		

Figure 51: Within-participant Contrast Matrix

4.4.3. Null Hypothesis

The null hypothesis matrix, Θ_0 , represents the test values the user expects to observe when the null hypothesis is true. When performing a power analysis, the values for the hypothesis tests are calculated as $\Theta = CBU$, and then compared against Θ_0 . Commonly, Θ_0 is a matrix of zeroes.

For example, suppose an investigator wants to compare resting metabolic rate between subjects with HIV lipodystrophy, subjects with HIV only, and healthy controls. The null hypothesis of no difference between the three groups is $\Theta_0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$, appearing as shown in Figure 52.

The screenshot shows the GLIMMPSE software interface. On the left is a sidebar with a 'Calculate' button at the top and a list of menu items: Start, Design, Coefficients, Hypothesis, Between Participant Contrast (with a green checkmark), Within Participant Contrast (with a green checkmark), Null Hypothesis Matrix (highlighted in blue with a green checkmark), Statistical Test (with a pencil icon), Type I Error (with a pencil icon), Variability, and Options. The main panel is titled 'Null Hypotheses: Θ_0 Matrix'. It contains the text: 'For $\Theta = CBU$, the general linear hypothesis is stated as $H_0 : \Theta = \Theta_0$. In most cases, the Θ_0 matrix will contain zeros. The number of rows in Θ_0 must equal the number of rows in C , and the number of columns must match the number of columns in U . To ensure conforming matrices, the dimensions of Θ_0 cannot be adjusted on this screen. Enter your Θ_0 matrix below.' Below this text is a matrix input area showing a 2x1 matrix with the values 0 and 0 in the two rows.

Figure 52: Null Hypothesis Matrix

Sometimes, however, the null hypothesis is based on previous studies or clinical experience. For example, suppose an investigator wants to compare foal birth weight between dams who are given feed formula A, feed formula B, and standard feed. In order to be cost effective, the new feed formulas must improve foal birth weight by more than 7 kg. The null hypothesis, then is $\Theta_0 = \begin{bmatrix} 7 \\ 7 \end{bmatrix}$, appearing as shown in Figure 53.

Calculate

Start

Design

Coefficients

Hypothesis

Between Participant Contrast ✓

Within Participant Contrast ✓

Null Hypothesis Matrix ✓

Statistical Test ✎

Type I Error ✎

Variability

Options

Null Hypotheses: Θ_0 Matrix

For $\Theta = CBU$, the general linear hypothesis is stated as

$$H_0 : \Theta = \Theta_0.$$

In most cases, the Θ_0 matrix will contain zeros.

The number of rows in Θ_0 must equal the number of rows in C , and the number of columns must match the number of columns in U . To ensure conforming matrices, the dimensions of Θ_0 cannot be adjusted on this screen.

Enter your Θ_0 matrix below.

2	×	1
7		
7		

Figure 53: Non-zero Null Hypothesis Matrix

Θ_0 has the same number of rows as C , and the same number of columns as U . Therefore, its size cannot be adjusted on this screen. The user need only enter the matrix cell values.

4.4.4. Statistical Tests

The *Statistical Tests* screen allows the user to select one or more statistical tests for the power or sample size calculations. A tutorial providing guidelines for selecting a test is available from the GLIMMPSE Tutorials page at <http://samplesizeshop.org/education/tutorials>. Full theoretical details are available in Muller and Stewart (2006). Select the statistical test(s) by clicking one or more check boxes. For designs with a Gaussian covariate, only the Hotelling-Lawley trace and the Univariate Approach to Repeated Measures are valid.

Calculate

Start

Design

Coefficients

Hypothesis

Between Participant Contrast ✓

Within Participant Contrast ✓

Null Hypothesis Matrix ✎

Statistical Test ✓

Type I Error ✓

Variability

Options

Statistical Tests

Select the statistical tests to include in your calculations. For study designs with a single outcome, power is the same regardless of the test selected. Note that only the Hotelling-Lawley Trace and the Univariate Approach to Repeated Measures are supported for designs which include a baseline covariate.

Note that only the Hotelling-Lawley Trace and the Univariate Approach to Repeated Measures are supported for designs which include a baseline covariate.

Click [here](#) to learn more about selecting an appropriate test.

Select one or more statistical tests

- ☒ Hotelling Lawley Trace
- ☐ Pillai-Bartlett Trace
- ☐ Wilks Likelihood Ratio
- ☐ Univariate Approach to Repeated Measures with Box Correction
- ☐ Univariate Approach to Repeated Measures with Geisser-Greenhouse Correction
- ☐ Univariate Approach to Repeated Measures with Huynh-Feldt Correction
- ☐ Univariate Approach to Repeated Measures, uncorrected

Figure 54: Statistical Tests

4.4.5. Type I Error

Enter the target values for Type I Error as decimals (i.e. 0.05) in the Type I Error Values box. The user may specify up to five Type I Error values.

Calculate

Start

Design

Coefficients

Hypothesis

Between Participant Contrast ✓

Within Participant Contrast ✓

Null Hypothesis Matrix ✓

Statistical Test ✎

Type I Error ✓

Variability

Options

Type I Error Rates

A Type I error occurs when a scientist declares a difference when none is actually present. The Type I error rate is the probability of a Type I error occurring, and is often referred to as α . Type I error rates range from 0 to 1. The most commonly used values are 0.01, 0.05, and 0.1.

Type each value into the list box and click "enter" on your keyboard. To remove an item, click the "x" next to the item.

Type I Error Rate

Enter a Type I error value

0.05 ✕

Figure 55: Type I Error

4.5. Variability

Variability describes how much measurements differ from each other. In this section, the user defines the covariance of errors and covariance related to the Gaussian covariate.

4.5.1. Error Covariance

For each independent sampling unit, Σ_e is the covariance of the random errors conditional on the values of the fixed predictors. The *Error Covariance* screen allows the user to define Σ_e by directly entering the covariance matrix values, as shown in Figure 56. To ensure conformance with the \mathbf{B} and \mathbf{U} matrices, the dimensions of the Σ_e matrix cannot be modified on this screen.

Calculate

Start

Design

Coefficients

Hypothesis

Variability

Error Covariance ✓

Outcomes Covariance ✓

Covariate ✓

Outcomes and Covariate ✓

Scale Factors ✓

Options

Covariance of Errors: Σ_e Matrix

For each independent sampling unit, Σ_e is the covariance of the random errors. For univariate designs, Σ_e will be a (1×1) matrix containing the variance of the error term. More complex structures may be entered for multivariate or repeated measures designs. Values for Σ_e are typically obtained from pilot data or previous studies.

Σ_e is a square, symmetric matrix with dimensions equal to the number of columns in B .

Enter values for Σ_e in matrix below.

4

×

4

1	0.2	0.1	0.5
0.2	1	0.2	0.1
0.1	0.2	1	0.2
0.5	0.1	0.2	1

Figure 56: Error Covariance

4.5.2. Outcomes Covariance

For designs with a Gaussian covariate, the user must specify the covariance of the outcomes, Σ_Y . For each independent sampling unit, Σ_Y is the covariance of the outcomes conditional on the fixed predictors. One can think of Σ_Y as the error covariance for each independent sampling unit in a model containing only the fixed predictors and excluding the Gaussian covariate. The *Outcomes Covariance* screen allows the user to define Σ_Y by directly entering the covariance matrix values, as shown in Figure 57. To ensure conformance with the B and U matrices, the dimensions of the Σ_Y matrix cannot be modified on this screen.

Calculate

Start

Design

Coefficients

Hypothesis

Variability

Error Covariance ✓

Outcomes Covariance ✓

Variance of Covariate ✓

Outcomes and Covariate ✓

Scale Factors ✓

Options

Covariance of Outcomes: Σ_Y

For each independent sampling unit, Σ_Y is the covariance of the outcomes conditional on the fixed predictors. One can think of Σ_Y as the error covariance for each independent sampling unit in a model containing only the fixed predictors and excluding the Gaussian covariate.

For univariate designs, Σ_Y will be a (1×1) matrix containing the variance of the outcome conditional on the fixed predictors. More complex structures may be entered for multivariate or repeated measures designs. Σ_Y is a square, symmetric matrix with dimensions equal to the number of columns in B .

Enter values for Σ_Y in the matrix below.

4

×

4

1	0.2	0.1	0.5
0.2	1	0.2	0.1
0.1	0.2	1	0.2
0.5	0.1	0.2	1

Figure 57: Outcomes Covariance

4.5.3. Variance of Covariate

For designs with a Gaussian covariate, the covariate is assumed to have a Gaussian distribution with mean zero and variance σ_g^2 . The *Variance of Covariate* screen allows the user to enter a value for σ_g^2 , as shown in Figure 58.

Figure 58: Variance of Covariate

4.5.4. Covariance of Outcomes and Covariate

When controlling for a Gaussian covariate, power is typically improved when the covariate explains some portion of the variance in the outcome. The covariance matrix between the outcomes and the Gaussian covariate, Σ_{YG} , describes the association between the outcomes and the Gaussian covariate. The *Covariance of Outcomes and Covariate* screen allows the user to specify values for Σ_{YG} , as shown in Figure 59. To ensure conformance with the Σ_Y matrix, the dimensions of the Σ_{YG} matrix cannot be modified on this screen.

Figure 59: Covariance of Outcomes and Covariate

4.5.5. Sigma Scale Factors

GLIMPSE allows users to specify scale factors for the covariance matrices. For the general linear multivariate model with fixed predictors, the scale factors are applied to the user-specified Σ_e matrix. For the general linear multivariate model with fixed predictors and a Gaussian covariate, the scale factors are applied to the Σ_e matrix, which is calculated from Σ_Y , Σ_g , and Σ_{Yg} . Since variability can dramatically impact power, it is common to calculate power for the proposed value, as well as alternative values such as half and twice the proposed value.

To specify one or more covariance scale factors, enter the scale factors in the Σ_E *Matrix Scale Factors* box. After each entry, press **Enter** on the keyboard. To delete a value, select the unwanted value and click **✕** to remove the value from the list, as shown in Figure 60.

Calculate

- Start
- Design
- Coefficients
- Hypothesis
- Variability
- Error Covariance ✓
- Outcomes Covariance ✓
- Variance of Covariate ✓
- Outcomes and Covariate ✓
- Scale Factors** ✓
- Options

Scale Factors for Covariance

Changes in variability can dramatically affect power. Scale factors allow you to compute power for alternative covariance values by scaling Σ_e . For example, entering the scale factors 0.5, 1, and 2 would compute power for Σ_e divided by 2, Σ_e matrix as entered, and Σ_e matrix multiplied by 2.

Type each value into the text box and click "enter" on your keyboard. To remove an item, click the "x" next to the item.

Scale Factors for Variance

Scale Factors for Variability

1 ✕

Figure 60: Covariance Scale Factors

4.6. Options

The screen shown in Figure 61 provides an introduction to the Options section.

Calculate

- Start
- Design
- Coefficients
- Hypothesis
- Variability
- Options**
- Power Method ✎
- Confidence Intervals ✓
- Power Curve 📄

Options: Introduction

In this selection, you may optionally request confidence intervals for power, and power plots. For designs with a baseline covariate, you may select from different power methods.

Figure 61: Options

4.6.1. Power Calculation Method

For designs with a baseline covariate, two different methods are available to calculate power: quantile and unconditional power. For theoretical details, please see [Glueck and Muller \(2003\)](#). Select the power methods by clicking the checkboxes shown in Figure 62. If quantile power is selected, the user must also specify one or more quantile values. For example, median power would be obtained by selecting *Quantile* and entering 0.5 in the *Quantiles* list box.

Calculate

Start

Design

Coefficients

Hypothesis

Variability

Options

Power Method ✓

Confidence Intervals ✓

Power Curve

Power Calculation Method

For designs including a baseline covariate, two methods are available to calculate power: unconditional power and quantile power. One can think of the random covariate values as having been sampled from a normal distribution. Thus there are many possible realizations of the same experiment, and each realization may have a different power. The unconditional power is defined as the average of the possible power values (Gatsonis and Sampson, 1989; Glueck and Muller, 2003). The $100 \times v$ th quantile power is the power value chosen so that power as small or smaller occurs in $100 \times v$ percent of all possible realizations of the experiment.

For a detailed description of unconditional and quantile power, please see [Gatsonis and Sampson \(1989\)](#) and [Glueck and Muller \(2003\)](#).

Select one or more power methods below

☐ Unconditional

☒ Quantile

Enter one or more quantiles in the list below

Enter a quantile

0.5 ✕

Figure 62: Power Method

4.6.2. Confidence Intervals

Power analysis involves some uncertainty in the choices for means and variability. Therefore, the *Confidence Intervals* screen allows the user to request confidence intervals on the power results. To include confidence intervals, uncheck the checkbox. The information on the confidence interval screen, shown in Figure 63, describes the data set (or publication) from which the choices for means and variances were obtained. For example, if a scientist was calculating power based on the means and variances obtained from pilot data, the scientist would enter information describing the pilot data set. The following information is required:

The *Assumptions* section allows the user to indicate if he or she is uncertain about the variance, but reasonably certain of the mean values, or uncertain of both the means and variance.

The *Upper and lower tail probabilities* define the width of the confidence interval. For example, a centered 95% confidence interval would have both upper and lower tail probabilities of 0.025.

The *Total sample size* value indicates the number of independent sampling units in the pilot data set (or publication).

The *Rank of the design matrix* describes a property of the predictor matrix used in the pilot data set. Please see [Muller and Stewart \(2006\)](#) for details about matrix rank.

Calculate

Start

Design

Coefficients

Hypothesis

Variability

Options

Power Method ✓

Confidence Intervals ✓

Power Curve ⌵

Confidence Interval Options

If the means (B) or the error covariance (Σ_e) are sample estimates, then the power values produced from these matrices will be random quantities. To account for this randomness, GLIMPSE can calculate confidence intervals for power values using the techniques described by [Taylor and Muller \(1995\)](#), [Gribbin \(2007\)](#), and [Park \(2007\)](#).

☐ Don't include confidence intervals for power

Select the assumptions for the confidence intervals:

☒ B is fixed, but Σ_e is estimated

☐ Both B and Σ_e are estimated

Enter the upper and lower tail probabilities for the confidence intervals.
We typically recommend the value 0.05 for the lower tail probability and 0 for the upper tail probability.

Lower Tail Probability

Upper Tail Probability

Describe the data from which you obtained the values for B and Σ_e .

Total sample size

Rank of the design matrix

Figure 63: Confidence Intervals

4.6.3. Power Curve Options

The *Power Curve Options* screen allows the user to create a power curve. A power curve describes the change in power (Y axis of the power curve) relative to the total sample size, regression coefficient scale factor, or the variability scale factor (all options for the X axis of the power curve).

To create a power curve, the user must 1) uncheck the check box, 2) select the value to appear on the horizontal axis, and 3) add one or more data series, as shown in Figure 64.

Depending on the study design, the user may request a large number of power or sample size values in a single request. A data series is defined by selecting a subset of the power or sample size values. The user creates a data series by selecting values for several study design variables and clicking the appropriate checkboxes. A data series will be displayed as a single line on the power curve plot.

Results

- Table
- Plot
- Matrices

Start

Design

Coefficients

Hypothesis

Variability

Options

Power Method ✓

Confidence Intervals ✓

Power Curve ✓

Power Curve Options

To create a power curve, uncheck the box below. Follow the prompts to define the curve.

☐ Don't create a power curve

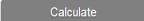
Select the quantity to display on the horizontal axis of the power curve.
The vertical axis will display the power value.

Total Sample Size

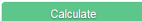
Select one or more data series by clicking the checkboxes
Double click the label to edit the legend label for the data series

<input type="checkbox"/> Label	Type I Error Rate	Means Scale	Variability Scale
<input checked="" type="checkbox"/> Series 1	0.05	2	3

Figure 64: Power Curve

Note that the *Power Curve Options* screen is the final screen in the GLIMMPSE wizard. If the study design is not complete, the Calculate button will be disabled .

4.7. Calculate

When sufficient information has been entered for your power or sample size calculation, the *Calculate* button will be highlighted green. Click  to receive the results of your power analysis. Example results are shown in Figure 65. For detailed information regarding the Power Results table, refer to Table 1. The resulting power curve is shown in Figure

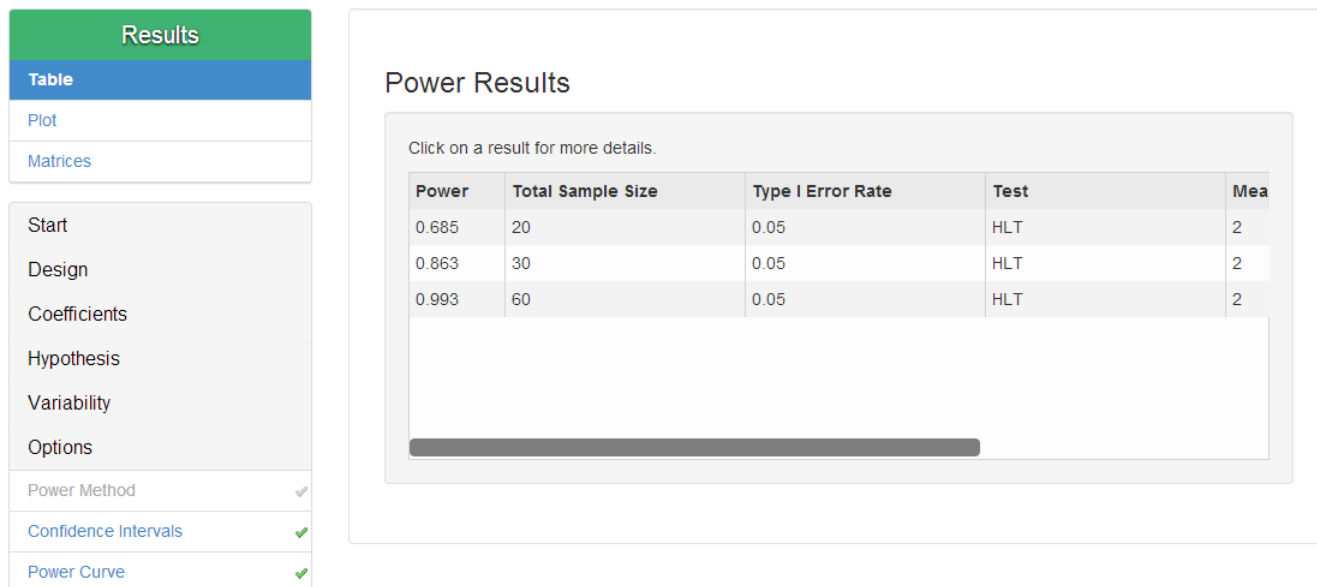


Figure 65: Results Table

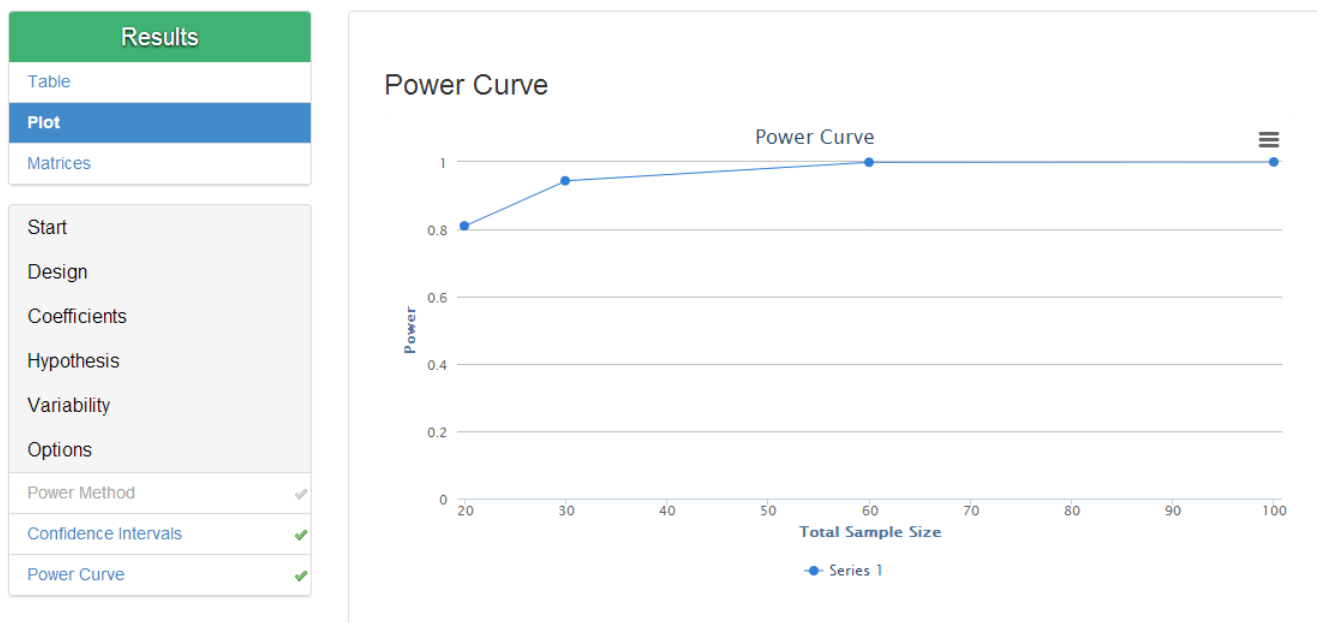


Figure 66: Results Plot

5. Additional GLIMPSE Resources

Additional resources for GLIMPSE are available at <http://samplesizeshop.org>. The Sample Size Shop project is a collaborative effort between the University of Florida and the University of Colorado Denver. The goals of the project are to develop new statistical methods for calculating power and sample size, provide user friendly software

to perform the power and sample size calculations, and educate researchers regarding both the methods and the software. The following online resources are available for the GLIMMPSE software.

1. Tutorials demonstrating power and sample size calculations with GLIMMPSE for a variety of study designs are available at <http://samplesizeshop.org/education/tutorials>
2. Validation reports showing the accuracy of GLIMMPSE calculations are available at <http://samplesizeshop.org/documentation/glimmpse/glimmpse-validation-results-2/>
3. Technical documentation for the software is available at <http://samplesizeshop.org/documentation/glimmpse/>
4. GLIMMPSE software modules are available for download from <http://samplesizeshop.org/software-downloads/glimmpse-software-downloads/>

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