The Book of Behavior Change

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Contents

Introduction

The Book of Behavior Change is an Open Access book that helps with the development of effective behavior change interventions as well as doing research into behavior change. Unlike for example Intervention Mapping, this book does not provide a complete protocol, instead focusing on identifying *what* to target, and *how* to target it, to maximize intervention effectiveness. Please be aware that this is a "*living*" book. This means that it will be updated over time and certain parts might be changed, extended or shortened.

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Academy of
Behavior Change

Chapter 1

Understanding human behavior

If you are reading this book, chances are you're already well aware of some of the many reasons to want to change human behavior.

(Obesity, substance use, exercise, etc etc, references, burden of disease, prevention, money, etc etc)

We define human behavior here as sequences of human muscle movement. Such motor activity originates in the motor cortex, and the firing patterns of motor neurons are determined by firing patterns of other neurons. Any change in human behavior, therefore, requires changing the firing patterns of these neurons that together make up the human brain. The human brain consists of roughly 90 billion of such neurons, and each is connected to on average 7000 other neurons. Directly targeting a subset of such neurons and connections is not feasible. However, these firing patterns can be targeted in a different way.

1.1 Psychology

1.2 Pragmatic nihilism

Chapter 2

Changing human behavior

2.1 ELPs: Evolutionary Learning Processes

2.2 BCP: Behavior Change Principles

Chapter 3

The behavior change toolbox

Some behaviors are easy to change, some are hard to change. Behavior change interventions are generally only required for the behaviors that are hard to change. Therefore, usually, those processes are complicated. It is easy, common even, to be overwhelmed by the multitude of things that need to be carefully mapped out in order to optimize the probability of an intervention being effective.

Therefore, a number of tools have been developed to support this process. Because of the complexity of the task, many of these tools are conceptual tools, that help to keep track of all the information that needs to be collected and organised. Other tools are more operational, providing an interface to conceptual tools or to analyses. In this chapter, we will discuss a number of tools.

3.1 Core processes

3.2 The causal-structural chain

The causal-structural chain is a conceptual tool that expresses one potential partial avenue to behavior change. Recall that all human behavior is caused elsewhere in the brain (Chapter 1), and changes in a brain in response to stimuli in one's environment are called learning (Chapter 2).

The causal-structural chain expresses the assumptions about which parts of the brain cause the behavior, and what can be done to influence those parts of the brain. In other words, it expresses the causal (what influences what) and structural (what consists of what) assumptions underlying a bit of an intervention. These assumptions are divided into three sections that together contain the seven links of the chain. These sections are behavior, psychology, and change.

The behavior section contains two links. The ultimate link is the target behavior of a given intervention. Target behaviors are generally formulated on a very general level, such as "exercise" or "condom use". As such, they consist of sub-behaviors. These sub-behaviors can be, for example, for exercise, "registering at a gym" and "scheduling gym visits", or for condom use, "buying condoms" and "negotiating condom use". These are distinguished from the overarching target behavior because the relevant determinants of these sub-behaviors can be different: for example, the reasons why people do or do not *buy* condoms can be very different from the reasons why they do or do not *carry* condoms or why they do or do not *negotiate* condom use with a sexual partner. These two links form the 'behavior' section of the causal-structural chain, and because the sub-behaviors together form the target behavior, their relationship is structural.

As discussed in Chapter 1, all (sub-)behavior is necessarily caused by people's psychology. The psychology section, therefore, captures the causes of behavior: psychology is causally linked to behavior. This section has two links as well: sub-determinants and determinants. These represent two more or less arbitrary levels of specificity that can be used to describe parts of the human psychology. Not entirely arbitrary, though. Sub-determinants are defined as aspects of the human psychology that are sufficiently specific to clearly verbalize or visualize them. They capture specific representations of the world that a person may have, or specific stimulus-response associations, or specific implicit associations. Sub-determinants can be clustered into clusters that contain sub-determinants that are similar (for example, all representations about risks) or or functionally similar (for example, all aspects of a person's psychology involved in self-monitoring). As such, sub-determinants together form determinants, and so, their relationship is structural.

As discussed in Chapter 2, all psychological changes in response to stimuli are learning. The change section, therefore, captures the causes of learning: change is causally linked to psychology. The change section consists of three links in the causal-structural chain, but the middle link is a bit different in that it represents conditions for the first link. This first link is a behavior change principle (BCP; see Chapter 2) that can change the sub-determinant in the fourth link. BCPs are general descriptions of procedures that can be followed to engage one or more evolutionary learning processes (ELPs; again, see Chapter 2). Successfully engaging those ELPs is not easy, and doing so required meeting a number of conditions. These conditions for effectiveness are included in the second link. The third link is the specific application of the BCP: the concrete, more or less tangible intervention product that the target population members will interact with. So, the BCP in the first link is applied in the application in the third link, in a way that satisfied the conditions for effectiveness in the second link.

The causal-structural chain is shown in Figure 3.1. If any of the links of the causal-structural chain is broken, it is very unlikely that the target behavior in the final link will change. Specifically:

- If the behavior change principle (BCP) does not engage one or more evolutionary learning principles (ELPs), no learning can occur. This means that no aspects of the target population's psychology can change, which means behavior will stay the same.
- If a BCP's conditions for effectiveness are not met, it will not successfully engage the underlying ELPs, which will diminish or eliminate its effectiveness.
- Because applications are the specific, tangible intervention components that make up the actual intervention, if an application does not contain a BCP, it cannot change any aspects of the target population's psychology.
- If an application successfully changes a sub-determinant, but that sub-determinant is not relevant, the targeted behavior will not change.
- Given that determinants consist of sub-determinants, the same holds for determinants: for changes in determinants to contribute to behavior change, they must be relevant to the targeted behavior.

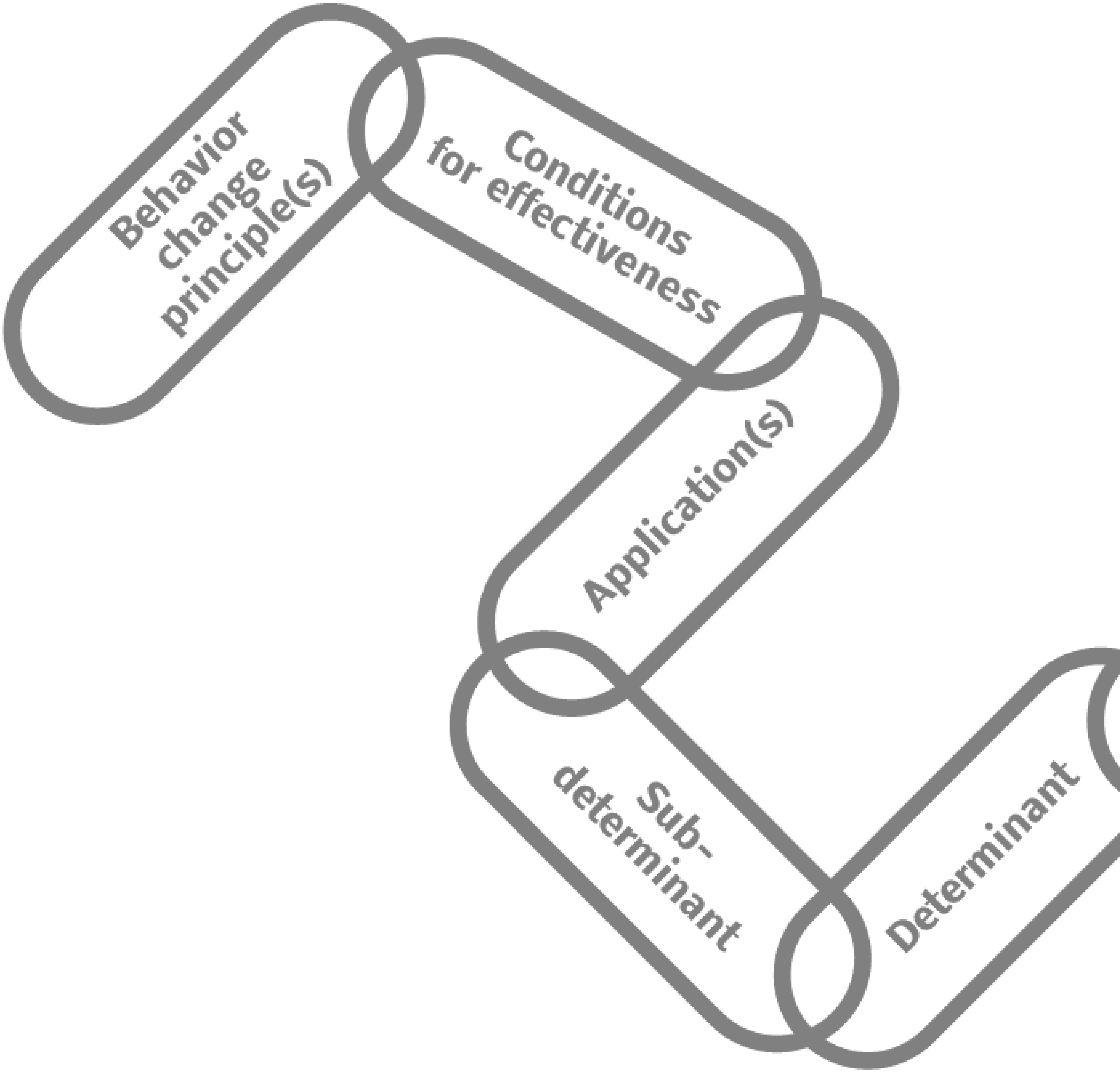


Figure 3.1: A visual representation of the causal-structural chain.

- If a sub-determinant changes, and therefore, the overarching determinant changes, and therefore, the associated behavior changes, that change only contributes to change in the ultimate target behavior if that behavior is indeed a sub-behavior of the target behavior.
- If the entire chain is intact, ultimately, the target behavior changes.

The causal-structural chain itself is hardly controversial. In fact, it does not do much more than provide a structure for a number of trivial facts. Still, it can be a very useful tool to organise the structural and causal assumptions underlying an intervention. It forms the basis of the Acyclic Behavior Change Diagram (ABCD) matrix and the ABCD itself, that will be discussed in Chapter 9.

3.2.1 A note about Intervention Mapping vocabulary

For those familiar with the Intervention Mapping framework for intervention development, the causal-structural chain will be familiar. In steps 2 and 3 of IM, the same elements are covered. The vocabulary is slightly different, though. In Intervention Mapping, sub-behaviors are called performance objectives. Sub-determinants are usually formulated according specific rules (i.e. using action verbs) and then called change objectives. Behavior change principles are called methods for behavior change.

3.3 Operational tools: software

A number of software solutions exist that support the development of behavior change interventions. Two of these will be discussed here, and both are Free/Libre Open Source Software (FLOSS) solutions. This means that they are free to download and install in perpetuity.

The first, Jamovi, is a very userfriendly general-purpose graphical user interface that can be used for a variety of analyses, unlocked through its ecosystem of modules. One of these modules, `behaviorchange`, contains a set of tools for behavior change researchers and intervention professionals. This module offers a way to access the basic functionality of a more powerful underlying package. This more powerful package is an R package called `behaviorchange`.

R is the second software solution. It was originally a statistical programming language, but it is not only open source, but also has a flexible infastructure allowing easy extension with user-contributed packages. Therefore, R is quickly becoming a multipurpose scientific toolkit, and one of its tools is the `behaviorchange` package.

When using R, most people use RStudio, a so-called integrated development environment. It has many features that make using R much more userfriendly and efficient. In this book, where we refer to using R, we actually mean using R through RStudio. Like Jamovi and R, RStudio is also FLOSS.

Figure 3.2: Jamovi logo.

3.3.1 Jamovi

You can download jamovi from https://www.jamovi.org/download.html. To use the `behaviorchange` module, you will require at least version 1.1. Once jamovi is installed, start it and click the button with the big plus to browse the jamovi Library (see Figure 3.3).

Look for the `behaviorchange` module and install it as shown in Figure 3.4.

3.3.1.1 Supplied `behaviorchange` datasets

The `behaviorchange` module comes with a number of datasets, which you can access through jamovi's data library. This is accessed by first clicking the hamburger menu (three horizontal lines) in the top-left of the jamovi screen. This opens up a menu where you can click 'open' and then 'Data library' (see Figure 3.5).

You can then open the `behaviorchange` directory as shown in Figure 3.6.

You then see an overview of the provided datasets (see 3.7; some datasets are ABCD matrices, see Chapter 9, and some are determinant studies, Chapter 6).

3.3.2 R and RStudio

Because RStudio makes using R considerably more userfriendly (and pretty), in this book, we will always use R through RStudio. Therefore, throughout this book, when we refer to R, we actually mean using R through RStudio.

R can be downloaded from https://cloud.r-project.org/:[1] click the "Download R for …" link that matches your operating system, and follow the instructions to download the right version. You don't have to start R - it just needs to be installed on your system. RStudio will normally find it on its own.

RStudio can be downloaded from https://www.rstudio.com/products/rstudio/download/. Once it is installed, you can start it, in which case you should see something similar to what is shown in Figure 3.8.[2]

R itself lives in the bottom-left pane, the console. Here, you can interact directly with R. You can open R scripts in the top-left pane: these are text files with the commands you want R to execute.

[1] Yes, that page looks a bit outdated

[2] It is easy to change RStudio's appearance; simply open the options dialog by opening the Tools menu and then selecting the Global Options; in section Appearance, the theme can be selected.

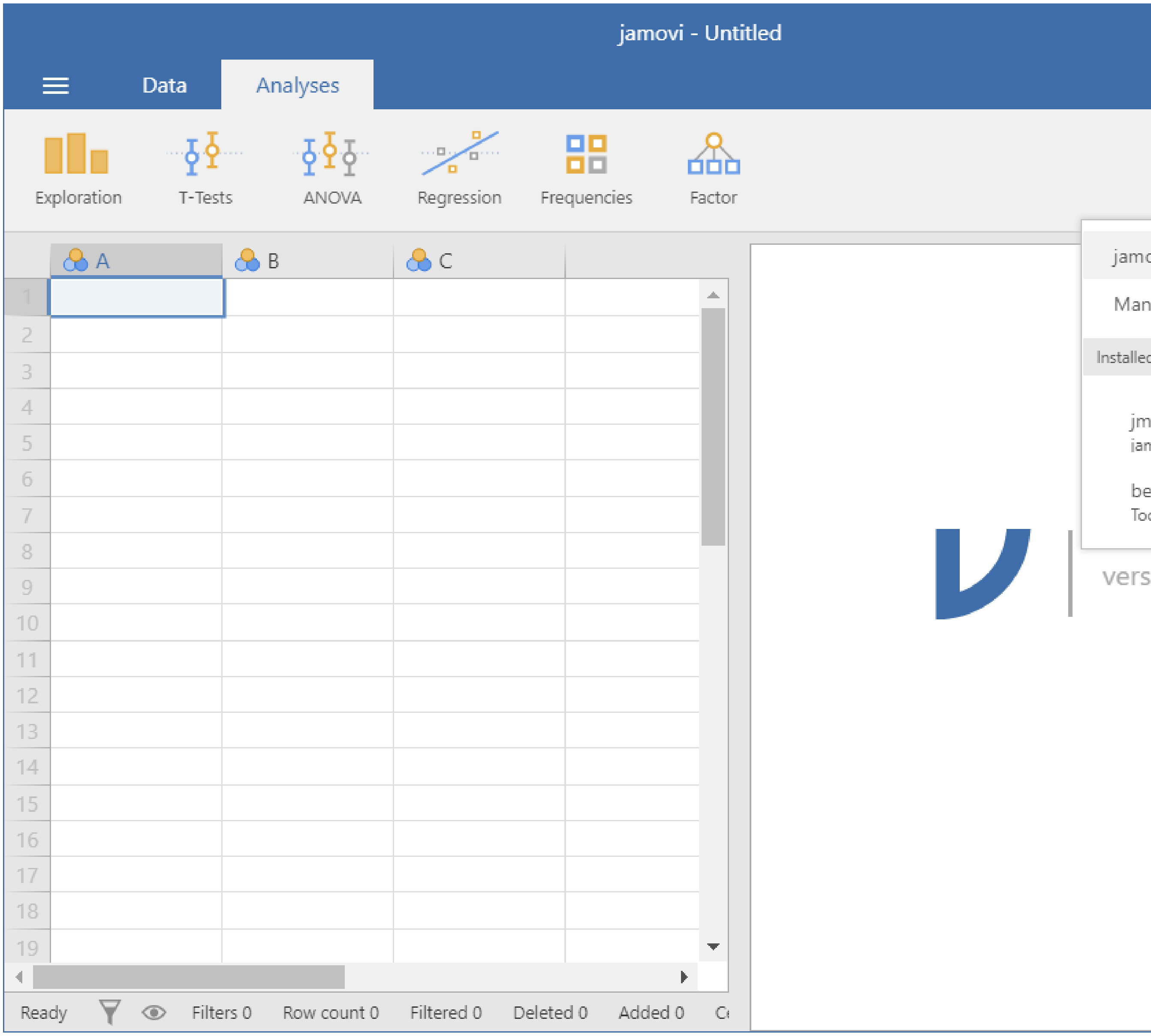


Figure 3.3: Jamovi after having clicked the big plus.

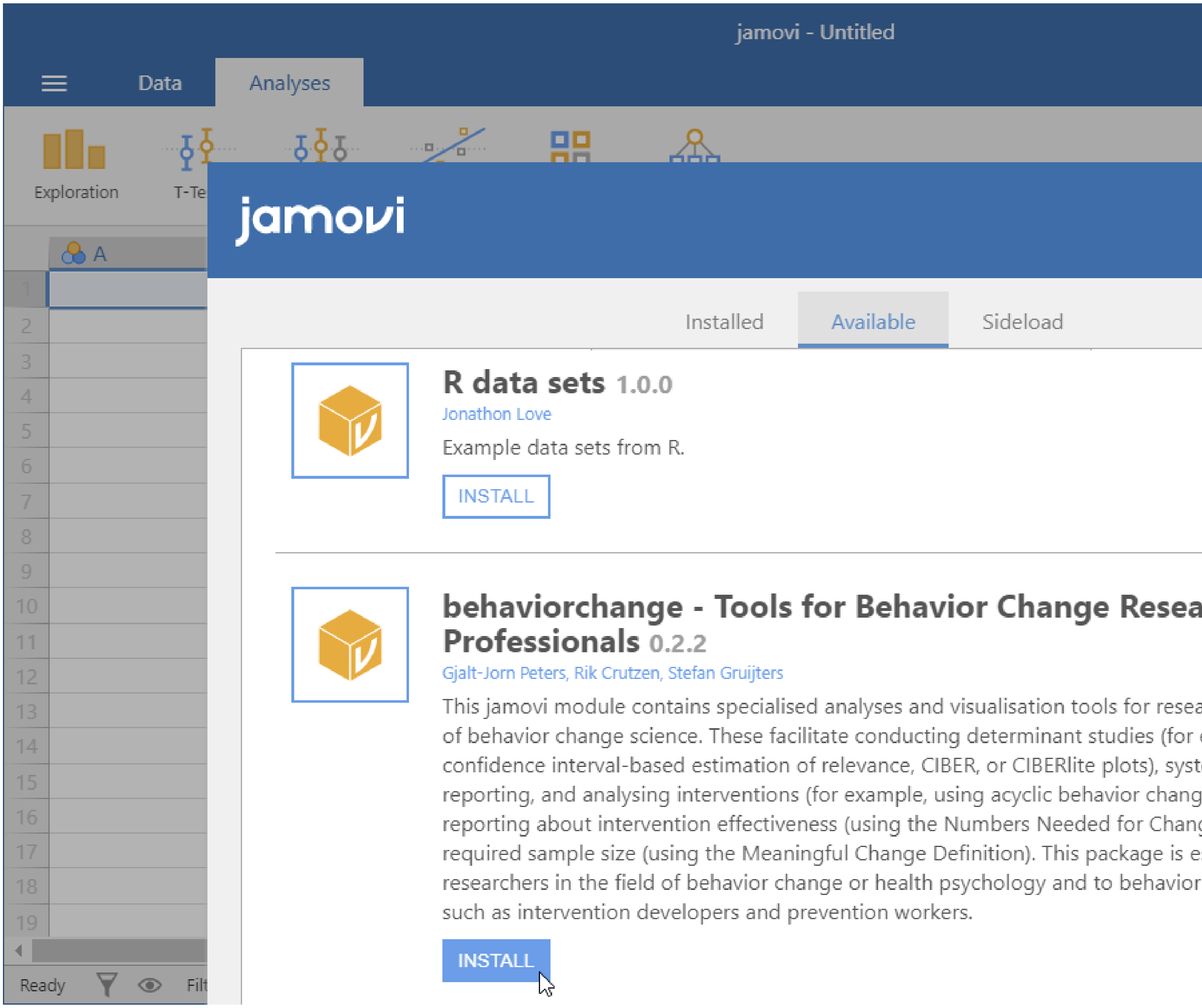


Figure 3.4: Jamovi after having clicked the big plus.

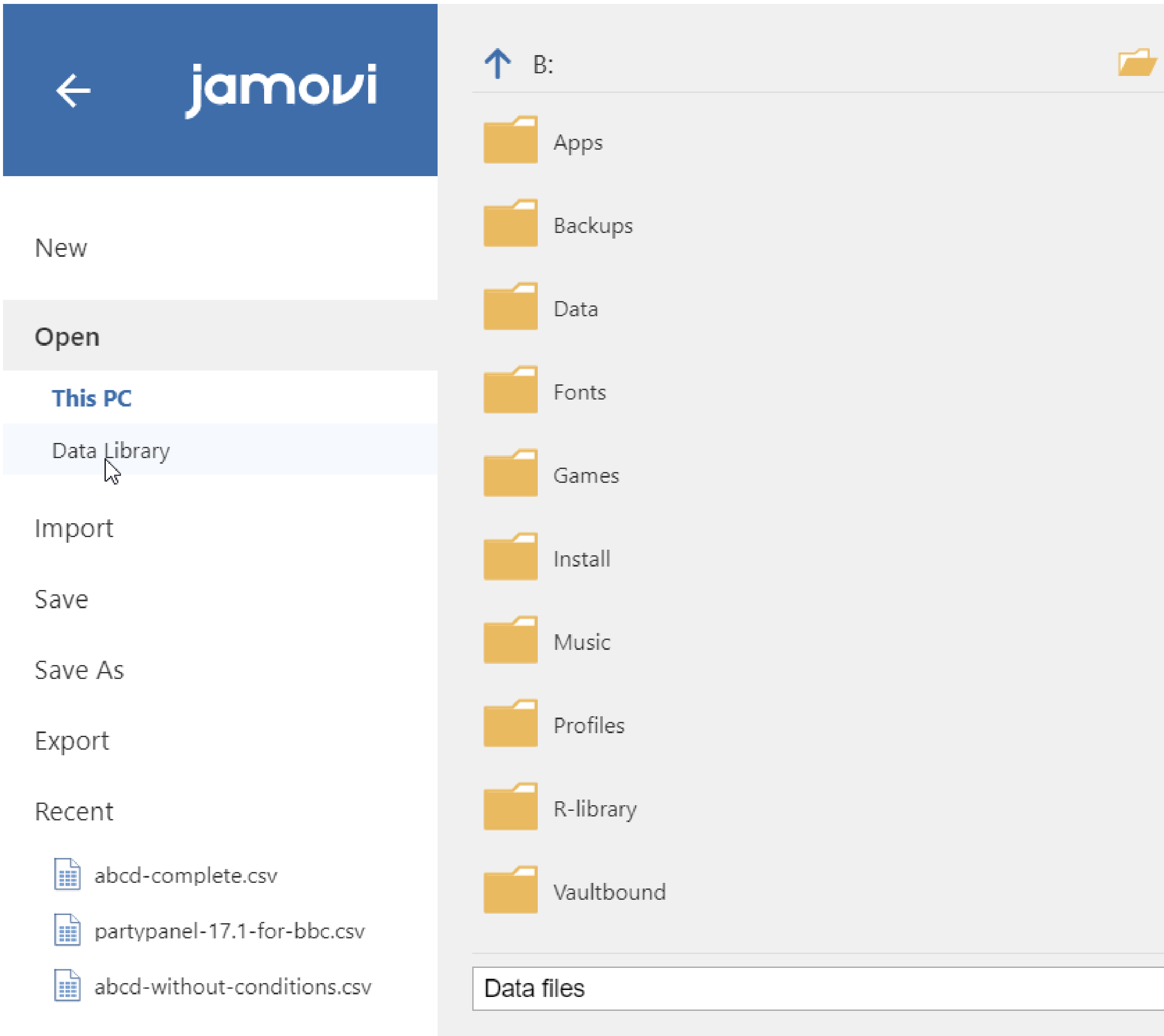


Figure 3.5: Opening jamovi's data library.

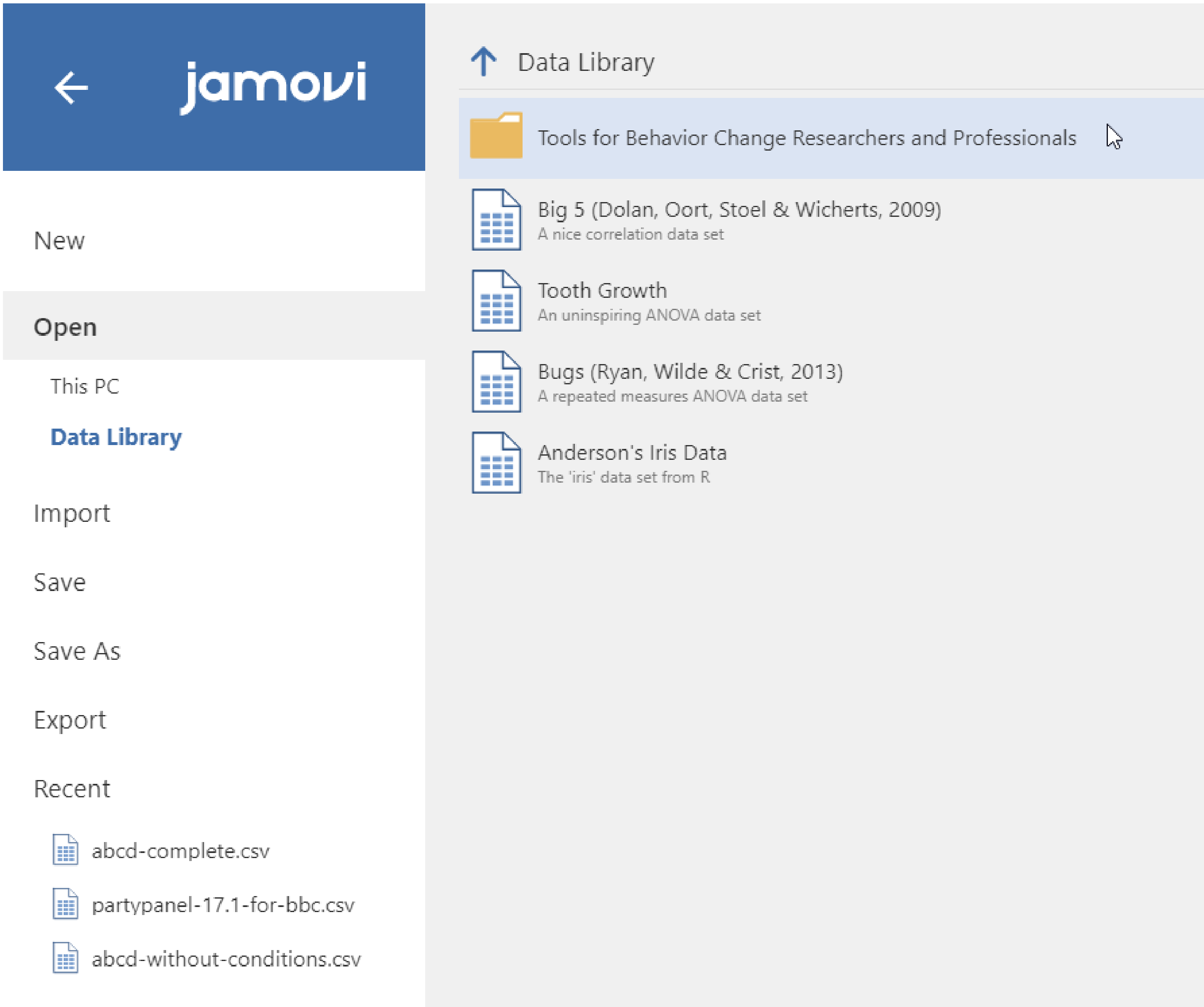


Figure 3.6: Opening the behaviorchange directory in jamovi's data library.

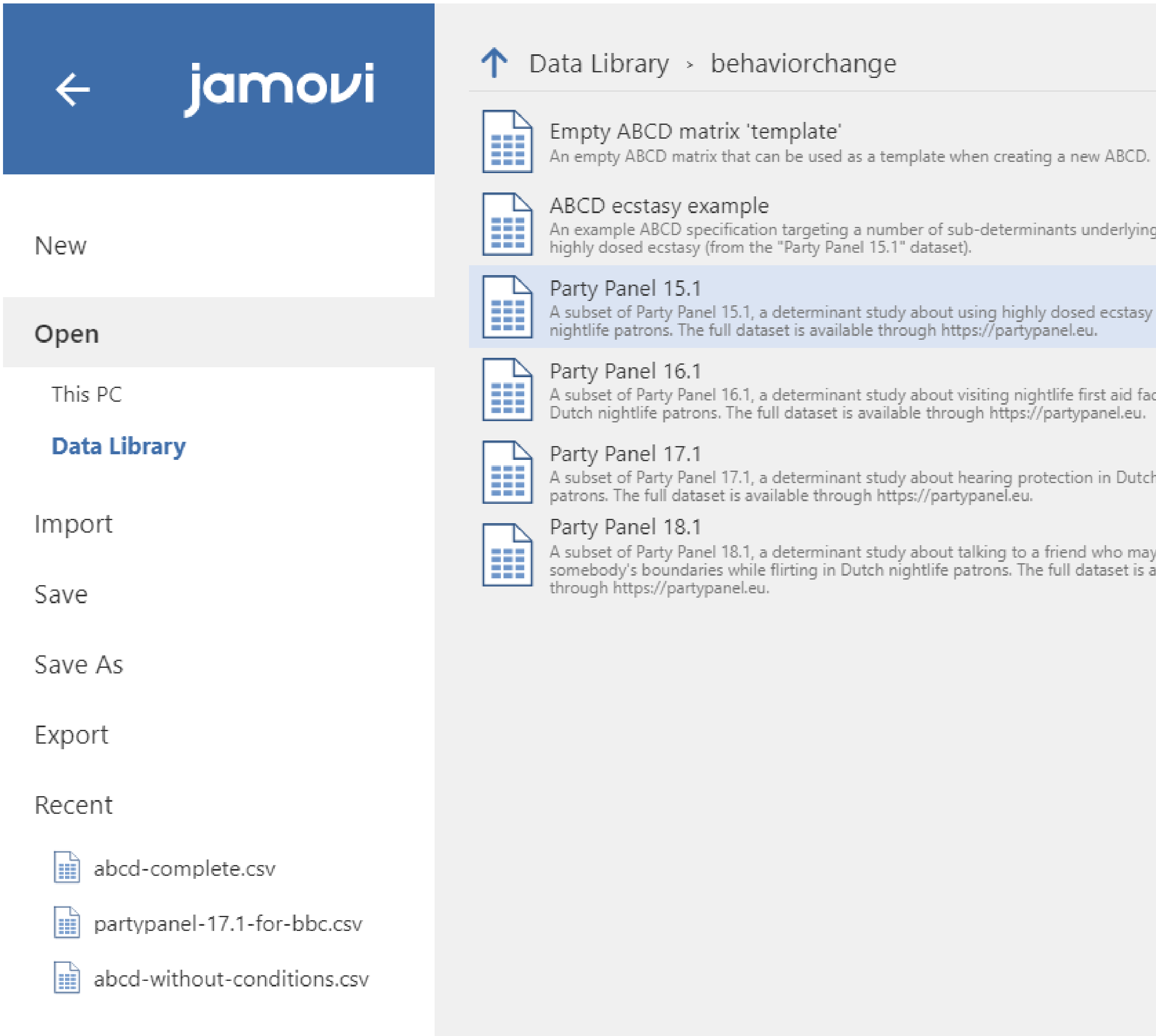


Figure 3.7: An overview of the behaviorchange datasets in jamovi's data library.

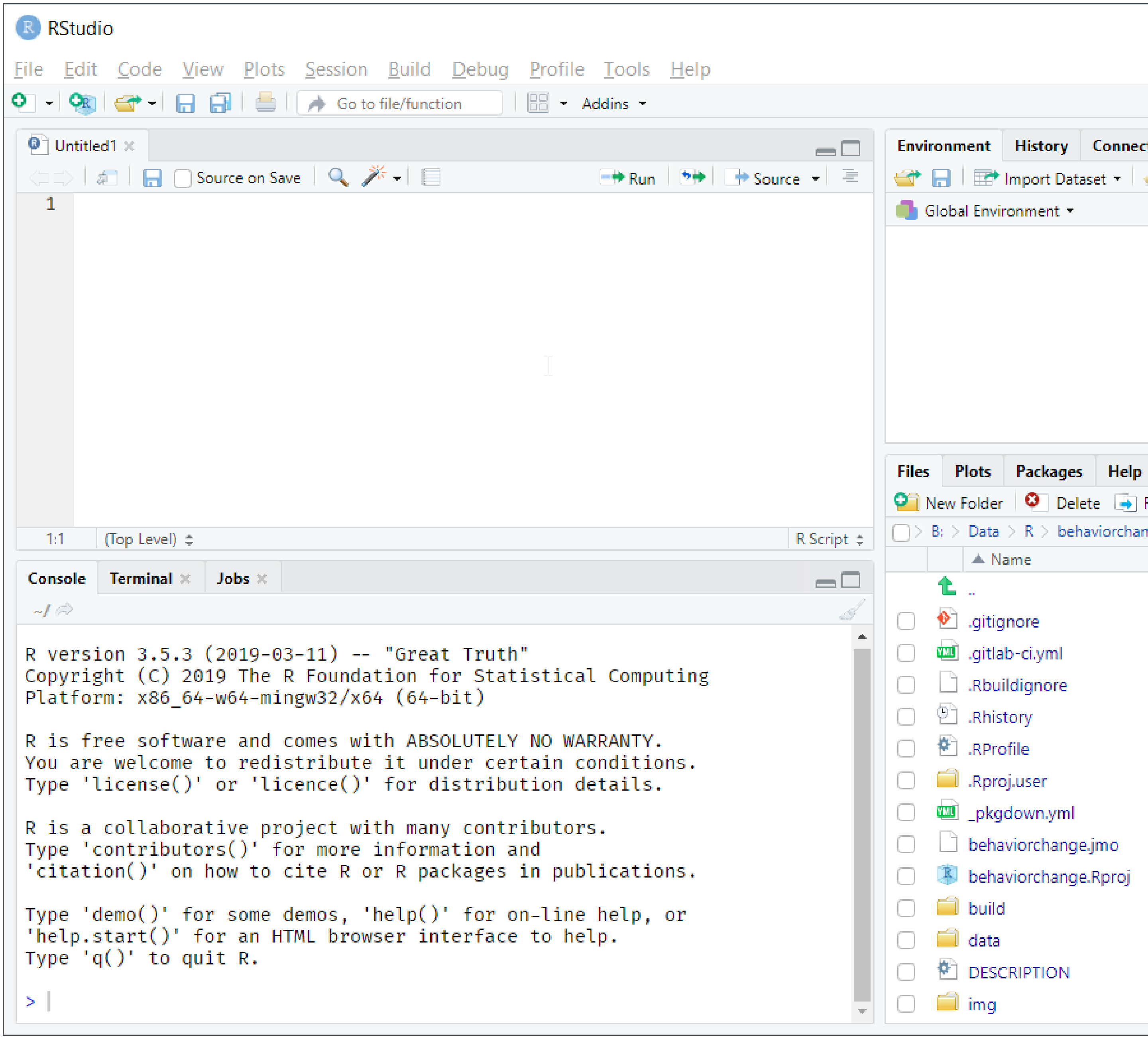


Figure 3.8: The RStudio integrated development interface (IDE).

The top-right pane contains the Environment tab, which shows all loaded datasets and variables; the History tab, which shows the commands you used; and the Connections and Build tabs, which you will not need. The bottom-right pane contains a Files tab, showing files on your computer; a Plots tab, which shows plots you created; a Packages tab, which shows the packages you have installed; a Help tab, which shows help ages about specific functions; and a Viewer tab, which can show HTML content that was generated in R.

The first thing to do is to install the `behaviorchange` package. To do this, go to the console (bottom-left tab) and type:

```
install.packages("behaviorchange");
```

This will connect to the Comprehensive R Archive Network (CRAN) and download and install the `behaviorchange` package. If you feel adventureous, you can also install the so-called development version ('dev version' for short) of `behaviorchange`. This is the most recent version, which will generally contain all the latest features, but may be less stable (i.e. contain more bugs). To conveniently install the dev version, another package exists called `remotes`. So if you want the dev version, execute these two commands:

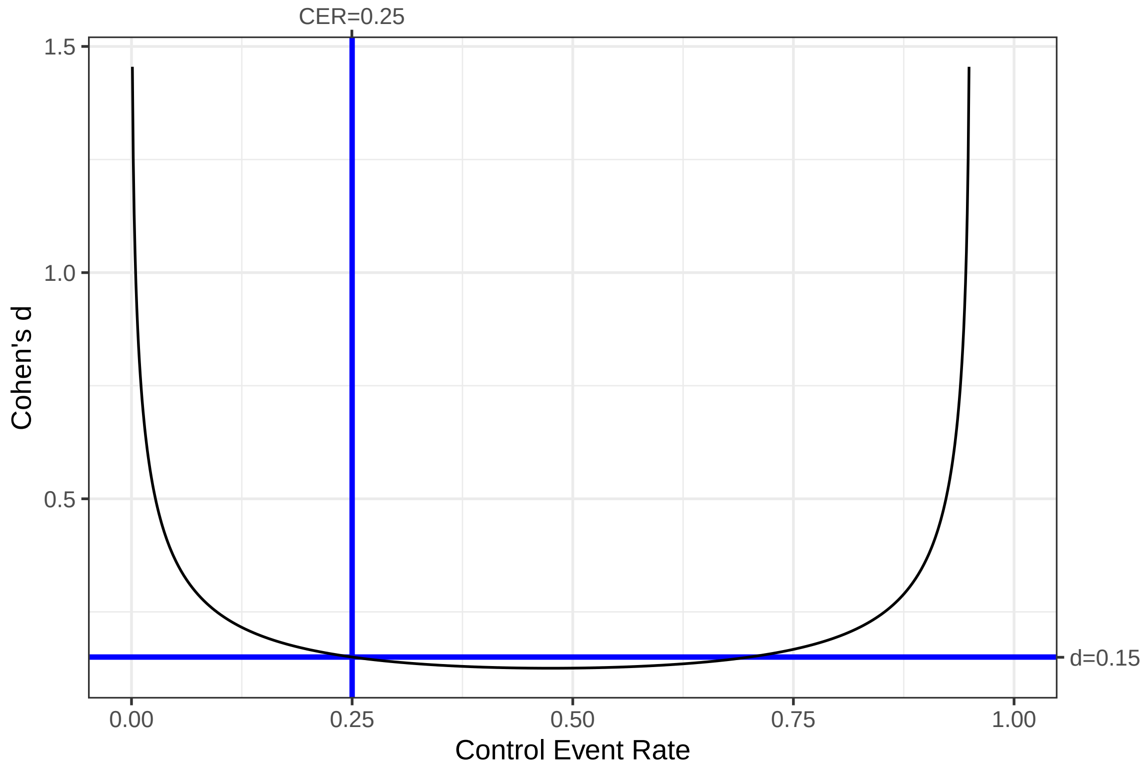
```
install.packages("remotes");
remotes::install_gitlab("r-packages/behaviorchange");
```

You can test whether you successfully installed the `behaviorchange` package by running functions that do not require data, such as the function to compute the Numbers Needed for Change (NNC) or to convert a Meaningful Change Definition to a Cohen's d value. For example, to compute the Cohen's d required to achieve a change of 5% in a variable with a control event rate (base rate) of 25% of the target populations already performing that desired behavior, you could use the following code:

```
behaviorchange::dMCD(cer = .25,
                     mcd = .05);
```

Running those code returns two things. First, the requested value of Cohen's d; and second, by default, a plot is returned that shows that Cohen's d value as a function of the base rate (control event rate) in the population. RStudio will normally print the Cohen's d value in the console itself, and show the plot in the bottom-right pane, in the Plots tab. Your results should look like this:

```
##        mcd
## cer         0.05
##    0.25 0.1500892
## attr(,"plot")
```

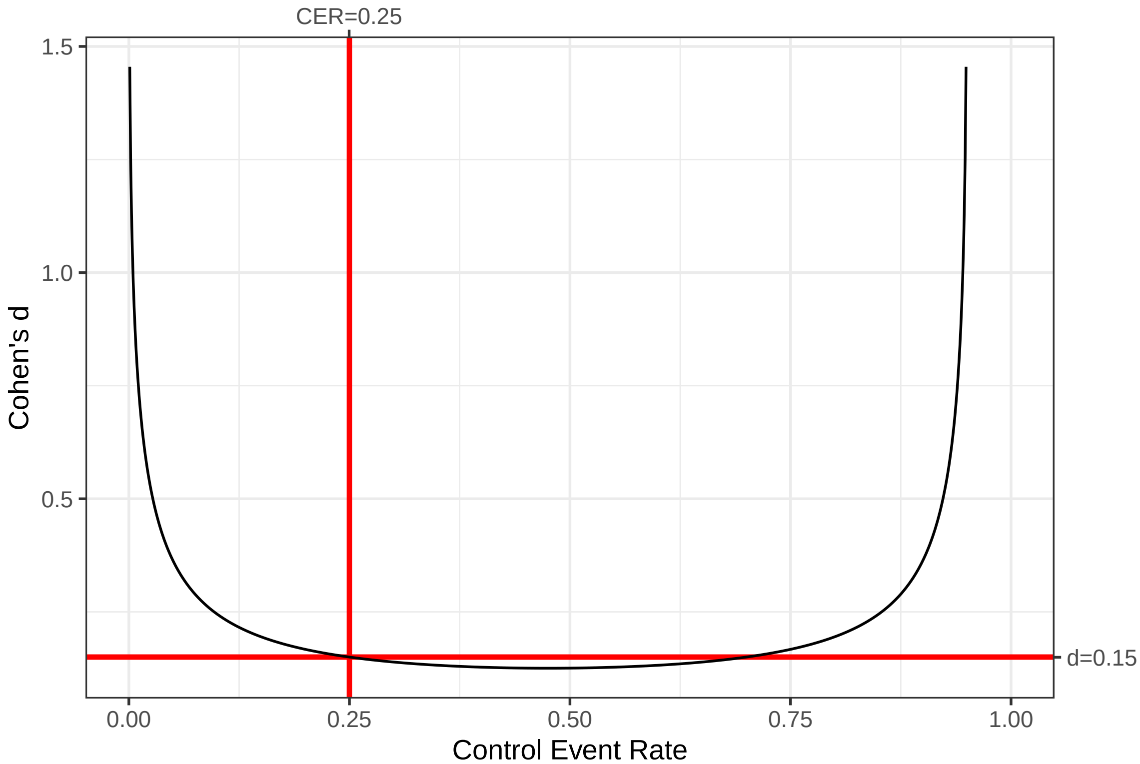


As you see, you specify what you want the function to do in between the parentheses that follow the function name. There so-called *arguments* or *parameters* provide the function with its input and tweak its behavior, for example by activating or deactivating its output. Those familiar with SPSS will recognize this behavior: in SPSS, the syntax commands also receive arguments, although their syntax is a bit different (i.e. the arguments to SPSS functions are placed directly following the function name, omitting the parentheses, and instead using forward slashes to indicate the argument names).

For example, to use a red line instead of a blue line in the plot, we can use:

```
behaviorchange::dMCD(cer = .25,
                     mcd = .05,
                     resultValueLineColor = "red");
```

```
##       mcd
## cer         0.05
##   0.25 0.1500892
## attr(,"plot")
```



RStudio can show the manual (help) page for any function in the right-most pane (in the Help tab). To request the help page for a function, type the function name directly preceded by a question mark into the console. For example:

```
?behaviorchange::dMCD;
```

3.3.2.1 Supplied `behaviorchange` datasets

The `behaviorchange` package comes with a number of datasets, which you can access in a similar way to how you access functions. Simply decide what name you would like to use to access the datasets and then assign the dataset using R's assignment operator `<-`. For example, to take the Party Panel 15.1 datasets and store it in a data.frame called `dat` (a name that is somewhat of a convention as a default):

```
dat <- behaviorchange::BBC_pp15.1;
```

Like for functions, you can get a bit of information about the dataset using R's help function, the question mark:

```
?behaviorchange::BBC_pp15.1;
```

In addition to these determinant studies, other datasets that are available are examples of ABCD matrices. You can get an overview of those using:

```
?behaviorchange::abcd_specs_examples
```

Chapter 4

Identifying determinants

Chapter 5

Identifying sub-determinants

Chapter 6

Selecting determinants

After identifying determinants and sub-determinants, the next step is to select those (sub-)determinants that are most relevant. The key reason is that resources are finite. This has an impact on the quantity and quality of intervention content that can be developed, but also delivered. The latter is especially relevant in case there are additional costs per participant (e.g., delivering an intervention in a face-to-face setting with a health professional). However, also when the additional costs per participants are low (e.g., when using a digital intervention), then there are still limits in terms of the amount of intervention content that participants can be exposed to. Although intervention content can be delivered in multiple sessions over a longer period of time, this might lead to increased levels of dropout (Rutherford et al., 2013), which also limits exposure to intervention content. So, a selection of (sub-)determinants that are targeted in an intervention is needed before developing intervention content. This selection should be based on established relevance of (sub-)determinants.

6.1 Establishing relevance

Due to a lack of clear guidelines for establishing relevance of (sub-)determinants, a variety of analytical approaches is used. For example, *dichotomization* of (a determinant of) behavior and then comparing means of (sub-)determinants or conducting *regression analyses* where (a determinant of) behavior is regressed on relevant (sub-)determinants. Use of these analytical approaches is problematic, in the context of establishing relevance of (sub-)determinans, as explained later. It is necessary to combine two types of analyses when establishing relevance: (1) assessing the univariate distribution of each (sub-)determinant and (2) assessing associations to behavior and/or determinants of behavior.

Assessing the associations of (sub-)determinants with behavior and/or determinants is important: those (sub-)determinants that are not associated to behavior and/or more proximal determinants will often be the least likely candidates to intervene upon. The univariate distributions are important because bimodal distributions may be indicative of subgroups, and strongly skewed distributions have implications for how a (sub-)determinant should be targeted. For example, if a (sub-)determinant is positively associated with behavior but left-skewed, most population members already have the desired value, so it should merely be reinforced in an intervention. Conversely, right-skewed positively associated (sub-)determinants imply a need for change, as most population members do not have the desired value yet. This latter category of sub-determinants would be more viable intervention targets as there is more room for improvement.

Before describing an analytical approach (see 6.2) that combines these two types of analyses and uses *confidence intervals* and *visualization* to establish relevance, we first describe the problems with commonly used analytical approaches, such as dichotomization and regression analyses.

6.1.1 Problems with dichotomization

Assessing associations can be done by correlation coefficients (e.g., when assuming interval level data) or by using independent-samples t-test (e.g., with Cohen's d as effect size for differences between groups). In the latter case, differences in (sub-)determinants between participants *with* and *without* a certain outcome (e.g., behavior, intention) are compared. This dichotomization of behavior or a proximal determinant such as intention leads to information loss and underestimation of variation (Altman and Royston, 2006; DeCoster et al., 2009; MacCallum et al., 2002). So, it cannot be recommended to dichotomize an outcome and then compare (sub-)determinants between particpants.

Another reason behind this is that Cohen's d point estimates, which are used when comparing differences between groups (e.g., intenders and non-intenders), can vary substantially from sample to sample (Peters and Crutzen, 2019). This renders them unfit for determinant selection on the basis of one sample. Although to a lesser extent, the same is true for estimates of means and correlation coefficients (Moinester and Gottfried, 2014). In short, accurate parameter estimation is a requirement for determinant selection (see 6.2.1), because comparison between estimates is needed. For example, the required sample for obtaining a medium-sized Cohen's d of .5 with a desired 95% confidence interval margin of error ('half-width'; also referred to as w) of .1 is 1585 (Peters and Crutzen, 2019). The required sample for obtaining a medium-sized correlation of .3 with the same w is 320. In other words, accurate estimation of correlation coefficients requires a much smaller sample in comparison with accurate estimation of Cohen's d. This is another reason, besides information loss and underestimation of variation, to *not* dichotomize outcomes.

It can be, however, that the outcome of interest *is* really dichotomous. For example, when asking whether a particpant is vaccinated for disease X. In that case, the analytical approach described later in this chapter can still be used, but it does require a large sample. A question to be asked first is whether the outcome of interest is *really* dichotomous. In other words, is there an underlying discontinuity or is the outcome (conventionally) treated as such. For example, if the outcome of interest is physical activity, then participants in the study can be categorized as adhering to guidelines on physical activity with regard to the recommended minutes of moderate to vigorous physical activity (MVPA) per day. However, there is no underlying discontuinity. It is more sensible to treat minutes of MVPA per day as a continuous outcome. The same goes, for example, for smoking behavior. While this is commonly treated as a dichotomous outcome when determining success in smoking cessation trials (West et al., 2005), there is no underlying discontinuity. It is merely a dichotomization of the number of cigarettes smoked in a given period.

So, only treat the outcome of interest as being dichotomous if there is an underlying discontuinity. Otherwise it might lead information loss and underestimation of variation and a much large sample is required for accurate estimation of parameters needed for determinant selection.

6.1.2 Problems with regression analyses

Regression analyses are useful to obtain a measure of the total explained variance in an outcome (e.g., R^2) based on *all* (sub-)determinants included in a model. This is indicative of the maximum effect that can be expected of an intervention that succesfully changes *all* (sub-)determinants. However, in the context of selecting determinants, the regression coefficients provide little information on relevance of a *specific* (sub-)determinants, because they are conditional upon the other predictors (e.g., other (sub-)determinants) in the model (Azen and Budescu, 2003; Budescu, 1993).

A convenient feature of regression analysis is that overlap between predictors in their explanation of the outcome is removed from the equation (quite literally, in the case of regression). Squaring a correlation coefficient always yields the proportion of explained variance: if a determinant, for example attitude, and an outcome, for example intention, have a bivariate (i.e. zero-order) correlation of $r = .32$, that means that they each explain .1 (i.e., .32 x .32) of each other's variance in the sample. The 95% confidence interval runs from [0.03; 0.19], which gives some idea of how far the explained variance in the population can be expected to deviate from that sample estimate. Another determinant, for example self-identity, has a correlation of $r = .47$ with intention, and so this determinant explains .22 of intention.

However, attitude and self-identity also correlate with each other ($r = .32$). It is therefore likely that they also share explained variance in intention. In that case, simply adding together the proportion of intention's variance they each explain (.1 + .22 = .32) would yield an overestimate of how much intention these determinants explain together.

This correction of overlap in explained variance is very useful, and enables better estimation of the variance explained by all predictors together. However, this overlap between predictors is in itself highly problematic when dealing with the separate regression coefficients of all psychological constructs used as predictors (e.g., overlap between (sub-)determinants of behavior; (Azen and Budescu, 2003; Budescu, 1993)).

Correlation between (sub-)determinants represents relevant information about human psychology. For example, the two (sub-)determinants may cover the same aspects of human psychology according to their definition. Or alternatively, the (sub-)determinant may be independent but causally related, either because they influence each other (directly or through one or more mediators) or are both influenced by the same third variable. It is hard to empirically distinguish between (sub-)determinants that influence or consist of each other (Peters and Crutzen, 2017), and the distinction is irrelevant with respect to the problem that surfaces in regression analyses.

In this case, removing the variance representing this overlap between (sub-)determinants means removing variance that corresponds to aspects of human psychology that fall within the definition of the (sub-)determinant. In other words, removing this shared variance from a (sub-)determinant and only considering variance that is not shared with other (sub-)determinants means that the resulting data series no longer represent the (sub-)determinant as originally operationalised, and therefore, as defined, but an unknown alteration of this (sub-)determinant. Therefore, removing this shared explained variance when estimating the regression coefficients means that these regression coefficients no longer represent the association of each (sub-)determinant to the outcome Instead, they represent the association of some unknown part of each (sub-)determinant with some unknown part of the criterion.

Another way to think about this is by using the formulation often invoked when explaining regression analyses: the regression coefficient expresses the association of a predictor to the criterion *holding all other predictors constant*. If two predictors overlap in their definition, or, in other words, if the definitions of the constructs represented by the two predictors contain the same aspects of human psychology, then 'holding all other predictors constant' means 'neglecting a part of human psychology'. This means the resulting situation is unrealistic and can never occur. This also means that the omitted aspects of human psychology are in fact important to predicting the relevant behavior. Therefore, a predictor that represents an important (sub-)determinant of behavior may nonetheless have a small regression coefficient, because an important part of the human psychology as defined in the (sub-)determinant's definition was omitted from the coefficient.

Thus, because estimates from regression analyses are problematic when establishing determinant relevance, it is better to base such decisions on the bivariate correlations, or more accurately, on the confidence intervals for these correlation coefficients, together with the information about the (sub-)determinants' distributions and means. We will now illustrate an anlytical approach for efficiently inspecting all this information simultaneously: Confidence Interval-Based Estimation of Relevance (CIBER).

6.2 CIBER: Confidence Interval-Based Estimation of Relevance

CIBER is based on *visulation* of *confidence intervals* concerning both means of (sub-)determinants and their estimated association to behavior and/or more proximal determinants of behavior. Before describing how to apply CIBER (see 6.3), we first explain the importance of confidence intervals and the need for visualisation in the context of determinant selection.

6.2.1 The importance of confidence intervals

When inspecting association and distribution estimates (e.g,. correlations and means), the population values are always unknown. The only way to learn about a population is by taking a random sample and inspecting that sample. So, sampling provides a way to 'look at' the population, without having access to the whole population. However, sampling, by its random nature, therefore also introduces random variation. This means that whatever is observed in the sample may not reflect the population. In other words, the specic estimate arrived at on the basis of any particular sample has next to no value. It is also necessary to know how accurate the estimate is: how much it can be expected to differ between samples.

This estimation of accuracy is based on the concept of the sampling distribution: the theoretical distribution containing all potential values for any sample estimate, given its (unknown) population value and the sample size. Because the population value is always unknown (otherwise there is no need to sample in the first place), the true sampling distribution is necessarily also known. However, for many parameters that can be estimated from a sample, the shape and spread of the sampling distribution are known. This means that the sampling distribution can be constructed for any hypothetical population value.

The best known example is perhaps the sampling distribution of the mean, which is approximately normally distributed (except for extremely small samples) with a standard deviation equal to the population standard deviation divided by the square root of the sample size. Knowing the sampling distribution's distribution shape and spread allow computation of intervals that contain, in innite repetitions of the sampling procedure, the population value in a given percentage of the samples: the confidence interval. A wide confidence interval means that the point estimate is very unreliable and can have a substantially different value in a new sample, whereas a narrow confidence interval means that a substantially different value in a new sample is less likely. These properties make them well suited for estimation of population values from sample data.

Therefore, whenever using sample data to draw conclusions for selecting determinants (or anything, really), point estimates should not be used. Instead, also considering estimate accuracy, for example by computing confidence intervals, allows taking the inevitable sampling and error variation into account.

6.2.2 The need for visualization

Adding confidence intervals to association and distribution estimates (e.g,. correlations and means) also means that determinant selection becomes almost an inhuman taks: For each (sub-)determinant, the univariate distribution and mean, as well the lower and upper confidence interval bounds would have to be inspected, as well as the correlation coefficients with behavior and perhaps a proximal determinant of behavior such as intention, again together with the lower and upper confidence interval bounds. Even with only 10 (sub-)determinants, this would mean simultaneously evaluating 60 estimates. Therefore, CIBER is based on data visualization.

Data visualization has three advantages in the context of determinant selection. First, visualization enables mapping the data onto spatial dimensions, facilitating comparison, which is necessary when making selections. Second, visualization foregoes the seeming accuracy and objectivity afforded by numbers (Peters, 2017). Given the relative width of most sampling distributions and the subsequent variation that occurs in estimates over samples (Moinester and Gottfried, 2014; Peters and Crutzen, 2019), caution in basing decisions on the exact computed numbers seems prudent. Third, visualization enables assessing confidence intervals for means in the context of the raw data.

When applying CIBER, confidence intervals are represented using the diamond shapes commonly used for the aggregated effect size in meta-analyses (Peters, 2017). Unlike error bars with whiskers, diamonds do not draw attention to the confidence interval bounds. They are an efficient method of representing both the mean and the confidence interval in one shape, allowing both stroke and fill colors, which makes it possible to use the fill color to further facilitate interpretation, and the stroke color to identify, for example, which determinant a shape represents. Another *advantage* is that it is *not easy to see the exact values* of the three estimates represented by the diamond (the mean and lower an upper confidence bounds). Although this might not seem like an advantage at first glance, this lack of clarity is consistent with the estimates' imprecision [i.e., their variation from sample to sample (as described in 6.2.1)]. These diamond plots are then used to visualize the raw data, the point estimate and confidence interval for the mean of the (sub-)determinant, and the point estimate and confidence interval for the assocation with the outcome (e.g., correlation with behavior and/or one or several more proximal determinants of behavior). Each (sub-)determinant, the question used to assess it, as well as the anchors can be shown.

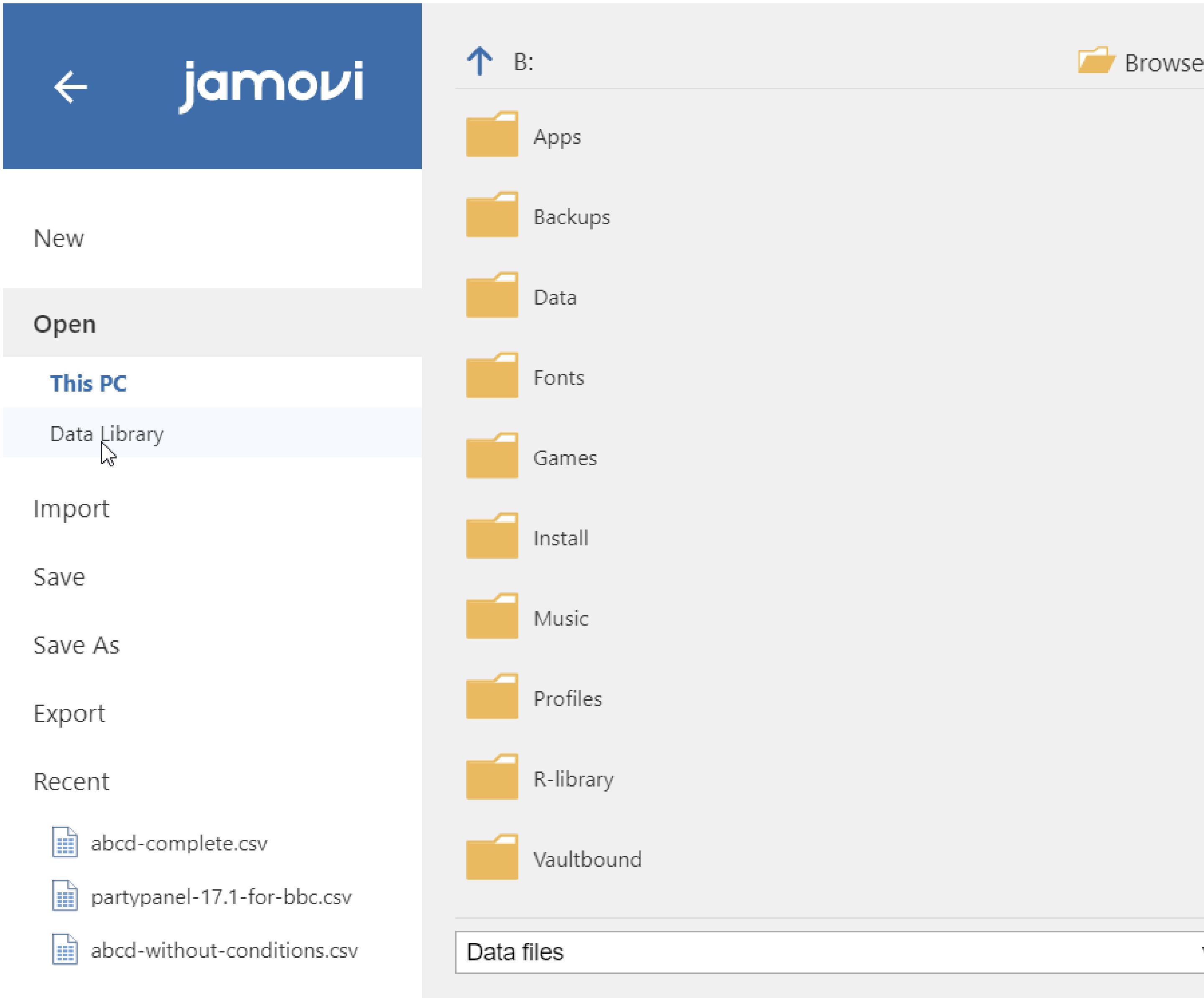
In short, CIBER acknowledges that several metrics need to be combined and interpreted in order for data to become valuable information for selecting determinants.

6.3 Applying CIBER

CIBER is a function in the R package *behaviorchange* and is also included in the jamovi module *Tools for Behavior Change Researchers and Professionals*. In this section, we start by explaining how to apply CIBER when using jamovi, as this has an easy-to-use point-and-click interface. Subsequently, we explain how to apply it when using R Studio. The latter uses scripts that allow working with more advanced settings.

One dataset is used throughout this chapter as an example. This data is collected as part of the Party Panel initiative. This semi-panel determinant study is used to map the (sub-)determinants of different nightlife-related risk behaviors each year. The data used in this chapter focuses on (sub-)determinants of protecting one's ears when exposed to loud music in nightlife settings. Specifically, three behaviors were explored: carrying hearing protection, wearing hearing protection, and buying hearing protection if one did not carry but was exposed to loud music. The study is described in more detail in the full report.

When using **jamovi**, the data can be downloaded and stored locally. Subsequently, click on the hamburger button in the top-left corner and Open > This PC to use the data in jamovi. This specic dataset is also supplied with the jamovi module itself. So, it can also be opened by clicking on Hamburger button > Open > Data Library > Tools for Behavior Change Researchers and Professionals (see Section #ref(jamovi-supplied-behaviorchange-datasets)).



When using **R studio**, the data can be imported directly from GitLab using the syntax below.

```
dat <- read.csv(paste0("https://gitlab.com/partypanel/partypanel-17.1",
                       "/raw/master/results%20-%20data/",
                       "partypanel-17.1-for-bbc.csv?inline=false"));
```

However, this specific dataset is also embedded within the R package *behaviorchange*. The dataset can be used by means of the syntax below.

```
dat <- behaviorchange::BBC_pp17.1
```

If you want to use your own data, then the syntax below can be used to open a dialog box and select the file containing the data.

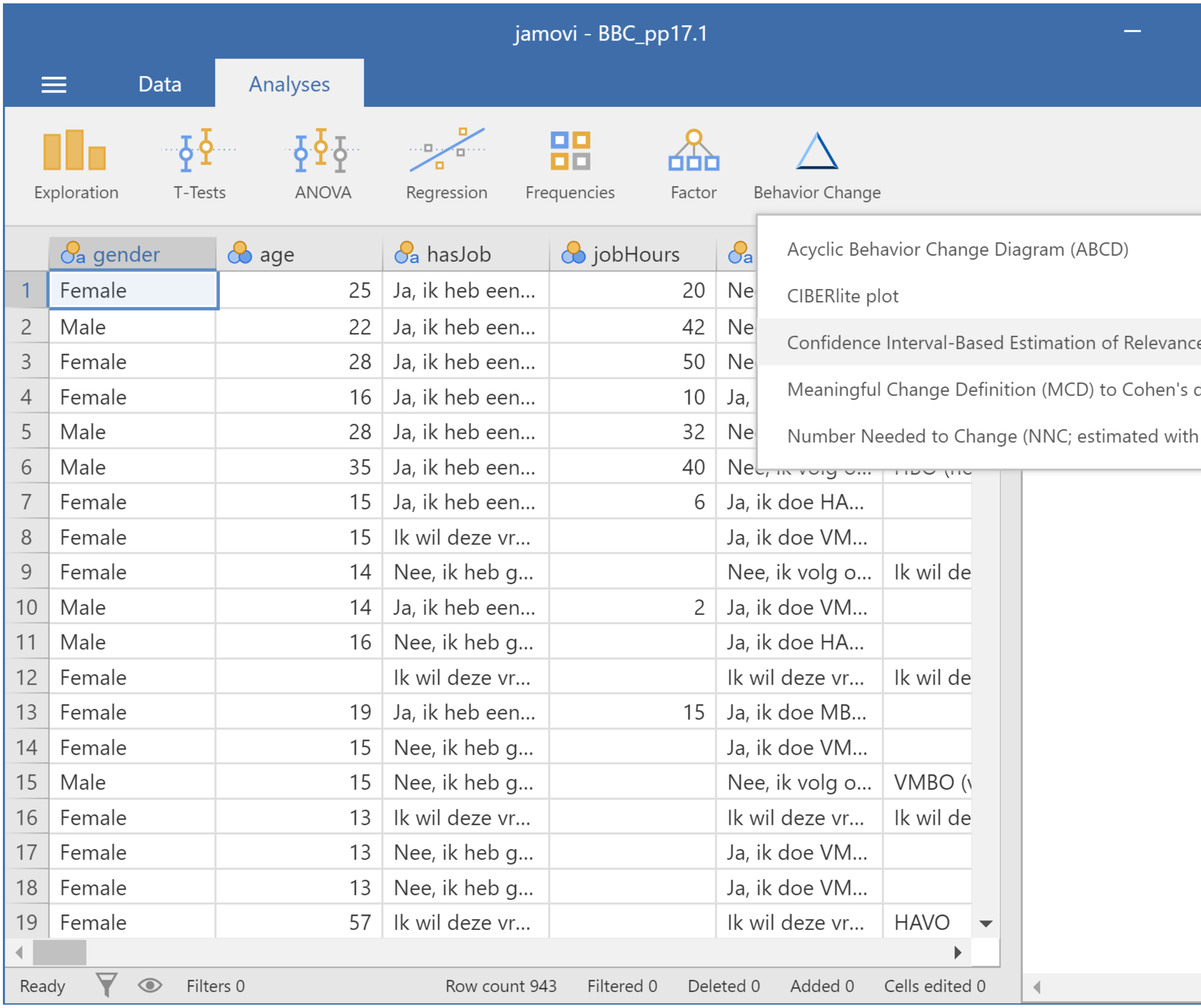
```
ufs::getDat()
```

6.3.1 Continous outcome

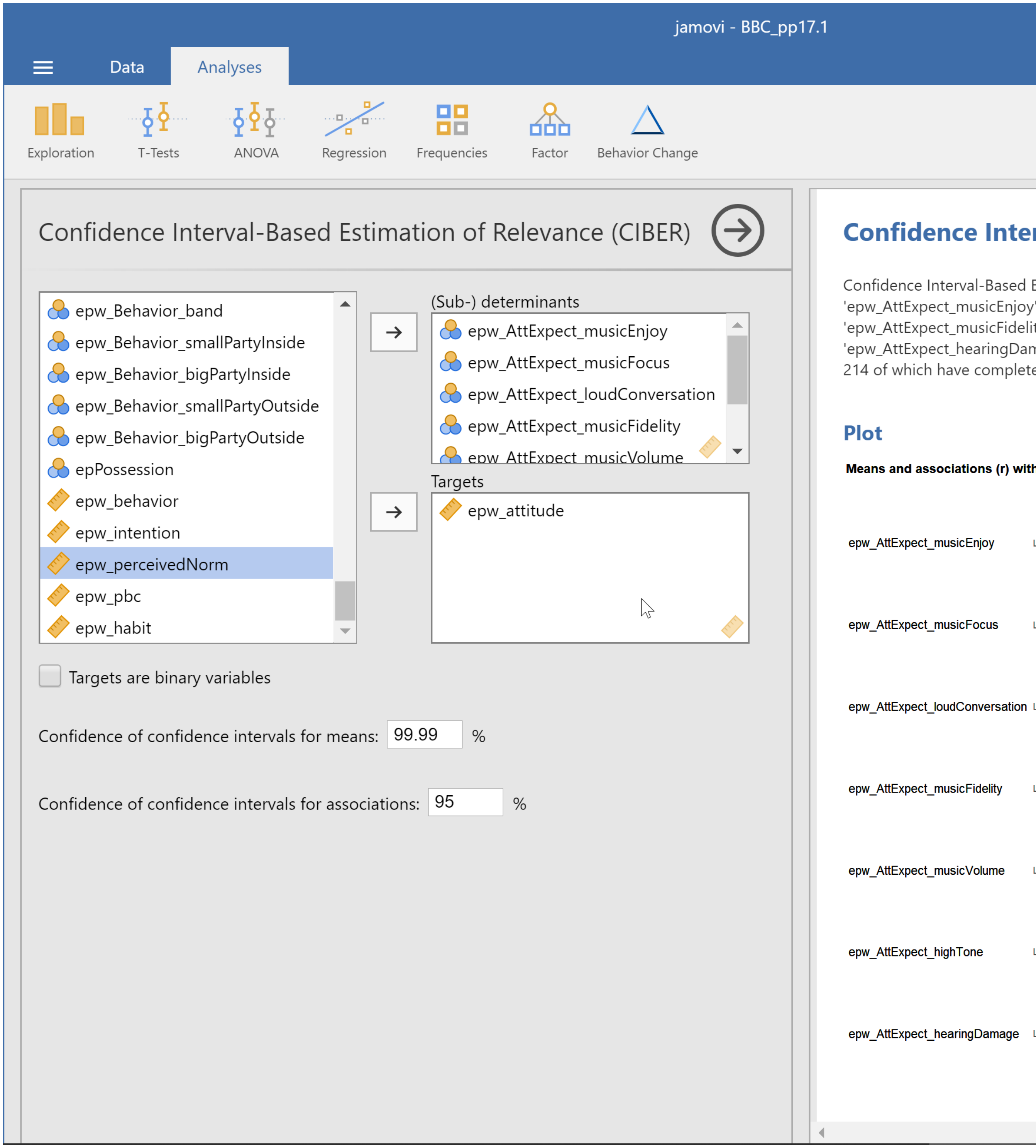
The behavior of interest in this section is wearing hearing protection. The first step is to explore the associations between sub-determinants and their overarching determinant; in this case how behavioral beliefs with regard to wearing hearing protection are associated with attitude towards wearing hear protection. The stem of the questions that were used to assess these behavioral beliefs started with "If I am somewhere where the music is loud, and I wear ear plugs, then…". The leaf of these questions as well as their anchors and the variable names used in the dataset are provided in the table below.

Variable name	Question	Left anchor	Right anchor
epw_AttExpect_hearingDamage	… is the chance that my hearing gets damaged…	Very small	Very big
epw_AttExpect_highTone	… is the chance at ringing in the ears the next day…	Very small	Very big
epw_AttExpect_musicVolume	… I hear the music…	Very soft	Very loud
epw_AttExpect_musicFidelity	… I hear the music…	Exactly the same	Extremely disturbed
epw_AttExpect_loudConversation	… I have … trouble with people talking loud.	Not at all	Much more
epw_AttExpect_musicFocus	… I can focus … on the music.	Much worse	Much better
epw_AttExpect_musicEnjoy	… I enjoy the music…	Much less	Much more

When using **jamovi**, click on Behavior Change > Confidence-Interval Based Estimation of Relevance (CIBER) to create CIBER plots.



The variables regarding the behavioral beliefs (as specified in the table) need to be dragged to the box *(Sub-) determinants*. The variable 'epw_attitude' contains the direct measurement of attitude (in line with the Reasoned Action Approach) and needs to be dragged to the box *Targets*. The CIBER plot will now be automatically generated and can be seen on the right side of the screen.


jamovi - BBC_pp17.1
Data
Analyses
Exploration
T-Tests
ANOVA
Regression
Frequencies
Factor
Behavior Change
Confidence Interval-Based Estimation of Relevance (CIBER)
epw_Behavior_band
epw_Behavior_smallPartyInside
epw_Behavior_bigPartyInside
epw_Behavior_smallPartyOutside
epw_Behavior_bigPartyOutside
epPossession
epw_behavior
epw_intention
epw_perceivedNorm
epw_pbc
epw_habit
(Sub-) determinants
epw_AttExpect_musicEnjoy
epw_AttExpect_musicFocus
epw_AttExpect_loudConversation
epw_AttExpect_musicFidelity
Targets
epw_attitude
Targets are binary variables
Confidence of confidence intervals for means: 99.99 %
Confidence of confidence intervals for associations: 95 %
Plot
epw_AttExpect_musicEnjoy
epw_AttExpect_musicFocus
epw_AttExpect_loudConversation
epw_AttExpect_musicFidelity
epw_AttExpect_musicVolume
epw_AttExpect_highTone
epw_AttExpect_hearingDamage

In the screenshot you can see that you can adjust the width of the confidence intervals for means and associations. The CIBER plot on the right will be automatically updated. You can save the CIBER plot by right-clicking on it > Image > Save... The CIBER plot can be saved in different formats: PDF, PNG, SVG, and EPS. The syntax underlying the point-and-click actions is displayed above the CIBER plot and is also automatically updated. Displaying the syntax can be switched on or off by clicking on the kebab-button (i.e., 3 dots) in the top-right corner and tick the box 'Syntax mode.' Editing the syntax, which allow working with more advanced settings, can only be done by using R studio.

When using **R studio**, the syntax below generates the CIBER plot regarding the behavioral beliefs, using the variable 'epw_attitude' as outcome.

```
behaviorchange::CIBER(data=dat,
                      determinants=c('epw_AttExpect_hearingDamage',
                                     'epw_AttExpect_highTone',
                                     'epw_AttExpect_musicVolume',
                                     'epw_AttExpect_musicFidelity',
                                     'epw_AttExpect_loudConversation',
                                     'epw_AttExpect_musicFocus',
                                     'epw_AttExpect_musicEnjoy'),
                      targets=c('epw_attitude'));
```

The diamonds in the left hand panel show the item means with 99.99% confidence intervals. The fill color of the diamonds is indicative of the item means - the redder the diamonds are, the lower the item means; the greener the diamonds are, the higher the items means (blue denotes means in the middle of the scale). The dots surrounding the diamonds show the item scores of all participants with jitter added to prevent overplotting. The diamonds on the right hand panel show the association strengths (i.e., correlation coefficients with 95% confidence intervals) between individual beliefs and the direct measure of attitude. The fill color of the diamonds is indicative of the association strengths and their direction - the redder the diamonds are, the stronger and more negative the associations are; the greener the diamonds are, the stronger and more positive the associations are; the grayer the diamonds are, the weaker the associations are. The confidence intervals of the explained variance (R^2) of the outcome (in this case the direct measurement of attitude) is depicted at the top of the figure and based on all (sub-)determinants that are included (in this case the behavioral beliefs).

The CIBER plot shows that participants, on average, think that chances of getting hearing damaging and riniging in the ears the next day are relatively low. However, these beliefs are not associated with the direct measurement of attitude. Participants' expecatations regarding disturbance of hearing music due to ear plugs score on the middle of the scale, but are much stronger associated with the direct measurement of attitude. In general, the explained variance in the direct measurement of attitude by these seven behavioral beliefs is rather limited. This indicates that other sub-determinants (i.e., behavioral beliefs) might contribute to explaining variance in the direct measurement of attitude.

The syntax canbe used to adjust the CIBER plot. For example, changing width of confidence intervals, but also changing the anchors and questions, the title, and the colours used within the

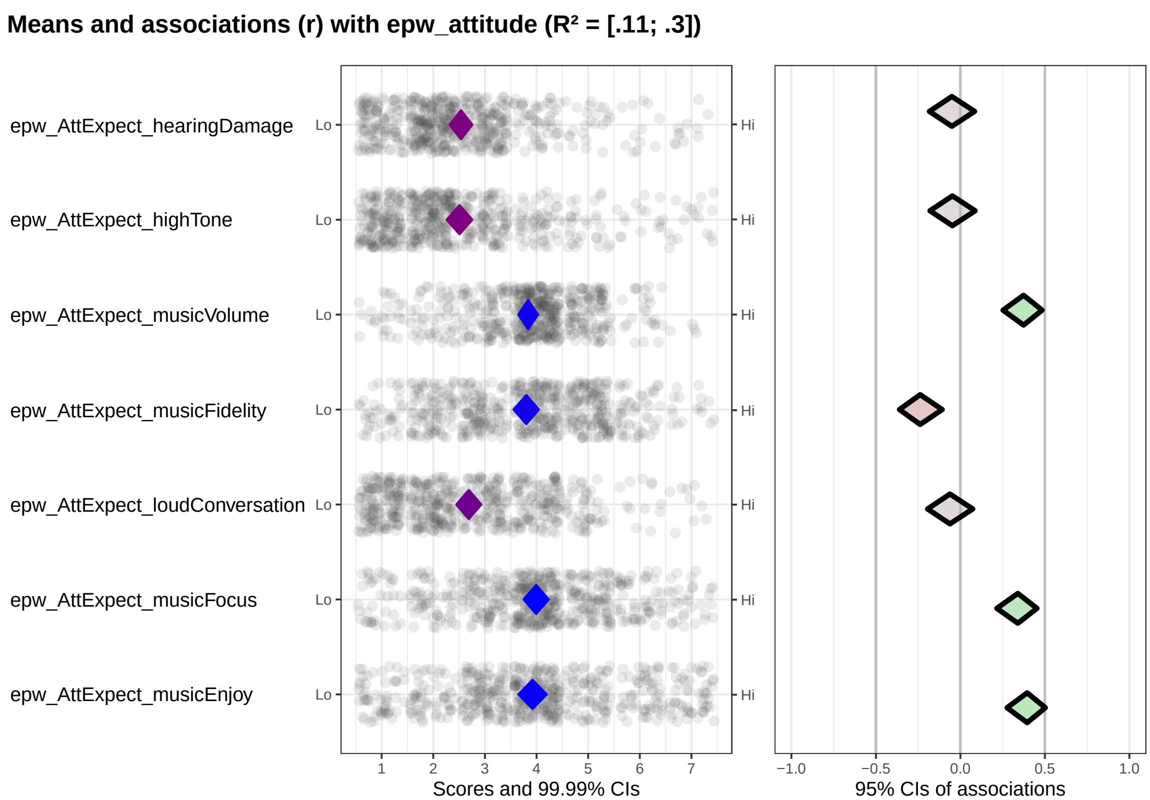


Figure 6.1: CIBER plot behavioral beliefs

CIBER plot as well as the orderning of determinants. The command below opens the helpfile which contains an overview of all the arguments that can be used within the CIBER function.

```
?CIBER
```

Two examples of using such arguments are provided below.

```
## Argument that can be used to change width of confidence intervals
conf.level = list(means = 0.9999,
                  associations = 0.95)

## Argument that can be used to change title of CIBER plot
titlePrefix = "Means and associations (r) with"
```

The syntax below shows which arguments can be used to save the CIBER plot in a separate file.

```
outputFile="filename_that_you_want_to_use.png",
outputParams=list(type="cairo-png")
```

The syntax below generates the CIBER plot regarding the direct measurement of attitude, perceived norm, and perceived behavioral control (in line with Reasoned Action Approach) as well as the Self-Report Behavioral Automaticity Index (SRBAI; Gardner et al., 2012), using the variables 'epw_behavior' and 'epw_intention' as outcomes. The stroke color of the diamonds (i.e., the "line color") can be used to differentiate associations between (sub-)determinants and different outcomes. In this example, the diamonds with a purple stroke show the associations with behavior and the diamonds with a yellow stroke show the association with intention.

```
behaviorchange::CIBER(data=dat,
                      determinants=c('epw_attitude',
                                     'epw_perceivedNorm',
                                     'epw_pbc',
                                     'epw_habit'),
                      targets=c('epw_behavior',
                                'epw_intention'));
```

The first tenet of pragmatic nihilism (see 1.2) is that psychological variables are usefully considered as metaphors rather than referring to entities that exist in the mind. The overlap in definitions between many theories' variables means that various theories can likely perform equally well in the prediction of behavior in any given situation, as long as the operationalisations of the theories' variables cover the relevant aspects of people's psychology. Considering psychological variables as possibly non-existent, but certainly useful metaphors, equal to their operationalisation for all practical purposes, means that distinguishing whether variables predict each other or contain each other becomes both hard and less relevant to successfully predicting and changing behavior. If experiential attitude and instrumental attitude together form attitude, changing either of them should result in a (smaller) change in attitude. Conversely, if attitude changes, depending on which

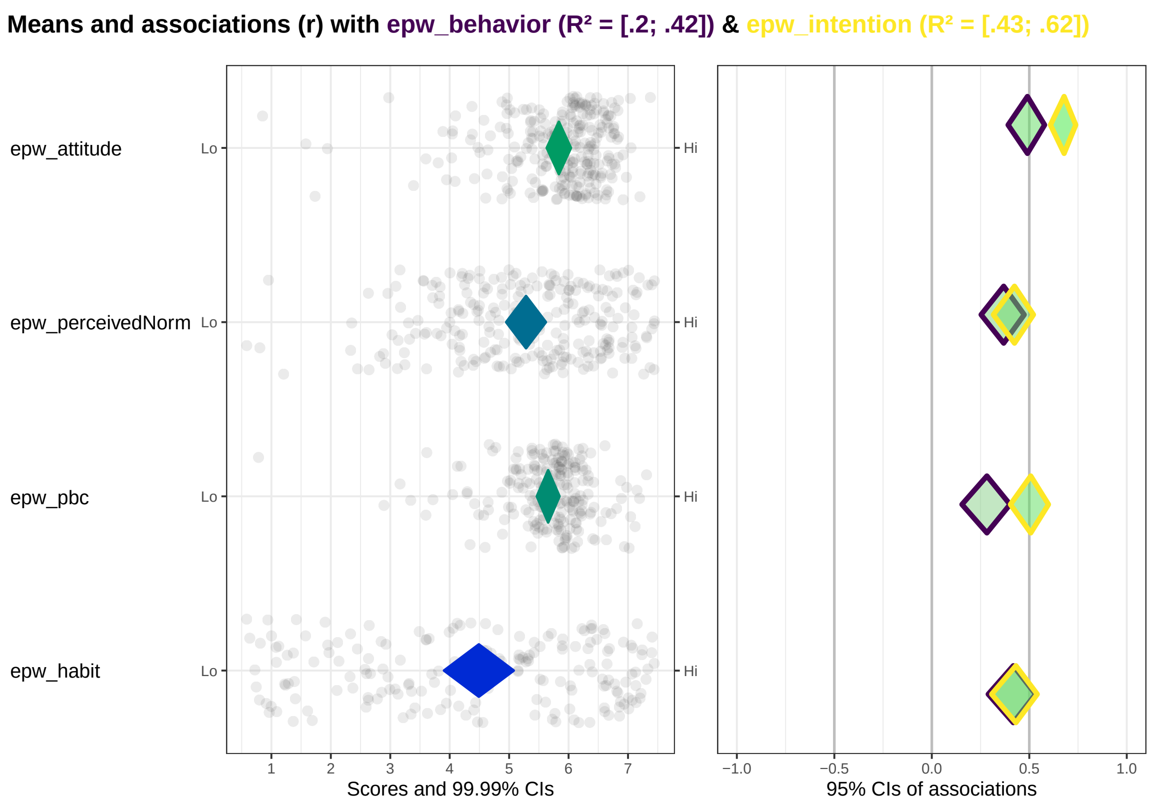


Figure 6.2: CIBER plot determinants

specific elements of attitude change, one or both of experiential and instrumental attitude also change. Acknowledging pragmatic nihilism justifies the generation of a CIBER plot including all (sub-)determinants (in this case behavioral, normative, and control beliefs as well as the seperate aspects assessed in the SRBAI), using the variables 'epw_behavior' and 'epw_intention' as outcomes again. To facilitate interpretation of the CIBER plot, the questions and anchors are also provided.

```
behaviorchange::CIBER(data=dat,
                      determinants=c('epw_AttExpect_hearingDamage',
                                     'epw_AttExpect_highTone',
                                     'epw_AttExpect_musicVolume',
                                     'epw_AttExpect_musicFidelity',
                                     'epw_AttExpect_loudConversation',
                                     'epw_AttExpect_musicFocus',
                                     'epw_AttExpect_musicEnjoy',
                                     'epw_NrmInjunct_partner',
                                     'epw_NrmInjunct_bestFriends',
                                     'epw_NrmInjunct_otherFriends',
                                     'epw_NrmInjunct_partyPeople',
                                     'epw_NrmInjunct_parents',
                                     'epw_NrmInjunct_siblings',
                                     'epw_PBCBeliefs_recognize',
                                     'epw_PBCBeliefs_remember',
                                     'epw_PBCBeliefs_fit',
                                     'epw_PBCBeliefs_fallOut',
                                     'epw_PBCBeliefs_intoxicated',
                                     'epw_Habit_automatic',
                                     'epw_Habit_withoutThinking',
                                     'epw_Habit_beforeRealising',
                                     'epw_Habit_withoutRemembering'),
                      targets=c('epw_behavior',
                                'epw_intention'));
```

Variable name	Question	Left anchor	Right anchor
Injunctive norms	And what do you think that these people think if you wear ear plugs if you are somewhere where the music is loud?		
epw_NrmInjunct_partner	My partner (girlfriend or boyfriend)	Very disapproving	Very approving
epw_NrmInjunct_bestFriends	My best friends	Very disapproving	Very approving
epw_NrmInjunct_otherFriends	My other friends	Very disapproving	Very approving
epw_NrmInjunct_partyPeople	Most people at the party	Very disapproving	Very approving

Variable name	Question	Left anchor	Right anchor
epw_NrmInjunct_parents	My parents/care takers	Very disapproving	Very approving
epw_NrmInjunct_siblings	My brothers/sisters	Very disapproving	Very approving
Perceived behavioral control			
epw_PBCBeliefs_recognize	I find it ... to recognize whether the music is so loud that ear plugs are needed.	Very difficult	Very easy
epw_PBCBeliefs_remember	If I am somewhere and I have my ear plugs with me, I find it ... to remember to wear them in time.	Very difficult	Very easy
epw_PBCBeliefs_fit	Ear plugs fit me ... most of the time.	Very unpleasant	Very pleasant
epw_PBCBeliefs_fallOut	Ear plugs fall out...	Not fast from my ears	Very fast from my ears
epw_PBCBeliefs_intoxicated	If I have used alcohol or something else, the chance that I remember to wear ear plugs is...	Much smaller	Much bigger
Habit	If I go somewhere where the music is loud, then wearing ear plugs is something I do...		
epw_Habit_automatic	...automatically		
epw_Habit_withoutThinking	...without thinking		
epw_Habit_beforeRealising	...before realising		
epw_Habit_withoutRemembering	...without consciously remembering that I did it		

6.3.2 Dichotomous outcome

The function 'binaryCIBER' is similar to 'CIBER.' Use of this function is *only* recommended if there is a real underlying discontuinity in the outcome of interest (see 6.1.1). In this case, the outcome of interest is whether participants possessed ear plugs (yes/no response). The syntax below generates a CIBER plot regarding some general beliefs concerning, using the variable 'epPossession' as outcome. When using **jamovi**, make sure to click 'Targets are binary variables' below the left hand panel. To facilitate interpretation of the CIBER plot, the questions and anchors are also provided.

The diamonds and dots in the left hand panel have show the the item means with confidence intervals and item scores of all participants, respectively. Two colours (both stroke and fill) are used to dinstinguish participants that scored 'no' and 'yes' on the outcome of interest (in this case; whether they possessed ear plugs). The two values regarding R^2 are Nagelkerke's R^2 and Cox-Snell's R^2 respectively. Cox-Snell's R^2 is based on the log likelihood for the model compared to the log likelihood for a baseline model. However, with categorical outcomes, its theoretical maximum value is less than 1. Nagelkerke's R^2 is an adjusted version of Cox-Snell's R^2 that adjusts the scale of the statistic to cover the full range from 0 to 1 (Nagelkerke, 1991).

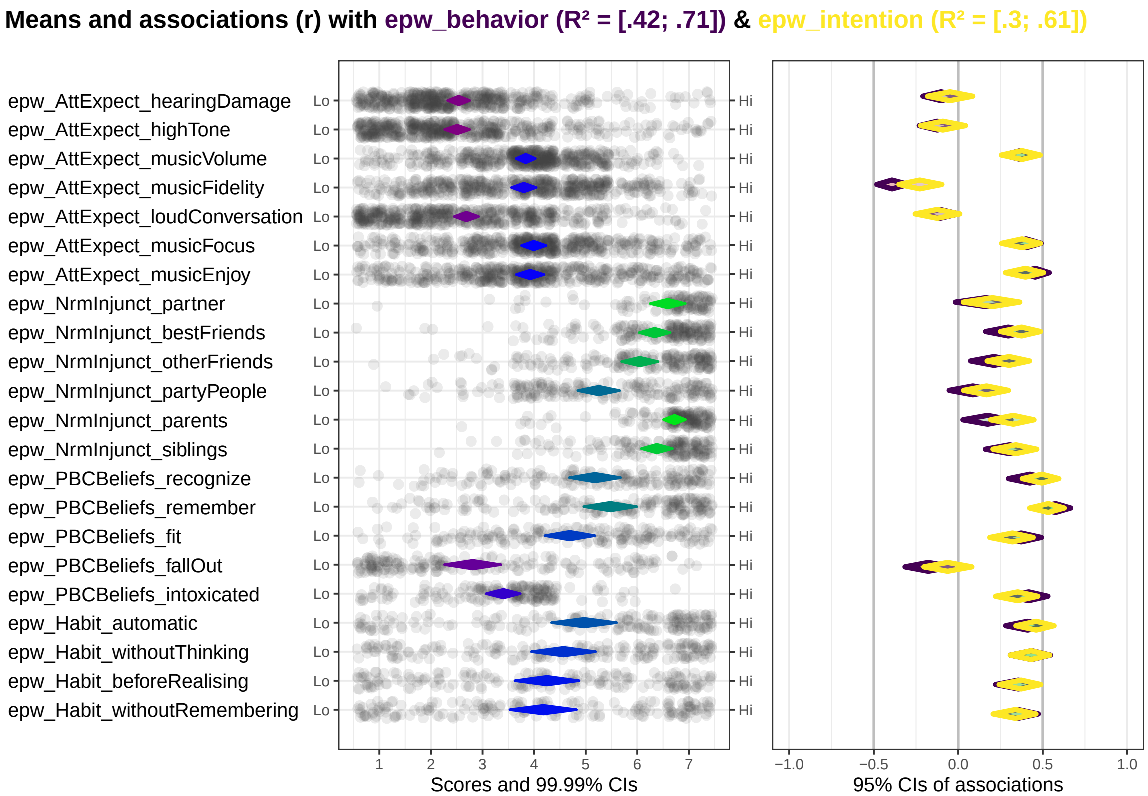


Figure 6.3: CIBER plot various beliefs

```
behaviorchange::binaryCIBER(data=dat,
                            determinants=c('epGeneralBeliefs_loudnessPreference',
                                           'epGeneralBeliefs_loudnessGenre',
                                           'epGeneralBeliefs_loudnessTooMuch',
                                           'epGeneralBeliefs_priceFoam',
                                           'epGeneralBeliefs_priceSilicon',
                                            'epGeneralBeliefs_priceCustom'),
                            targets=c('epPossession'),
                            categoryLabels = c('no',
                                               'yes'));
```

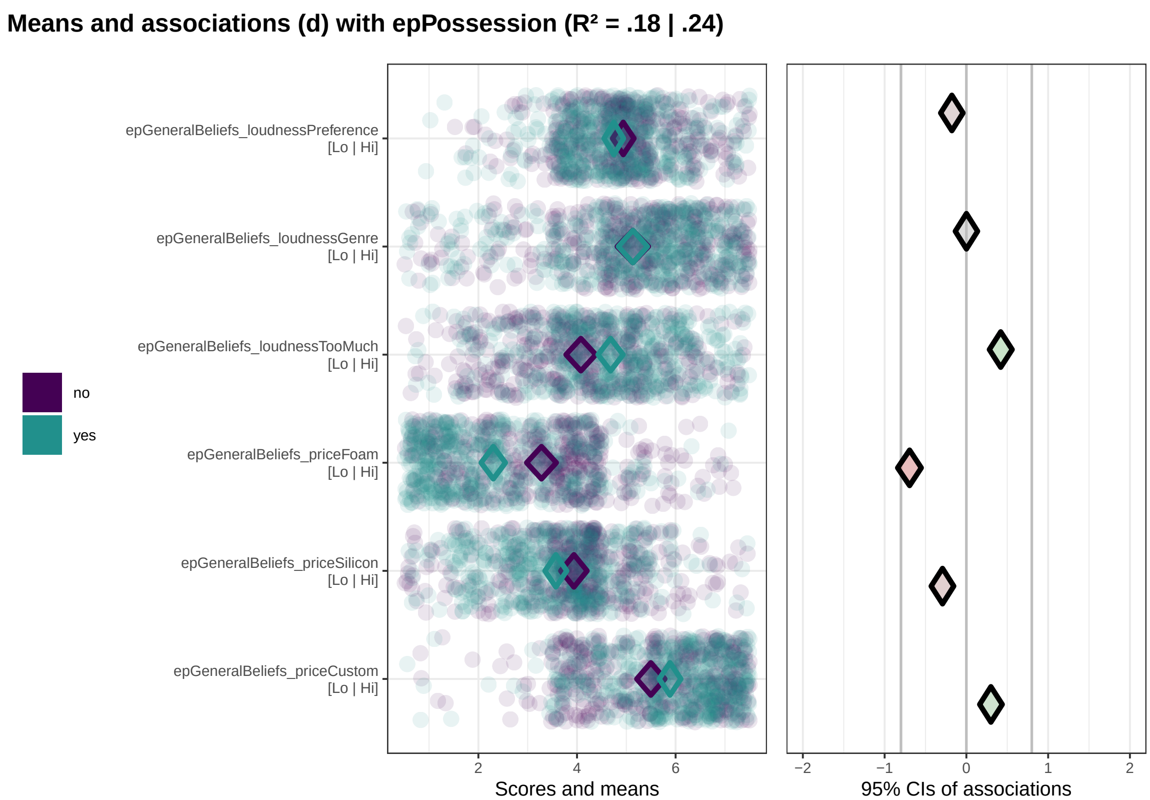


Figure 6.4: CIBER plot dichotomous outcome

Variable name	Question	Left anchor	Right anchor
epGeneralBeliefs_loudnessPreference	I appreciate it if music at parties and gigs is…	As soft as possible	As loud as possible

Variable name	Question	Left anchor	Right anchor
epGeneralBeliefs_loudnessGenre	Does it depend on the music genre how loud you want to hear music at parties and gigs?	Not at all	Very strongly
epGeneralBeliefs_loudnessTooMuch	I think that music at parties and gigs is...	Never too loud	Always too loud
epGeneralBeliefs_priceFoam	I think foam or rubber ear plugs are...	Very cheap	Very expensive
epGeneralBeliefs_priceSilicon	I think universal ear plugs are...	Very cheap	Very expensive
epGeneralBeliefs_priceCustom	I think tailored ear plugs are...	Very cheap	Very expensive

Chapter 7

Identifying Behavior Change Principles

Once it is clear which aspects of the human psychology need to be targeted with an intervention to promote the desired behavior, it becomes possible to start thinking about how to target those aspects. This is when the Methods for Behavior Change (BCMs, the term used in Intervention Mapping terminology, (Bartholomew et al., 1998)) or Behavior Change Techniques (BCTs, the term used in the Behavior Change Wheel literature, (Abraham and Michie, 2008)) come in. In this book, we will use the term Behavior Change Principles (BCPs, (Crutzen and Peters, 2018)):

> A BCP is any principle or any set of principles that can be applied to change behaviour, or more accurately, determinants of behaviour, with the assumption that it will be effective. Stated more strongly, we would argue that any intervention that successfully changes one or more determinants of behaviour must therefore involve one or more BCPs.

If you are familiar with BCTs but not with BCMs, it is important at this point to clearly understand the difference; ((Crutzen and Peters, 2018)):

> The idea is that BCMs are effective if the parameters for use are properly respected when translating BCMs to practical applications (Kok et al., 2016). In this vocabulary, there is a clear distinction between the active ingredients (the BCM) and the operationalisation of these principles (the practical application). The description of BCTs, on the other hand, 'is precise enough to achieve reliability of recognition but the definition does not require that BCTs be effective' (Michie et al., 2015), which is one of the reasons BCTs are not suited for intervention development. BCTs, therefore, are somewhat of an amalgam of BCMs (hypothetically effective methods of behaviour change) and practical applications (operational definitions) that may include inactive ingredients. Those BCTs that are ineffective therefore involve no BCPs; and of those that are effective, their description may contain elements that are not required to adequately leverage the relevant BCPs.

Behavior change princples

In essence, this means figuring out how to help the target population individuals to learn specific things (see Chapter 2).

Behavior change principles

Chapter 8

Selecting Behavior Change Principles

Chapter 9

Tying it all together

Identifying (Chapters 4 and 5) and selecting (Chapter 6) determinants and sub-determinants and identifying (Chapter 7) and selecting (Chapter 8) behavior change principles (BCPs) usually means that an overwhelming amount of information has been collected and processed, and many decisions have been made. Therefore, it can often happen that one feels a bit overwhelmed and loses overview. At this point, it can be useful to tie everything together in one visualisation.

Fortunately, a tool exists to do exactly that: the acyclic behavior change diagram (ABCD). ABCDs consist of two components. The diagram itself is one component: a visual representation of the most important structural and causal assumptions underlying an intervention. This diagram is generated based on the other component: the ABCD matrix. This matrix is just a table with seven columns, where each row represents one causal-structural chain (see Section 3.2). As such, the seven columns of the ABCD matrix correspond to the seven links of the causal-structural chain.

9.1 The ABCD matrix

From left to right, the ABCD matrix columns are:

1. **Behavior Change Principles** (e.g. methods of behavior change or behavior change techniques, BCTs);
2. **Conditions for effectiveness** (conditions that must be satisfied for the BCP to successfully engage underlying evolutionary learning principles, ELPs);
3. **Applications** (concrete, more or less tangible intervention products that implement the BCPs);
4. **Sub-determinants** (specific aspects of the human psychology that are targeted by the applications);
5. **Determinants** (overarching constructs of similar of functionally similar sub-determinants);
6. **Sub-behaviors** (specific behaviors, each predicted by different sub-determinants);
7. **Target behavior** The ultimate target behavior.

Because every row represents one causal-structural chain, a full ABCD matrix contains many of the important assumptions underlying an intervention. Because the matrix has a standardized format, it can easily be shared and read into a variety of programs. In addition to helping intervention developers to get their assumptions clear, and preventing them from forgetting things, ABCD matrices remove the need for coding a lot of the intervention content and logic. In fact, the ABCD matrix clearly shows

The matrix format allows editing the ABCD matrix in spreadsheet software, enabling use of real-time collaboration suites such as Collabora, Google Sheets or Office 365. In addition, the ABCD matrix is the input for the acyclic behavior change diagram itself.

9.2 The Acyclic Behavior Change Diagram

Although this ABCD matrix has the benefit of being machine-readable and easy to edit, dozens of sub-determinants are often targeted. Getting an overview of the entire underlying logic model can therefore be hard. In addition, once familiar with the ABCD matrix, they are a useful tool, but intervention developers will often need to communicate with other parties, such as the producers of the intervention such as advertising agencies, who will not be familiar with behavior change and intervention development tools.

Acyclic behavior change diagrams address this. They are standardized diagrams that are generated from an ABCD matrix. Although ABCDs are not machine readable, they are more human-readable than ABCD matrices. ABCDs visually represent the seven columns of the ABCD matrix, but with cells with the same content merged to be represented by the same element. In other words, assuming the final column has the same target behavior specified, only one element will appear representing the target behavior. The only exception is formed by the determinants, which are only merged within the corresponding sub-behaviors. After all, although the determinants that determine two sub-behaviors may have the same name, they represent different things in reality.

By visually merging duplicated elements of the structural-causal chains in the ABCD matrix, it is easier to get an overview of the logic model represented in the ABCD matrix (and underlying the intervention). Although ABCDs can get rather big, they're pretty much the simplest overview of why an intervention will work (or not). As such, ABCDs are very useful when communicating with colleagues, members of an intervention planning group, or other parties, such as the executive intervention producers (e.g. advertising agencies).

9.3 An example

For example, imagine that an intervention developer is developing an intervention for target behavior Following ecstasy dosing recommendations, and they distinguished sub-behaviors 'Decide to follow the dosing recommendations' & 'In advance, with the groups of friends, discuss everybody's planned dose.'. Their determinant studies yielded a determinant structure, and based on the CIBER plots, they selected sub-determinants: 'If I use a high dose of ecstasy, I will feel less connected to others.', 'If I use a high dose of ecstasy, I will feel more isolated.', 'If I use a high dose of ecstasy, I will remember less', 'Most people approve of avoiding a high dose of ecstasy.' & 'I can explain why

I want to follow the dosing recommendations.', falling under determinants 'Attitude', 'Perceived norm' & 'Perceived behavioral control'.

Based on this information, they selected the behavior change principles 'Persuasive communication', 'Information about others' approval' & 'Modeling (vicarious learning)'. They intend to implement these in applications 'An infographic shows how the effects of ecstasy change as the dose increases.', 'Show the Party Panel result that illustrates that most people want to dose relatively low (compared to the strength of available ecstasy pills).' & 'A comic with examples of how to discuss the dose you plan to take.', and in doing so, will strive to satisfy the following conditions for effectiveness that they identified: 'Messages must be relevant and not deviate too much from existing beliefs; can be stimulated with surprise and repetition; contains arguments.', 'Others do indeed approve of the target behavior.' & 'The message recipient must identify with the model; the model has to be a coping model, struggling with the behavior, not a mastery model; the model must be positively reinforced.'.

Presented like this, obtaining an overview of this information is hard. In addition, many intervention developers do not report this information like this. If they would, extracting the exact behavior change principles they used, and the exact sub-determinants they target, would be relatively easy. Often, however, this information is not explicitly listed in articles or manuals.

The ABCD matrix offers a standardized way to include this information:

Behavior Change Principles	Conditions for effectiveness	Applications	Sub-determinants	Determinants	Sub-behaviors	Target behavior
Persuasive communication	Messages must be relevant and not deviate too much from existing beliefs; can be stimulated with surprise and repetition; contains arguments.	An infographic shows how the effects of ecstasy change as the dose increases.	If I use a high dose of ecstasy, I will feel less connected to others.	Attitude	Decide to follow the dosing recommendations	Following ecstasy dosing recommendations
Persuasive communication	Messages must be relevant and not deviate too much from existing beliefs; can be stimulated with surprise and repetition; contains arguments.	An infographic shows how the effects of ecstasy change as the dose increases.	If I use a high dose of ecstasy, I will feel more isolated.	Attitude	Decide to follow the dosing recommendations	Following ecstasy dosing recommendations
Persuasive communication	Messages must be relevant and not deviate too much from existing beliefs; can be stimulated with surprise and repetition; contains arguments.	An infographic shows how the effects of ecstasy change as the dose increases.	If I use a high dose of ecstasy, I will remember less	Attitude	Decide to follow the dosing recommendations	Following ecstasy dosing recommendations
Information about others' approval	Others do indeed approve of the target behavior.	Show the Party Panel result that illustrates that most people want to dose relatively low (compared to the strength of available ecstasy pills).	Most people approve of avoiding a high dose of ecstasy.	Perceived norm	Decide to follow the dosing recommendations	Following ecstasy dosing recommendations

(continued)

Behavior Change Principles	Conditions for effectiveness	Applications	Sub-determinants	Determinants	Sub-behaviors	Target behavior
Modeling (vicarious learning)	The message recipient must identify with the model; the model has to be a coping model, struggling with the behavior, not a mastery model; the model must be positively reinforced.	A comic with examples of how to discuss the dose you plan to take.	I can explain why I want to follow the dosing recommendations.	Perceived behavioral control	In advance, with the groups of friends, discuss everybody's planned dose.	Following ecstasy dosing recommendations

This matrix can be processed into an ABCD, producing this result:

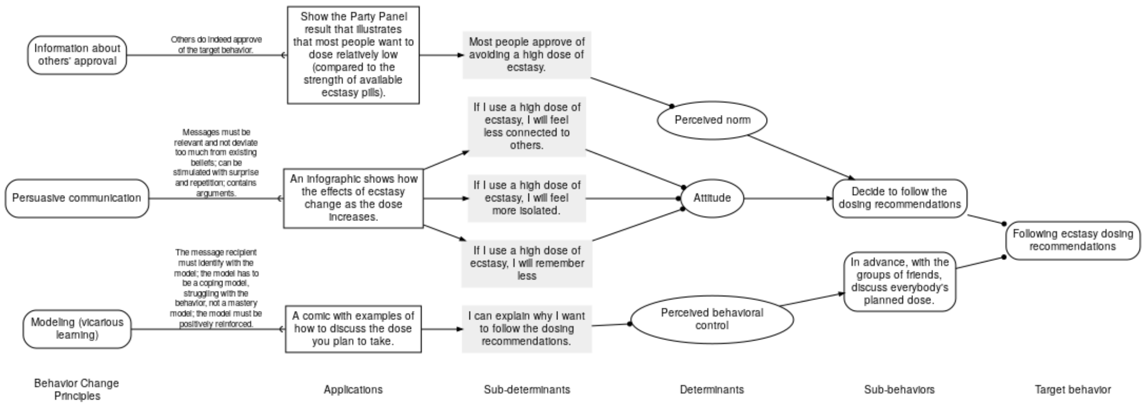


Figure 9.1: An example of an acyclic behavior change diagram.

Even though in this book, the font will likely be too small to easily read, you can already see that it is much easier to get an idea of the assumptions underlying this hypothetical mini-intervention. Apparently, the intervention targets two sub-behaviors and three determinants, using three behavior change principles in three applications. It is easy to see whether important determinants are omitted, or whether conditions for effectiveness were not taken into account.

In addition, the visualisation of the logic model makes it easier to communicate with, for example, members of an intervention planning group, such as stakeholders or target population members. It also facilitated supervision of the executive program producers, such as advertising agencies. Because they often lack knowledge about behavior change, instead having specialized in creative processes, an ABCD is a convenient tangible tool to make sure none of the targeted sub-determinants or conditions for effectiveness gets lost in translation.

9.4 Creating an ABCD

You can create an ABCD using whichever spreadsheet editor you like. Because the ABCD is generated from the ABCD matrix, any application that lets you edit a table with seven columns can be used. There are at present three ways to produce an ABCD from an ABCD matrix. First, you can use jamovi; second, you can use R; and third, you can use an online app. Using jamovi is the most userfriendly, because it offers both the ability to edit the spreadsheet with changes immediately reflected in the diagram. However, as yet, it is not yet possible to save the generated diagram. We will also describe how to use R.

9.4.1 Creating an ABCD in jamovi

One of the datasets supplied with the `behaviorchange` jamovi module (see Section 3.3.1.1) is an empty ABCD template. You can simply open it and adjust it right in jamovi's spreadsheet editor. To order the diagram, open the Behavior Change menu that contains the `behaviorchange` module analyses, and select "Acyclic Behavior Change Diagram (ABCD)" (see Figure **??**).

In the dialog that appears, enter the seven columns of the ABCD matrix (see Figure **??**).

As soon as all seven columns are specified, jamovi will generate the diagram (see Figure **??**).

With every change, jamovi will automatically regenerate the diagram. This means that the ABCD matrix can now be edited to immediately see the changes reflected in the diagram. On the one hand, this provides a convenient method for working with the ABCD. However, at the time of writing this chapter, jamovi does not yet support wrapping the text in the spreadsheet editor, which makes editing longer texts inconvenient.

In addition, when collaborating with multiple people, it can be convenient to use an online spreadsheet that can be edited simultaneously by everybody. Multiple such services exist: the free/libre and open source Collabora is one; Google docs is another; and Microsoft Office 365 yet another one. The contents of such a spreadsheet can then simply be copy-pasted into jamovi.

It is still convenient, however, to first load the template, so that all variable/column names are already configured properly. Then simply select the cell in the first row and the first column and copy-paste the ABCD matrix, so that the cells from the template are overwritten.

To export an ABCD, right-click it.

9.4.2 Creating an ABCD in R

To create an ABCD in R, the `abcd()` function in the `behaviorchange` package can be used. If the ABCD matrix has already been loaded, it is very simple. For example, imagine that the ABCD matrix has been loaded into a data.frame called `dat`. In that case, the ABCD can be generated using this command:

```
behaviorchange::abcd(dat);
```

To load a file into R, many methods exist. An easy one is to use the `getDat()` function from the `ufs` package. Because the `behaviorchange` package also uses `ufs` functions, the `ufs` package is automatically installed if you install `behaviorchange`, so you should have `ufs` installed already. The `getDat()` function opens a dialog that allows you to select a file, which `getDat()` then opens, storing the data in a data.frame called `dat`:

```
getDat();
```

To save an ABCD to a file, an `outputFile` can be specified. The ABCD is then stored to that file.[1]

[1] Under the hood, the function `DiagrammeR::export_graph()` is used. The `file_type` is extracted from the `outputFile` using `tools::file_ext()`.

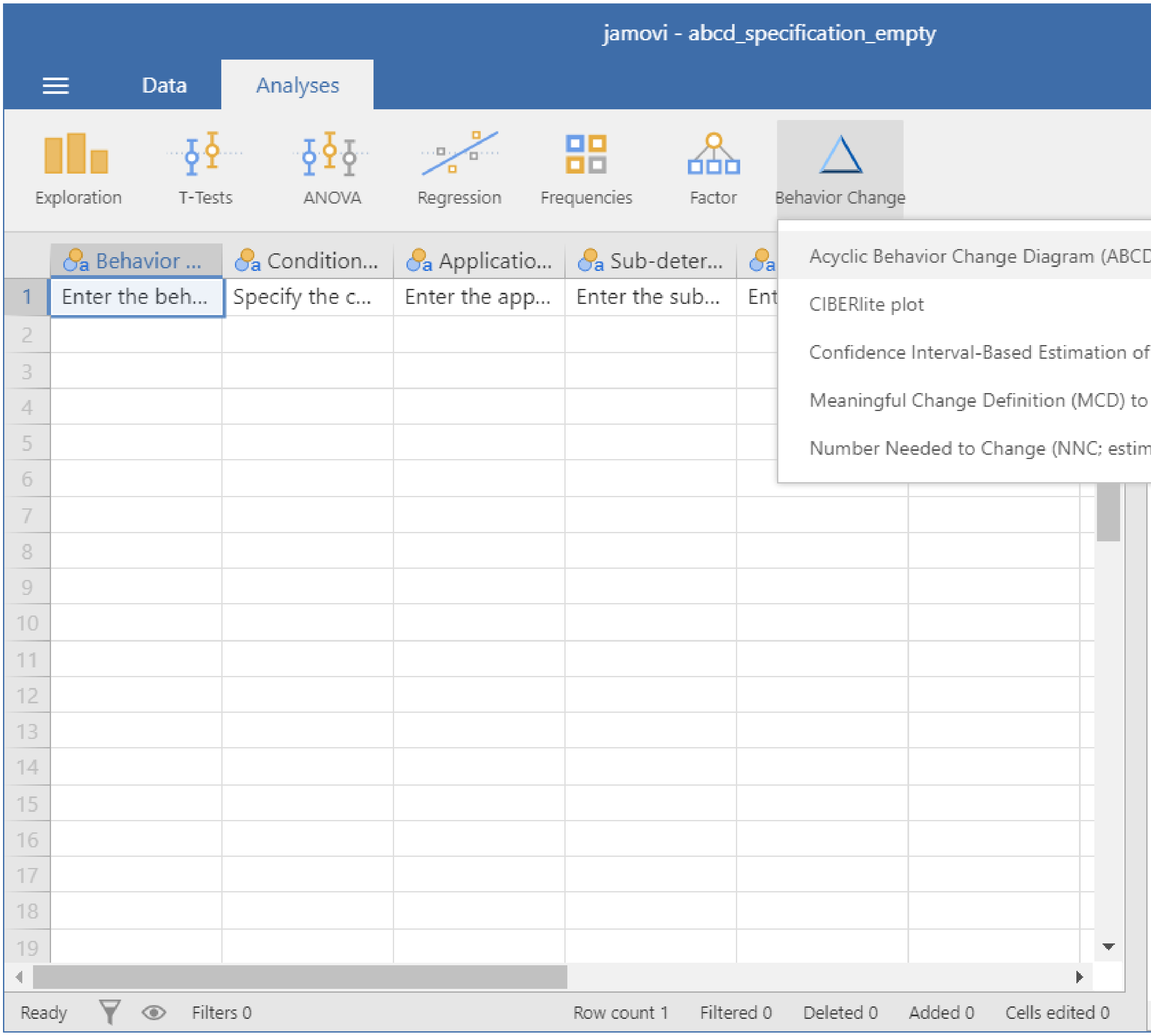


Figure 9.2: Opening the ABCD analysis in jamovi.

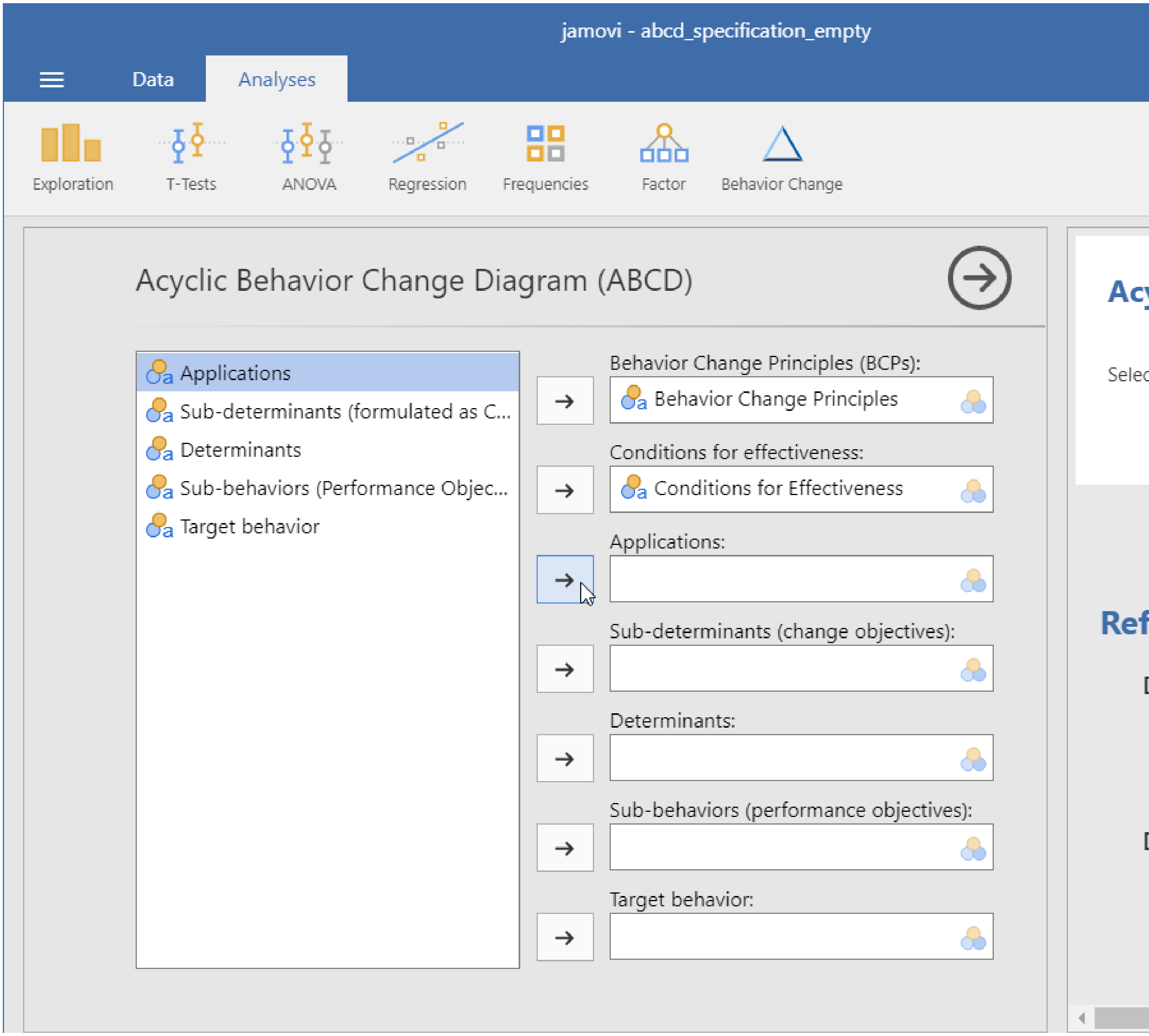


Figure 9.3: The dialog for specifying an ABCD in jamovi.

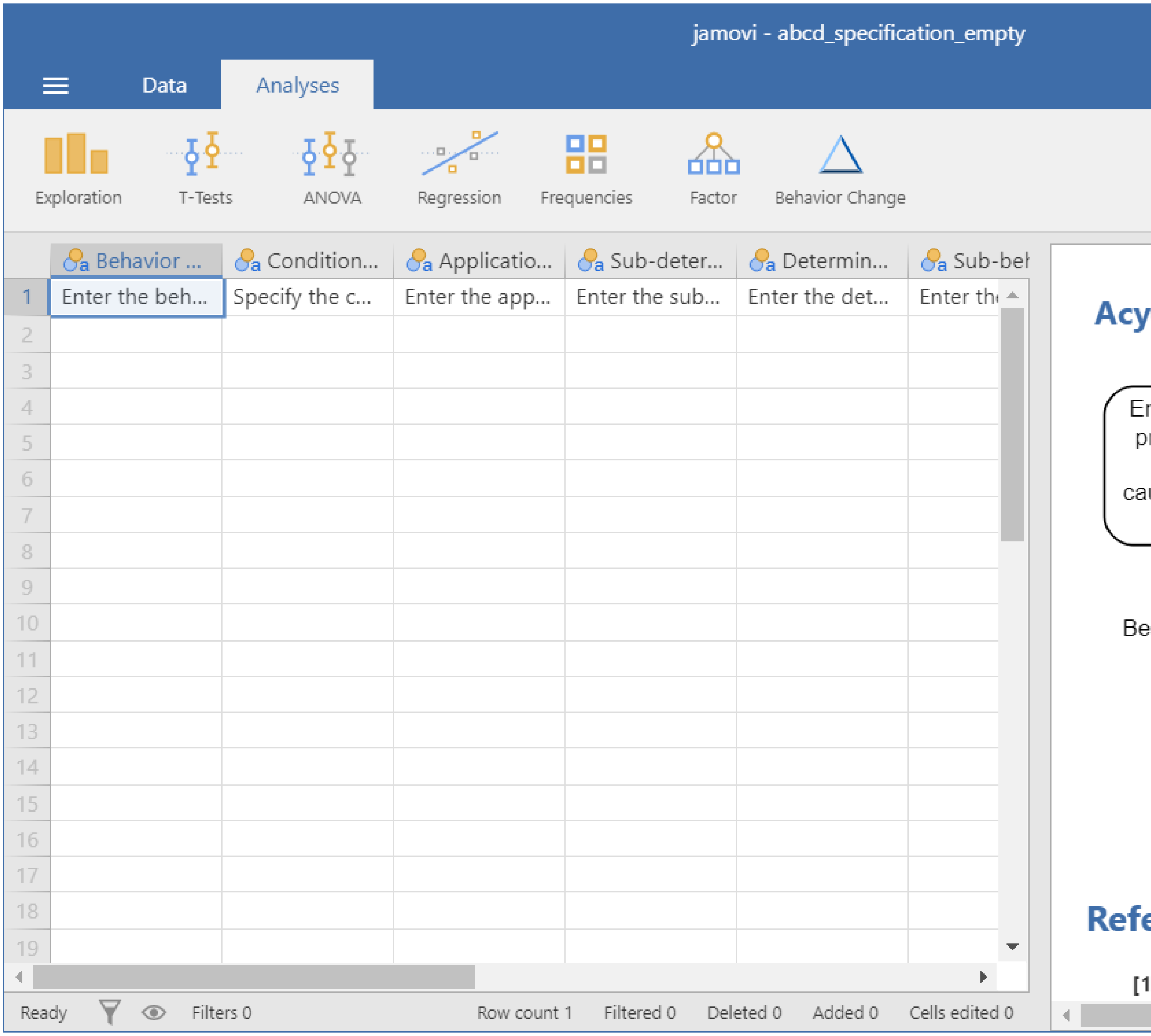


Figure 9.4: The ABCD generated from the empty ABCD matrix template.

For example, the following command saves the ABCD to a file called `abcd.png` in the user's home directory (e.g. the "Documents" directory on a Windows PC):

```
behaviorchange::abcd(dat,
                     outputFile="~/abcd.png");
```

Other extensions can also be specified. For example, if the ABCD is exported to a `.svg` file (a Scalable Vector Graphic), it can then be edited using for example Inkscape, and excellent Free/Libre and Open Source Software package.

Chapter 10

Zooming out

ABCD is one of the things that forms the input for the professionals who will develop the interventions.

Chapter 11

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