

Classical & Bayesian Instrument Development

University of Kansas Department of Biostatistics

A web application for psychometric analyses

Reliability estimation using a web application

Sponsored by R03NR013236

This GUI references the [Lavaan](#) , [MCMCpack](#) , [OpenBUGS](#) and [psy](#) packages and was built using [Shiny](#).

Authors: Alex Karanevich, Lili Garrard, Marge Bott, Larry Price, Byron Gajewski

2015

Teach yourself CBID

Who should take the tutorial?

You will get the most out of this tutorial if you know the very basics of confirmatory factor analysis and reliability (e.g. Cronbach's alpha).

If confirmatory factor analysis is new to you, you may want to check out the learning resources at <http://lavaan.ugent.be/> before taking this tutorial.

Get started with CBID

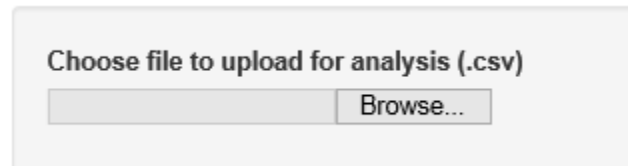
These four tutorials will take you from a confirmatory factor analysis consumer to a user. Also, you will be able to better estimate measures of reliability of your instruments using both classical and Bayesian perspectives.

Click the Tutorial 1 button to get started!

- [Tutorial 1](#) – Data file preparation
- [Tutorial 2](#) – One-factor model

Tutorial 1 – Data file preparation

Before getting started with CBID, please ensure that your data file(s) are properly prepared according to the following **general** requirements:



1. CBID only accepts data files in .csv format for uploading. Most data processing software (e.g., Microsoft Excel, SPSS) will have an option to save the file in .csv format.
2. Data file(s) should be structured in the long format (i.e., subjects as rows and items as columns) and only contain relevant variables (items) used for factor analysis. For example, if data were collected from 50 subjects on 5 items, the data file should have 50 rows and 5 columns, with each column representing one item on the instrument.
3. The first row of the data file should be reserved for item names (e.g., item1, item2) as CBID reads in the first row as variable names used in the analysis. Item names should be descriptive and precise.
4. If your file contains data for multiple groups and separate analysis needs to be conducted for each group, please create a separate data file for each group prior to uploading. CBID currently does not have the function to separate groups or create subsets of data.
5. If your file contains data collected from negatively worded items, please ensure that the negatively worded items have been properly reverse coded prior to uploading. This step is essential to prevent issues from a domain sampling perspective.

Selecting **Bayesian analysis** will provide three options: flat prior, previous data, and expert prior. Both *previous data* and *expert prior* options will require users to upload a separate *prior* data file (i.e., previously collected participant data or subject experts' content data). This is in addition to the currently collected participants' data file. The additional *prior* data file will be used to compute the *priors* needed for Bayesian analysis. The following requirements apply if Bayesian analysis will be performed:

1. The variable or item names in the first row of the *prior* data file must match the variable or item names in the first row of the participants' data file. If the two files do not have matching item names, CBID will output an error message.
2. Both the *prior* data file and the participants' data file must have the same number of columns.
3. If *previous data* is selected, a data file containing previously collected data can be uploaded, as shown in the screen shot below.

How to get the prior distribution?

Previous Data ▼

Choose prior data to upload (.csv)

Browse...

4. If *expert prior* is selected, a data file containing subject experts' content data can be uploaded, as shown in the screen shot below.

How to get the prior distribution?

Expert Prior ▼

Choose expert data to upload (.csv)

Browse...

[Return to Main Menu](#)

Tutorial 2 – One-factor model

CBID offers two approaches to help establish evidence of construct validity: classical and Bayesian. In this tutorial, we will go through a simple example of each to demonstrate how to use CBID.

The screen shot below shows what CBID looks like when first initiated in your selected web browser.

Classical & Bayesian Instrument Development (Beta Version)

This GUI references the [Lavaan](#), [MCMCpack](#), [OpenBUGS](#) and [psy](#) packages and was built using [Shiny](#).
Authors: Alex Karanevich, Lili Garrard, Marge Bott, Larry Prieo, Byron Gajewski

View the [Tutorial](#)

Choose file to upload for analysis (.csv)

Data type

Ordinal Interval

Analysis type

Classical Bayesian

Show modification indices?

Yes No

Number of factors

Summary:

[1] "Submit a file first!"

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Now, let's consider a simple one-factor model with 6 items. Each item can be rated on a 5-point scale. We will follow the steps below to conduct the analysis.

Step 1: Upload the relevant participants' data file

Below is a partial screen shot of the sample participants' data file (*participants.csv*) that we will use. Notice that the first row of this .csv file is reserved for the item names and only the relevant variables are included in the file.

	A	B	C	D	E	F
	Item1	Item2	Item3	Item4	Item5	Item6
	3	2	3	1	5	4
	5	4	2	5	2	4
	3	1	1	1	1	1
	2	3	4	4	5	2
	1	2	3	2	1	2
	4	1	1	1	2	2
	2	1	4	2	1	3

Prior to uploading *participants.csv* to CBID, users will see the following option:

Choose file to upload for analysis (.csv)

Browse...

Click on *Browse* and a new window will open for users to locate the data file used for analysis. Once the data file is selected, click *Open* in the new window and CBID will display a blue bar to indicate a successful upload (shown below).

Choose file to upload for analysis (.csv)

S:\Biostats\BIO-STAT\Ga Browse...

Upload complete

Step 2: Select the appropriate data type

Data type

Ordinal Interval

Responses collected from participants can be treated as either interval or ordinal, depending on the number of response categories per item. Traditionally, participant responses are often modeled as interval, even for binary response options. With the advancement in statistical methodology and software, we recommend users to select the *Ordinal* option if the number of response categories for the majority of the items is less than 5. Otherwise, the *Interval* option can be selected. For the classical approach, choosing to model the data as either *Ordinal* or *Interval* will produce different results as different estimators are used to estimate the model parameters. Maximum likelihood (ML) estimator is used for the *Interval* option and weighted least squares means- and variance-adjusted (WLSMV) estimator is used for the *Ordinal* option. For the current example, we will model the data as ordinal.

Step 3: Select analysis type

In this step, users will select whether to conduct a classical or Bayesian analysis. For the first demonstration, we will select *Classical*.

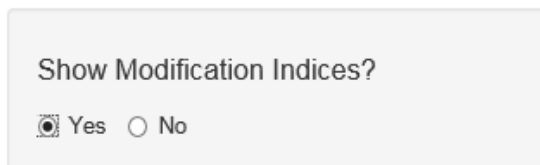
Analysis type

Classical Bayesian

Classical Approach

Step 4: Select modification indices

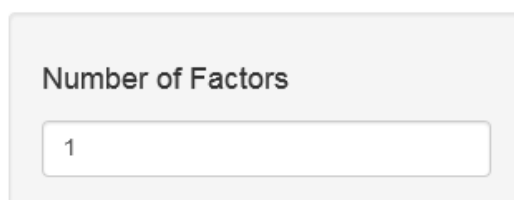
Users may choose to view modification indices if the *Classical* approach is selected, by using the following option. For this example, we want to view the modification indices outputs.



Show Modification Indices?
 Yes No

Step 5: Select the number of factors

Users need to specify the number of factors or the number of constructs of interest. For this example, we select a one-factor model.



Number of Factors
1

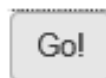
As previously mentioned, CBID extracts the first row of the participants' data file as the variable names used in analysis. By selecting the number of factors in the model, CBID automatically displays the following option for users to specify the items that load on the single factor. Suppose all 6 items load on the single factor, labeled generically by CBID as *Factor 1*.

Factor 1 items

Item1 Item2 Item3 Item4 Item5 Item6

Step 6: Run the analysis

After all options have been appropriately selected, we can now run the entire analysis by clicking on the *Go* button.



Go!

Step 7: Review the outputs

The outputs are organized in 5 sections: [model fit indices](#), [parameter estimates](#), [modification indices](#), [entire reliability](#) and Cronbach's alpha, and potential warning or error messages. Below are screen shots for each of the sections, based on our sample data.

Model fit indices:

Summary:

lavaan (0.5-18) converged normally after 12 iterations				
Number of observations		50		
Estimator	DWLS		Robust	
Minimum Function Test Statistic	6.989		10.124	
Degrees of freedom	9		9	
P-value (Chi-square)	0.638		0.341	
Scaling correction factor			0.811	
Shift parameter			1.509	
for simple second-order correction (Mplus variant)				
Model test baseline model:				
Minimum Function Test Statistic	148.560		120.175	
Degrees of freedom	15		15	
P-value	0.000		0.000	
User model versus baseline model:				
Comparative Fit Index (CFI)	1.000		0.989	
Tucker-Lewis Index (TLI)	1.025		0.982	
Root Mean Square Error of Approximation:				
RMSEA	0.000		0.050	
90 Percent Confidence Interval	0.000	0.133	0.000	0.173
P-value RMSEA <= 0.05	0.719		0.436	
Weighted Root Mean Square Residual:				
WRMR	0.423		0.423	

Parameter estimates (partial outputs):

Parameter estimates:						
Information			Expected			
Standard Errors			Robust.sem			
	Estimate	Std.err	Z-value	P(> z)	Std.lv	Std.all
Latent variables:						
F1 =~						
Item1	0.326	0.143	2.276	0.023	0.326	0.326
Item2	0.839	0.097	8.643	0.000	0.839	0.839
Item3	0.717	0.098	7.338	0.000	0.717	0.717
Item4	0.680	0.118	5.758	0.000	0.680	0.680
Item5	0.457	0.133	3.424	0.001	0.457	0.457
Item6	0.546	0.113	4.819	0.000	0.546	0.546
Intercepts:						
Item1	0.000				0.000	0.000
Item2	0.000				0.000	0.000
Item3	0.000				0.000	0.000
Item4	0.000				0.000	0.000
Item5	0.000				0.000	0.000
Item6	0.000				0.000	0.000
F1	0.000				0.000	0.000
Thresholds:						
Item1 t1	-0.772	0.200	-3.864	0.000	-0.772	-0.772
Item1 t2	-0.412	0.185	-2.233	0.026	-0.412	-0.412
Item1 t3	0.100	0.179	0.560	0.576	0.100	0.100
Item1 t4	0.842	0.204	4.123	0.000	0.842	0.842
Item2 t1	-0.772	0.200	-3.864	0.000	-0.772	-0.772
Item2 t2	-0.050	0.179	-0.280	0.779	-0.050	-0.050
Item2 t3	0.412	0.185	2.233	0.026	0.412	0.412
Item2 t4	0.915	0.209	4.376	0.000	0.915	0.915
Item3 t1	-0.583	0.191	-3.059	0.002	-0.583	-0.583
Item3 t2	0.151	0.180	0.840	0.401	0.151	0.151
Item3 t3	0.583	0.191	3.059	0.002	0.583	0.583
Item3 t4	0.842	0.204	4.123	0.000	0.842	0.842
Item4 t1	-0.412	0.185	-2.233	0.026	-0.412	-0.412
Item4 t2	0.202	0.180	1.119	0.263	0.202	0.202

Modification indices (partial outputs):

```

Modification Indices:

      lhs op  rhs  mi mi.scaled  epc sepc.lv sepc.all sepc.nox
1    F1 =~ Item1 0.000  0.000 0.000  0.000  0.000  0.000
2    F1 =~ Item2 0.000  0.000 0.000  0.000  0.000  0.000
3    F1 =~ Item3 0.000  0.000 0.000  0.000  0.000  0.000
4    F1 =~ Item4 0.000  0.000 0.000  0.000  0.000  0.000
5    F1 =~ Item5 0.000  0.000 0.000  0.000  0.000  0.000
6    F1 =~ Item6 0.000  0.000 0.000  0.000  0.000  0.000
7  Item1 |   t1 0.000  0.000 0.000  0.000  0.000  0.000
8  Item1 |   t2 0.000  0.000 0.000  0.000  0.000  0.000
9  Item1 |   t3 0.000  0.000 0.000  0.000  0.000  0.000
10 Item1 |   t4 0.000  0.000 0.000  0.000  0.000  0.000
11 Item2 |   t1 0.000  0.000 0.000  0.000  0.000  0.000
12 Item2 |   t2 0.000  0.000 0.000  0.000  0.000  0.000
13 Item2 |   t3 0.000  0.000 0.000  0.000  0.000  0.000
14 Item2 |   t4 0.000  0.000 0.000  0.000  0.000  0.000
15 Item3 |   t1 0.000  0.000 0.000  0.000  0.000  0.000
16 Item3 |   t2 0.000  0.000 0.000  0.000  0.000  0.000
17 Item3 |   t3 0.000  0.000 0.000  0.000  0.000  0.000
18 Item3 |   t4 0.000  0.000 0.000  0.000  0.000  0.000
19 Item4 |   t1 0.000  0.000 0.000  0.000  0.000  0.000
20 Item4 |   t2 0.000  0.000 0.000  0.000  0.000  0.000
21 Item4 |   t3 0.000  0.000 0.000  0.000  0.000  0.000
22 Item4 |   t4 0.000  0.000 0.000  0.000  0.000  0.000
23 Item5 |   t1 0.000  0.000 0.000  0.000  0.000  0.000
24 Item5 |   t2 0.000  0.000 0.000  0.000  0.000  0.000
25 Item5 |   t3 0.000  0.000 0.000  0.000  0.000  0.000
26 Item5 |   t4 0.000  0.000 0.000  0.000  0.000  0.000
27 Item6 |   t1 0.000  0.000 0.000  0.000  0.000  0.000
28 Item6 |   t2 0.000  0.000 0.000  0.000  0.000  0.000
29 Item6 |   t3 0.000  0.000 0.000  0.000  0.000  0.000
30 Item6 |   t4 0.000  0.000 0.000  0.000  0.000  0.000

```

Entire reliability and Cronbach's alpha:

```

[[1]]
[1] "Entire Reliability: 0.836"

[[2]]
[1] "Cronbach's Alpha: 0.72"

```

Potential warnings:

For this example, the warnings simply let the users know that there were empty cells in the cross tabs produced by the 6 items.

```

[[3]]
[1] "Potential warnings printed below: "

[[4]]
[1] "lavaan WARNING: empty cell(s) in bivariate table of Item2 x Item1"
[2] "lavaan WARNING: empty cell(s) in bivariate table of Item3 x Item1"
[3] "lavaan WARNING: empty cell(s) in bivariate table of Item4 x Item1"
[4] "lavaan WARNING: empty cell(s) in bivariate table of Item5 x Item1"
[5] "lavaan WARNING: empty cell(s) in bivariate table of Item6 x Item1"
[6] "lavaan WARNING: empty cell(s) in bivariate table of Item3 x Item2"
[7] "lavaan WARNING: empty cell(s) in bivariate table of Item4 x Item2"
[8] "lavaan WARNING: empty cell(s) in bivariate table of Item5 x Item2"
[9] "lavaan WARNING: empty cell(s) in bivariate table of Item6 x Item2"
[10] "lavaan WARNING: empty cell(s) in bivariate table of Item4 x Item3"
[11] "lavaan WARNING: empty cell(s) in bivariate table of Item5 x Item3"
[12] "lavaan WARNING: empty cell(s) in bivariate table of Item6 x Item3"
[13] "lavaan WARNING: empty cell(s) in bivariate table of Item5 x Item4"
[14] "lavaan WARNING: empty cell(s) in bivariate table of Item6 x Item4"
[15] "lavaan WARNING: empty cell(s) in bivariate table of Item6 x Item5"

```

Bayesian Approach

Step 4: Select the source of prior

We briefly mentioned in Tutorial 1 that Selecting *Bayesian* approach will provide three options: flat prior, previous data, and expert prior. For this example, we will go through demonstrations of using the *Flat Prior*, *Previous Data*, and *Expert Prior* options.

Analysis type

Classical Bayesian

How to get the prior distribution?

Flat Prior

Flat Prior

Previous Data

Expert Prior

Flat prior—non-informative normal priors are pre-specified within CBID and users are not required to specify their own flat priors.

Step 5: Select the number of factors

Users need to specify the number of factors or the number of constructs of interest. For this example, we select a one-factor model. Multi-factor models are currently under construction within CBID.



A screenshot of a web interface showing a text input field titled "Number of Factors". The field contains the number "1".

As previously mentioned, CBID extracts the first row of the participants' data file as the variable names used in analysis. By selecting the number of factors in the model, CBID automatically displays the following option for users to specify the items that load on the single factor. Suppose all 6 items load on the single factor, labeled generically by CBID as *Factor 1*.

Factor 1 items

Item1 Item2 Item3 Item4 Item5 Item6

Step 6: Run the analysis

After all options have been appropriately selected, we can now run the entire analysis by clicking on the *Go* button.



Step 7: Review the outputs

The Bayesian analysis will only output relevant results, such as the Monte Carlo Markov chain (MCMC) procedure acceptance rates, the factor loading estimates and standard errors (labeled as *Estimate* and *Std*), the 95% credible interval for the factor loadings, the entire reliability estimate (along with standard error and 95% credible interval), and any potential warning messages. Desirable MCMC acceptance rates should be between 20-50%.

Summary:

```

Acceptance rates:
Item1 Item2 Item3 Item4 Item5 Item6
0.21 0.37 0.28 0.28 0.25 0.23

[[1]]
[[1]][[1]]
      Estimate   Std 2.5% CI 97.5% CI
Item1  0.269 0.139  0.026  0.551
Item2  0.883 0.064  0.731  0.968
Item3  0.742 0.102  0.507  0.905
Item4  0.696 0.112  0.440  0.873
Item5  0.461 0.140  0.158  0.705
Item6  0.515 0.136  0.216  0.746

[[1]][[2]]
      Entire Reliability   Std 2.5% CI 97.5% CI
[1,]                   0.884 0.041  0.793  0.95

[[2]]
[1] "No warnings to report"

```

Previous data—users are required to upload a separate prior data file, which contains data collected from previous participants.

Below is a screen shot of the sample previous data file (*priordata.csv*) that we will use. For example, we have reliable and relevant data collected previously from 100 participants. Notice that the item names of the previously collected data file matches item names from the current participants' data file. The number of columns also matches in both data files.

	A	B	C	D	E	F
1	Item1	Item2	Item3	Item4	Item5	Item6
2	3	3	3	3	3	3
3	5	1	4	4	3	3
4	5	4	5	5	5	4
5	3	3	3	3	3	3
6	5	3	4	4	5	3
7	5	4	4	4	4	4

Step 5: Upload previous data file

Prior to uploading *priordata.csv* to CBID, users will see the following option:

Analysis type

Classical Bayesian

How to get the prior distribution?

Previous Data ▼

Choose prior data to upload (.csv)

Browse...

Click on *Browse* and a new window will open for users to locate the data file used for analysis. Once the data file is selected, click *Open* in the new window and CBID will display a blue bar to indicate a successful upload (shown below).

Choose prior data to upload (.csv)

S:\Biostats\BIO-STAT\Ga Browse...

Upload complete

Step 6: Select the number of factors

Users need to specify the number of factors or the number of constructs of interest. For this example, we select a one-factor model.

Number of Factors

1

As previously mentioned, CBID extracts the first row of the participants' data file as the variable names used in analysis. By selecting the number of factors in the model, CBID automatically displays the following option for users to specify the items that load on the single factor. Suppose all 6 items load on the single factor, labeled generically by CBID as *Factor 1*.

Factor 1 items

Item1
 Item2
 Item3
 Item4
 Item5
 Item6

Step 7: Run the analysis

After all options have been appropriately selected, we can now run the entire analysis by clicking on the *Go* button.

Go!

Step 8: Review the outputs

The Bayesian analysis will only output relevant results, such as the Monte Carlo Markov chain (MCMC) procedure acceptance rates, the factor loading estimates and standard errors (labeled as *Estimate* and *Std*), the 95% credible interval for the factor loadings, the entire reliability estimate (along with standard error and 95% credible interval), and any potential warning messages. Two sets of MCMC acceptance rates will be displayed for the *Previous data* option, one set each for the previously collected participants' data and the current participants' data.

Desirable MCMC acceptance rates should be between 20-50% for each item. However, it is still acceptable if the majority of the items have acceptable rates within the range, with the rest of the items falling slightly outside the range (as shown in our example below).

Summary:

```

Acceptance rates:
Item1 Item2 Item3 Item4 Item5 Item6
0.43 0.35 0.57 0.54 0.46 0.36

Acceptance rates:
Item1 Item2 Item3 Item4 Item5 Item6
0.22 0.27 0.3 0.31 0.25 0.24
[[1]]
[[1]][[1]]
      Estimate  Std 2.5% CI 97.5% CI
Item1  0.542 0.112 0.292 0.729
Item2  0.723 0.061 0.584 0.819
Item3  0.846 0.066 0.685 0.936
Item4  0.854 0.063 0.703 0.941
Item5  0.626 0.092 0.419 0.776
Item6  0.616 0.089 0.419 0.762

[[1]][[2]]
      Entire Reliability  Std 2.5% CI 97.5% CI
[1,]                   0.901 0.022 0.853 0.936

[[2]]
[1] "No warnings to report"

```

Expert prior—users are required to upload a separate prior data file, which contains data collected from subject experts.

Below is a screen shot of the sample experts' data file (*expertdata.csv*) that we will use. For example, we consulted a panel of 6 subject experts and asked the experts to rate the relevancy of each item to the domain of interest, on a 4-point relevancy scale. Notice that the item names of the experts' data file matches item names from the participants' data file. The number of columns also matches in both data files.

	A	B	C	D	E	F
1	Item1	Item2	Item3	Item4	Item5	Item6
2	4	4	3	4	4	4
3	4	4	4	4	3	3
4	2	4	3	3	3	3
5	2	4	4	4	4	4
6	1	4	3	4	4	4
7	3	2	2	3	2	3

Step 5: Upload expert prior data file

Prior to uploading *expertdata.csv* to CBID, users will see the following option:

Analysis type

Classical Bayesian

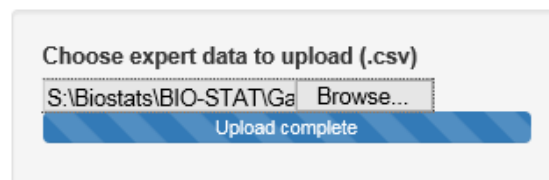
How to get the prior distribution?

Expert Prior

Choose expert data to upload (.csv)

Browse...

Click on *Browse* and a new window will open for users to locate the data file used for analysis. Once the data file is selected, click *Open* in the new window and CBID will display a blue bar to indicate a successful upload (shown below).



Step 6: Select expert level of expertise

Depending on the expertise level of the experts used for content validity analysis, users can select either *Moderate* or *High* options. If the experts exhibit a high level of expertise in the area of interest, *High* option should be selected. However, for other circumstances, if the panel exhibits a moderate level of expertise in the area, *Moderate* option is more appropriate. For this demonstration, we will assume that the panel consisted of experts that exhibit a high level of expertise in the area.

Level of Expertise?

Moderate High

Step 7: Select the number of factors

Users need to specify the number of factors or the number of constructs of interest. For this example, we select a one-factor model.

Number of Factors

1

As previously mentioned, CBID extracts the first row of the participants' data file as the variable names used in analysis. By selecting the number of factors in the model, CBID automatically displays the following option for users to specify the items that load on the single factor. Suppose all 6 items load on the single factor, labeled generically by CBID as *Factor 1*.

Factor 1 items

Item1 Item2 Item3 Item4 Item5 Item6

Step 8: Run the analysis

After all options have been appropriately selected, we can now run the entire analysis by clicking on the *Go* button.

Go!

Step 9: Review the outputs

The outputs are similar to the outputs of using flat prior and previous data, including the Monte Carlo Markov chain (MCMC) procedure acceptance rates, the factor loading estimates and standard errors (labeled as *Estimate* and *Std*), the 95% credible interval for the factor loadings, the entire reliability estimate (along with standard error and 95% credible interval), and any potential warning messages. Desirable MCMC acceptance rates should be between 20-50%.

Summary:

```

Acceptance rates:
Item1 Item2 Item3 Item4 Item5 Item6
 0.21  0.31  0.26  0.28  0.25  0.25
[[1]]
[[1]][[1]]
      Estimate   Std 2.5% CI 97.5% CI
Item1   0.339 0.099  0.130  0.519
Item2   0.761 0.067  0.607  0.867
Item3   0.564 0.076  0.400  0.694
Item4   0.669 0.076  0.497  0.792
Item5   0.483 0.092  0.286  0.645
Item6   0.550 0.085  0.363  0.696

[[1]][[2]]
      Entire Reliability   Std 2.5% CI 97.5% CI
[1,]                   0.79 0.034  0.718  0.848

[[2]]
[1] "No warnings to report"

```

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Articles

1. Alonso, A., Laenen, A., Molenberghs, G., Geys, H., & Vangeneugden, T. (2010). A Unified Approach to Multi-item Reliability. *Biometrics*, 66(4), 1061-1068.
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