



# How to analyze (faked) Implicit Association Test data by applying diffusion model analyses with the fast-dm software: A companion to Röhner & Ewers (2016)

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**Abstract** ■ The Implicit Association Test (IAT) is a popular and frequently used measure in research on implicit associations. However, an important drawback of the traditional computation of IAT results with the so-called *D* measure is that the *D* measure may verifiably include more than just indications of the implicit associations that should be measured. It can also be contaminated by faking and other sources of variance. The *D* measure does not differentiate between different sources of variance. With the help of diffusion model analyses, IAT results can be analyzed and interpreted in a more detailed manner because three separable IAT effects (i.e.,  $IAT_v$ ,  $IAT_a$ , and  $IAT_{t_0}$ ) can be computed from the parameters from diffusion model analyses. These effects have been assumed to separate faking- and construct-specific variance from each other. Thus, a possible advantage of using diffusion model analyses instead of the traditional IAT effect is that less contaminated and more interpretable IAT effects are produced (i.e.,  $IAT_v$ , which captures the construct-related variance;  $IAT_a$  and  $IAT_{t_0}$ , which capture the faking-specific variance). This paper was written to demonstrate how to use the software fast-dm to compute these three newly developed IAT effects and to describe how to interpret them.

**Keywords** ■ IAT, diffusion model analyses, fast-dm,  $IAT_v$ ,  $IAT_a$ ,  $IAT_{t_0}$ . **Tools** ■ Fast-DM.

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## Introduction

The Implicit Association Test (IAT; Greenwald, McGhee, & Schwartz, 1998) is a computerized decision task that is frequently used to assess implicit associations. Along with its popularity, its reliability and validity have been documented in several studies (e.g., Bosson, Swann, & Pennebaker, 2000; Hofmann, Gawronski, Gschwendner, Le, & Schmitt, 2005). The IAT consists of several blocks (see Figure 1 for an example of an extraversion IAT) in which participants are asked to assign stimuli that appear in the middle of the computer screen to different categories. Using an extraversion IAT (Back, Schmukle, & Egloff, 2009) as an example, participants are confronted with stimuli that represent exemplars of the categories self-relevant versus non-self-relevant and extraversion-related versus introversion-

related. The categories are presented in the upper corners of the display screen. The participants' task is to respond to exemplars of each category by pressing a key on the same side as the label (e.g., *d* for the left side and *k* for the right side). The idea behind the IAT is that the sorting task should be easier and therefore completed more quickly when the two concepts that share one response key are strongly associated.

By contrast, if they are only weakly associated, the sorting task should be more difficult and thereby executed more slowly. A participant's performance on this task is recorded in terms of reaction times and errors. The result of the IAT (i.e., the IAT effect) is traditionally computed as a mean difference in reaction times between two critical block phases (i.e., the incompatible and the compatible phases) divided by their overall standard deviation. It is



**Figure 1** ■ The IAT procedure with an extraversion IAT as an example. The two critical block phases of the IAT are colored grey. The presentation of the combined phases can be counterbalanced in IATs. That is, you can decide whether the participants will be presented the compatible phase as the third and fourth blocks and the incompatible phase as the sixth and seventh blocks or vice versa. Within this figure, we present only the most common order to avoid unnecessarily complicating the description of the IAT.

Block	Phase	Task	Example trial
1	Practice	Sort extraversion-related versus introversion-related stimuli (e.g., talkative, shy) appearing in the middle of the computer screen into either the category EXTRAVERSION or INTROVERSION by pressing the <i>d</i> key for EXTRAVERSION or the <i>k</i> key for INTROVERSION.	
2	Practice	Sort self-relevant versus non-self-relevant stimuli (e.g., I, others) appearing in the middle of the computer screen into either the category ME or NOT ME by pressing the <i>d</i> key for ME or the <i>k</i> key for NOT ME.	
3 and 4	Combined and Congruent	Sort extraversion-related versus introversion-related stimuli (e.g., talkative, shy) and self-relevant versus non-self-relevant stimuli (e.g., I, others) appearing in the middle of the computer screen into either the categories EXTRAVERSION or ME by pressing the <i>d</i> key or INTROVERSION or NOT ME by pressing the <i>k</i> key.	
5	Practice	Sort non-self-relevant versus self-relevant stimuli (e.g., I, others) appearing in the middle of the computer screen into either the category NOT ME or ME by pressing the <i>d</i> key for NOT ME or the <i>k</i> key for ME.	
6 and 7	Combined and Incongruent	Sort extraversion-related versus introversion-related stimuli (e.g., talkative, shy) and non-self-relevant versus self-relevant stimuli (e.g., I, others) appearing in the middle of the computer screen into either the categories EXTRAVERSION or NOT ME by pressing the <i>d</i> key or INTROVERSION or ME by pressing the <i>k</i> key.	



called the  $D$  measure. This  $D$  measure, however, may sometimes be contaminated by construct-irrelevant sources of variance (e.g., method-specific variance; faking-related variance; Mierke & Klauer, 2003; Röhner, Schröder-Abé, & Schütz, 2011, 2013). The latter might be of particular concern among researchers as not only has the fakeability of the IAT been well documented by many studies (Fiedler & Bluemke, 2005; Röhner et al., 2011, 2013), but also, the IAT is often used to measure associations with socially stigmatized or sensitive topics (e.g., pedophilia, racism, stereotypes, and sexism; Greenwald et al., 1998; Agerström & Rooth, 2011; Banse, Schmidt, & Clarbour, 2010; Banse, Seise, & Zerbes, 2001; Carlsson & Björklund, 2010; Gray, Brown, MacCulloch, Smith, & Snowden, 2005; Greenwald & Banaji, 1995; Latu et al., 2011) which might increase the motivation to fake.

Thus, a possible and welcome alternative to analyzing and interpreting the results of the IAT effect came from diffusion model analyses that can be applied to analyze the results of fast binary decision tasks, including the IAT (e.g., Klauer, Voss, Schmitz, & Teige-Mocigemba, 2007; Ratcliff, 1978, 2014; van Ravenzwaaij, van der Maas, & Wagenmakers, 2011; A. Voss, Voss, & Lerche, 2015). Diffusion models have become very popular and have been applied to a variety of decision tasks such as recognition memory tasks (Ratcliff, 1978; Spaniol, Madden, & Voss, 2006), lexical decision tasks (Ratcliff, Gomez, & McKoon, 2004; Wagenmakers, Ratcliff, Gomez, & McKoon, 2008), and perceptual discrimination (A. Voss, Rothermund, & Voss, 2004; A. Voss, Rothermund, & Brandstädter, 2008). Diffusion models in general supply the stochastic approach that enables researchers to understand decisional processes on the basis of several parameters that can be estimated with diffusion modeling. The assumption behind diffusion models is that people continuously collect information in order to make a decision. When transferred to the IAT, this means that people collect information from the stimulus that is presented on the computer screen in order to decide which of the four categories (e.g., self-relevant vs. non-self-relevant and extraversion-related vs. introversion-related in the extraversion IAT) the stimulus (e.g., talkative) belongs to.

After collecting sufficient information, they make their decision. Transferred to the IAT, this means they press the respective key (e.g.,  $d$  or  $k$  in the extraversion IAT) to indicate their decision. One can distinguish between the basic diffusion model and the extended diffusion model. The basic diffusion model includes the parameters  $z_r$ ,  $v$ ,  $a$ , and  $t_0$ . The diffusion process underlying the diffusion model is exemplarily represented in Figure 2. Parameter  $z_r$  represents the starting point of the decision process. Starting from parameter  $z_r$ , a participant samples information. The parameters  $v$  and  $a$  refer to the actual decision process.

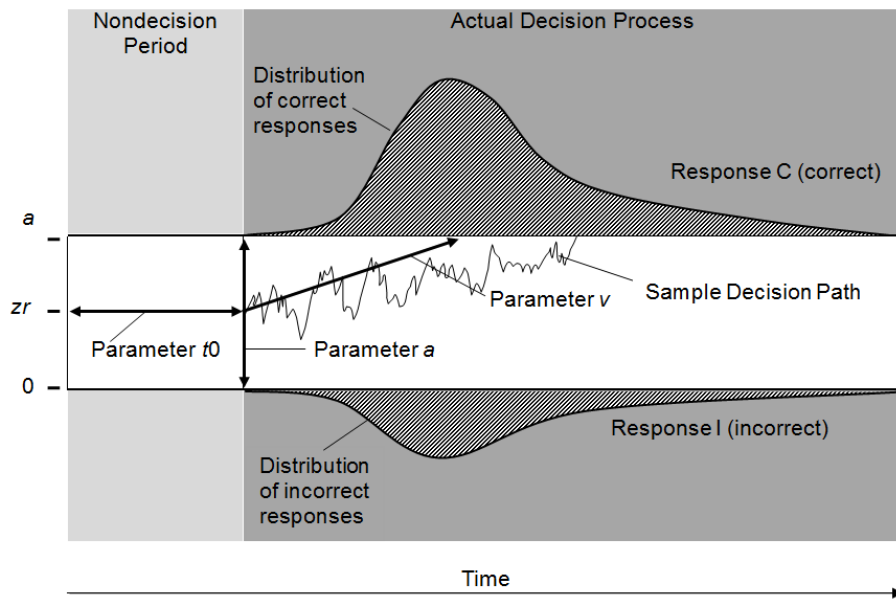
Parameter  $v$  represents the average speed (i.e., the ease) of information uptake, and parameter  $a$  represents the response caution (i.e., whether a participant responds slowly by trying to avoid errors or whether he or she tries to respond quickly by taking the risk of committing errors). Parameter  $t_0$  does not belong to the actual decision process but to the nondecision period (i.e., the time before and after a decision process). It includes, for example, the perceptual encoding of the stimulus and the motor execution.

Within the extended diffusion model, there are the following additional parameters: the intertrial variability of the (relative) starting point (i.e., parameter  $s_{zr}$ ), the intertrial variability of the drift (i.e., parameter  $s_v$ ), the intertrial variability of nondecisional components (i.e., parameter  $s_{t_0}$ ), and the difference in response execution speed (i.e., parameter  $d$ ). According to previous research, parameters  $v$ ,  $a$ , and  $t_0$  can be considered to be most informative (Schmitz & Voss, 2012) and have been shown to be associated with different processes from the decision process (Schmitz & Voss, 2012; Klauer et al., 2007). By contrast, the intertrial variability parameters of the extended diffusion model suffer from a comparably low reliability (Schmitz & Voss, 2012) and often require a very large number of trials of about  $N = 1000$  (A. Voss et al., 2015), which is not achieved in typical IATs. Thus, for analyzing the IAT effect, the parameters  $a$ ,  $v$ , and  $t_0$  from the basic diffusion model are recommended.

The benefit of analyzing the IAT effect with diffusion model analyses instead of the traditional  $D$  measure is that diffusion model analyses deliver detailed information about the cognitive processes underlying performance on the IAT (Röhner & Ewers, 2016; A. Voss, Nagler, & Lerche, 2013). In other words, instead of having one IAT effect (i.e., the  $D$  measure) that does not separate different sources of variance at all (e.g., construct-related variance vs. faking-related variance), diffusion model analyses provide three different IAT effects (i.e.,  $IAT_v$ ,  $IAT_a$ , and  $IAT_{t_0}$ ; Klauer et al., 2007) that can be computed from the above-mentioned parameters  $v$ ,  $a$ , and  $t_0$  in the compatible and incompatible IAT phases to attempt to separate the different sources of variance from each other (Klauer et al., 2007; Röhner & Ewers, 2016). Previous research has already successfully demonstrated that  $IAT_v$  is significantly related to construct-specific variance, whereas  $IAT_a$  and  $IAT_{t_0}$  have been supposed to capture faking-related variance (Klauer et al., 2007). Thus, a possible advantage of using diffusion model analyses instead of the traditional IAT effect is that less contaminated and more interpretable IAT effects are produced (i.e.,  $IAT_v$ , which captures the construct-related variance;  $IAT_a$  and  $IAT_{t_0}$ , which capture the faking-specific variance). In this vein, our own research on this has revealed that diffusion model analy-



**Figure 2** ■ The diffusion process underlying the diffusion model. The diffusion model distinguishes between the non-decision parameter (parameter  $t_0$ ) and parameters from the actual decision process (parameters  $v$  and  $a$ ). The X-axis represents time and is read from left to right. The Y-axis represents the response-related decision with two response criteria, which are placed at 0 (for incorrect responses) and  $a$  (for correct responses). The counter begins fluctuating as a function of information that accumulates with time at the postulated point  $z_r$ . The accumulation of information includes systematic as well as random influences. As soon as one of the two response criteria is crossed, the decision process is terminated, and the respective response is initiated. In the sample path for one trial, the participant accumulates enough information to provide the correct response. Parameter  $v$  is the mean amount of accumulated information for one participant across a certain number of trials (e.g., one phase in an IAT). Distributions of correct and incorrect responses are displayed outside their respective response criteria. Copyright 2016 by the Psychonomic Society. All rights reserved. Used with permission.



ses are useful for analyzing and interpreting the IAT effect and even shed more light on the faking process (Röhner & Ewers, 2016).

Several programs have been developed to execute diffusion model analyses. Among those most prominent are the Diffusion Model Analysis Toolbox (DMAT; Vandekerckhove & Tuerlinckx, 2007, 2008), the EZ-diffusion model (EZ; Wagenmakers, van der Maas, & Grasman, 2007; Wagenmakers, van der Maas, Dolan, & Grasman, 2008), and fast-dm (A. Voss et al., 2015; A. Voss & Voss, 2007, 2008). All of these software solutions have individual advantages, and the user must choose a proper solution according to his or her research goal. For analyzing IAT data, fast-dm best addresses a user's needs for several reasons. DMAT, in contrast to fast-dm, requires a sufficiently high number of correct and incorrect trials (i.e.,  $N > 500$ ; A. Voss et al., 2015), whereas its efficiency is comparably low. The critical block phases of the IAT usually consist of about 100

trials per phase (Greenwald et al., 1998; Bar-Anan & Nosek, 2014; Nosek & Smyth, 2007), and therefore, DMAT requires more trials than usually available in IATs. The program EZ (Wagenmakers et al., 2007), in contrast to fast-dm, makes use of a limited amount of information from the reaction time distributions as only the mean and variance of the correct responses and the accuracy rate are used in parameter estimation. Information about erroneous responses is not considered in the parameter estimation. As faking on the IAT sometimes includes the manipulation of errors (Röhner et al., 2013), errors are a relevant source of information. Therefore, although EZ will work for analyzing IAT results in general, it might be problematic to use it for faked IAT data (at least when fakers manipulate their errors). Thus, fast-dm can be considered the best solution when IATs have to be analyzed with diffusion model analyses. The present article provides a detailed description of how to analyze (faked) IAT data with fast-dm.



## Step-by-Step Tutorial

### *Before you can Start: Some Prerequisites*

You used experimental software to collect your IAT data under either standard instructions or faking instructions (for further information see Röhner et al., 2013) via computer, you saved the IAT output data (e.g., as \*.dat-files), and you downloaded and installed fast-dm on your computer. If you have not already downloaded and installed fast-dm, start with step 0. Otherwise, you can skip step 0 and start with step 1.

### *Step 0: Download and Install Fast-dm*

**0.1** Go to the fast-dm homepage (<http://www.psychologie.uni-heidelberg.de/ae/meth/fast-dm/>). Scroll down to “fast-dm Downloads”. Download fast-dm. You have to choose between fast-dm-30 and fast-dm-30.2. Fast-dm-30.2 additionally contains a guessing parameter  $p$  that, however, on account of small trials (as in the IAT)  $p$  has to be set to 0 (see <http://www.psychologie.uni-heidelberg.de/ae/meth/fast-dm/#intro>). THE CURRENT ANALYSES USED: fast-dm-30.

**0.2** Depending on the system software, you have to choose one of the available zip-files. Choose the zip-file “Windows Binaries” or “Source”. Download the zip-file. THE CURRENT ANALYSES USED: “Windows Binaries”.

**0.3** Unzip the file.

**0.4** Install fast-dm. HOW TO DO THIS ON WINDOWS VS. LINUX: For Windows users, the fast-dm.exe is ready to use. Linux users proceed with the following to install fast-dm: You have to start a command console and cd into the directory. Type: “./configure”. Type: “make”. Type: “make install”.

### *Step 1: Prepare the Control File for Use*

The control file is a kind of script that determines the details of the diffusion model analyses. In other words, a text-file is used to adapt fast-dm to the needs of the IAT data set. The current file written for the current analyses is represented in Listing 1.

**1.1** Copy and paste the contents of Listing 1 in a text-file called experiment.ctl.

**1.2** Save the control file titled “experiment.ctl” into the fast-dm folder. THE CONTENTS OF THE CONTROL FILE: In the first line, the estimation procedure is selected. You can choose from Maximum Likelihood, Kolmogorov Smirnov, or Chi-Square. In the second line, the precision of the calculation is determined. In the third to seventh lines, the

parameters to be estimated and the parameters to be fixed are indicated.<sup>1</sup> In the eighth line,  $p$  can be determined (only when using fast-dm-30.2). In the next line, the variable name for the columns in the IAT data files are defined for later use. In the next line, the kind of files that represent the input IAT data files are indicated. In the last line, the name of the common output file is determined.

THE CURRENT ANALYSES USED: a very high precision setting of 5 (see Listing 1). Because the value of the precision of the calculation is associated with the calculation time, and the default value of 3 is sufficient for most applications, you may use a value of 3 here instead of 5. If you want to set the precision of the calculation to 3, you should change the value in the second line accordingly from 5 to 3 before running fast-dm. THE CURRENT ANALYSES USED: \*.txt-files as input files.

### *Step 2: Format the IAT Data Files for Analyses with Fast-dm, one File per Participant and per Condition*

There are several ways to pretreat the IAT data for fast-dm. The description below corresponds to how we did this in the current analyses.

**2.1** Transfer the IAT output files to new IAT input data files (i.e., \*.txt - or \*.dat-files), which contain only the coding of the variables RESPONSE (i.e., erroneous or correct answer) and TIME (in seconds) from the whole IAT output. Listing 2 exemplarily shows the input data of a participant in the current study.

PLEASE CONSIDER: Fast-dm needs the reaction times in seconds and not in milliseconds. So if your experimental software delivers the reaction times (i.e., TIMES) in milliseconds, also transform them from milliseconds into seconds before saving this information in the new files. Also take care to create one file for every participant in each combined IAT phase and, when using repeated-measures designs, within every measurement occasion as well.

**2.2** Correct files for outliers if desired. To do so, go through the new output files and remove outliers from the individual response-time distribution if participants have reaction times below 0.2 sec or above 5 sec (A. Voss & Voss, 2008; A. Voss et al., 2013).

### *Step 3: Run the Diffusion Model Analyses with Fast-dm on the IAT Data Files*

**3.1** Estimate independent diffusion models for each participant and each combined IAT phase and, in the case of repeated-measures designs, also within each of the measurement occasions.

<sup>1</sup>Note that fast-dm can also be used to fit each condition that a participant could have. For the current analyses, we let all the parameters vary freely from one condition to another.





**Listing 1** ■ Example of the experiment.ctl-file. This is the experiment.ctl-file we wrote for our analyses in fast-dm 30. If you use fast-dm 30.2, you should additionally type “set p 0” as described in the step-by-step tutorial.

```
method ks
precision 5
set zr 0.5
set d 0
set szr 0
set sv 0
set st0 0
format RESPONSE TIME
load *.txt
log parameter.log
```

**3.1.1** Copy the pretreated IAT data input files and paste them into the fast-dm folder.

**HOW TO DO THIS ON WINDOWS VS. LINUX:** Windows users - run the fast-dm exe. Linux users - complete the following steps: Open a command window and cd to fast-dm. Type: “fast-dm”.

**3.1.2** Transfer the outcome into a statistical software program by using the saved \*.log-file. We present some exemplarily output data files in Output 1.

#### **Step 4: Check the Model Fits**

Check the plausibility of the data with the help of the Kolmogorov backward equation. In the current analyses, participant’s data that showed a poor model fit (i.e.,  $p < .05$ ) were discarded. The power of the Kolmogorov backward equations depends on the number of trials. A small number of trials as is typical in IATs might be related to low power or a criterion that is too liberal. Thus, graphical inspections of the overlaid observed and predicted cumulative distributions function (i.e., cdfs) should be executed as an additional step to check the model fit.

**4.1** Create the observed (empirical) cumulative distribution functions (i.e., observed cdfs) separately for each IAT phase, for each experimental group, and in the case of repeated-measures, for each measurement occasion as well.

**4.1.1** Import the prepared IAT input files (see section 2 in the protocol) into a statistical software program (e.g., spreadsheet).

**4.1.1.1** Multiply all TIMEs with a RESPONSE 0 (i.e., erroneous answer) by -1 in the spreadsheet.

**4.1.1.2** Using a mouse transfer the TIMEs that were multiplied by -1 (for erroneous answers) and the unmodified TIMEs (for correct answers) into a new column.

**4.1.1.3** Sort all TIMEs in this new column in an ascending manner.

**4.1.1.4** Using the right click button of the mouse, add a new column and put the cumulated densities in it. To do so, assign the ratio of 1 divided by the number of values in the new column to the lowest value. Assign the ratio of 2 divided by the number of values in the new column to the second lowest value. Continue to do so until all values are assigned (i.e., the highest value has a ratio of 1).

**4.1.1.5** Plot the observed (empirical) cdfs with a statistical software.

**4.2** Create the predicted (parameter-based) cumulative distribution functions (i.e., predicted cdfs) separately for each IAT phase, for each experimental group, and in the case of repeated-measures, for each measurement occasion as well.

**4.2.1** Fast-dm provides plot-cdf to create values of predicted cdfs from a certain parameter set. To do so, give a command to fast-dm. Here is an example of the final command used with the current analyses: "plot-cdf.exe -a 1.78 -z 0.5 -v 2.14 -t 0.39 -d 0 -Z 0 -V 0 -T 0 -o cdf.lst".

**4.2.2** Note down the values for parameter  $v$ , parameter  $a$ , and parameter  $t_0$  separately for each IAT phase, for each experimental group, and in the case of repeated-measures, for each measurement occasion as well. **THE CURRENT ANALYSES USED:** the means of participants’ values in the parameters to create the cdfs with plot cdf.

**4.2.3** Start a command console.

**4.2.4** Type: "plot-cdf.exe -a -z -v -t -d -Z -V -T -o cdf.lst". Add the values for the parameters into the command line. Add the value for parameter  $a$  behind a. Add the value 0.5 for parameter  $z_r$  behind z. Add the value for parameter  $v$  behind v. Add the value for



**Listing 2** ■ Example of an input-data file of the participant “example 1” from the current study. This input file shows the first 20 lines of the input data of the congruent IAT phase. The first column represents the variable RESPONSE (i.e., erroneous or correct answer). The second column represents the variable TIME (in seconds).

```

1      1.16
1      0.758
1      0.529
1      0.641
1      0.974
1      0.971
1      0.695
1      1.577
1      1.177
0      1.42
1      0.859
1      1.497
1      0.616
1      0.757
1      0.582
1      1.065
1      0.634
1      0.719
1      0.893
1      1.121

```

parameter  $t_0$  behind  $\tau$ . Add the value 0 for parameter  $d$  behind  $d$ . Add the value 0 for parameter  $s_{zr}$  behind  $Z$ . Add the value 0 for parameter  $s_v$  behind  $V$ . Add the value 0 for parameter  $s_{t0}$  behind  $T$ . Define the file name in which the generated data will be saved behind  $\circ$ .

#### 4.2.5 Press Enter.

PLEASE CONSIDER: The predicted cdfs are given as plain text in the outcome files. Plot it by using statistical software.

**4.3** Summarize the predicted (parameter-based) and observed (empirical) cdfs in one graph with a statistical software program in order to obtain the overlaid predicted and observed cdfs (see Figure 3 for an example).

PLEASE CONSIDER: Do so for each IAT phase, for each experimental group, and for each measurement occasion when there are repeated measures.

#### **Step 5: If the Model Fits are ok, Compute the Compatibility Effects**

Compute the compatibility effects  $IAT_v$ ,  $IAT_a$ , and  $IAT_{t_0}$  by subtracting the estimated parameters of the compatible phase from the estimated parameters of the incompatible phase as follows (Klauer et al., 2007):

**5.1** Compute  $IAT_v$  by subtracting parameter  $v$  of the compatible phase from parameter  $v$  of the incompatible

phase.

**5.2** Compute  $IAT_a$  by subtracting parameter  $a$  of the compatible phase from parameter  $a$  of the incompatible phase.

**5.3** Compute  $IAT_{t_0}$  by subtracting parameter  $t_0$  of the compatible phase from parameter  $t_0$  of the incompatible phase.

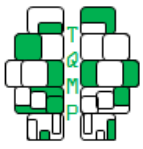
PLEASE CONSIDER: Do so separately for each measurement occasion in the case of repeated-measures designs.

#### **Step 6: Analyze the Results**

Use these compatibility effects to analyze the IAT results beyond the traditional IAT  $D$  measure (Greenwald, Nosek, & Banaji, 2003a, 2003b).

#### **Results**

Following the protocol above will lead to the parameters  $v$ ,  $a$ , and  $t_0$  in the diffusion model, per IAT phase (i.e., compatible vs. incompatible), and for each participant at each measurement occasion. In addition, you will be given data from the model fit from the Kolmogorov backward equation and the graphical displays of the model fit. To interpret the graphical displays, compare the graphs from the predicted and the observed cdfs. Figure 3 exemplarily shows the overlaid predicted and observed cdfs for all experimental groups and measurement occasions in the



**Output 1** ■ Example of the output data of a participant “example 1” from the current study. This output file shows the results of the congruent IAT phase.

```
a = 1.616943
v = 1.941225
t0 = 0.405591
precision = 5.000000
method = KS
penalty = 0.000000
fit index = 0.981973
time = 21.430000
```

compatible IAT phase of our recent study (Röhner & Ewers, 2016). Note that in this example the graphs from the predicted and the observed cdfs are very close to each other. The more they overlay the better the model fit is. Last but not least, you will be given the computed IAT effects  $IAT_v$ ,  $IAT_a$ , and  $IAT_{t_0}$ , which were based on the parameters from the diffusion modeling.

To convey an impression of the advantage from analyzing IAT results with diffusion model analyses in addition to the  $D$  measure, we represent some results from our current study that was examined to investigate the effectiveness of diffusion model analyses with fast-dm in order to analyze and interpret non-faked and faked IAT results (for further information see Röhner and Ewers, 2016; see also Röhner et al., 2013). In Table 1 the impact of faking on the traditional IAT effect (i.e.,  $D$  measure) and on IAT effects from diffusion model analyses (i.e.,  $IAT_v$ ,  $IAT_a$ , and  $IAT_{t_0}$ ) is represented in the form of between and within post hoc comparisons from a total of four repeated-measures ANOVAs. Looking at the columns under the heading “ $D$  measure”, the results demonstrate that the  $D$  measure was significantly impacted by the faking intentions of participants in all of the four faking conditions (see Table 1). Thus, the  $D$  measure’s construct-related variance was contaminated by the faking-related variance under all faking conditions, and it was not at all possible to separate one from the other. Looking at the columns under the heading “ $IAT_v$ ,  $IAT_a$  and  $IAT_{t_0}$ ”, the results show that in one out of four faking conditions (i.e., under informed faking of low scores),  $IAT_v$  indeed was not significantly impacted by faking, and  $IAT_a$  captured the faking-specific variance. From a practical standpoint, this is indeed the most likely, and from a test-taker’s standpoint, the easiest faking condition (Röhner & Ewers, 2016). In the other three faking conditions (i.e., under naïve faking or the faking of high scores),  $IAT_v$  was, however, impacted by faking, and  $IAT_a$  did not capture all of the faking-specific variance. Although somewhat disappointing at first glance, these results provide us with worthwhile information about the faking process. Note that these conditions are more dif-

ficult to fake, and consequently, we can see the use of helping strategies that are implemented by participants to make the faking-task easier and that thus impact  $IAT_v$  (Röhner & Ewers, 2016).  $IAT_{t_0}$  was not affected by faking at all. This can be interpreted as an indication that faking represents a process that takes place within the decision process and not outside of it.

Taken together, although it is not yet possible to clearly separate faking- and construct-related variance from each other by using the three IAT effects that can be computed from the diffusion model analyses in all faking conditions, diffusion model analyses allow us to better understand the faking process in the IAT, and under specific faking conditions, they allow us to separate faking- from construct-related variance.

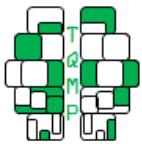
## Discussion

Diffusion model analyses are useful for analyzing and interpreting IAT results. However, there are some advantages and disadvantages that users have to keep in mind.

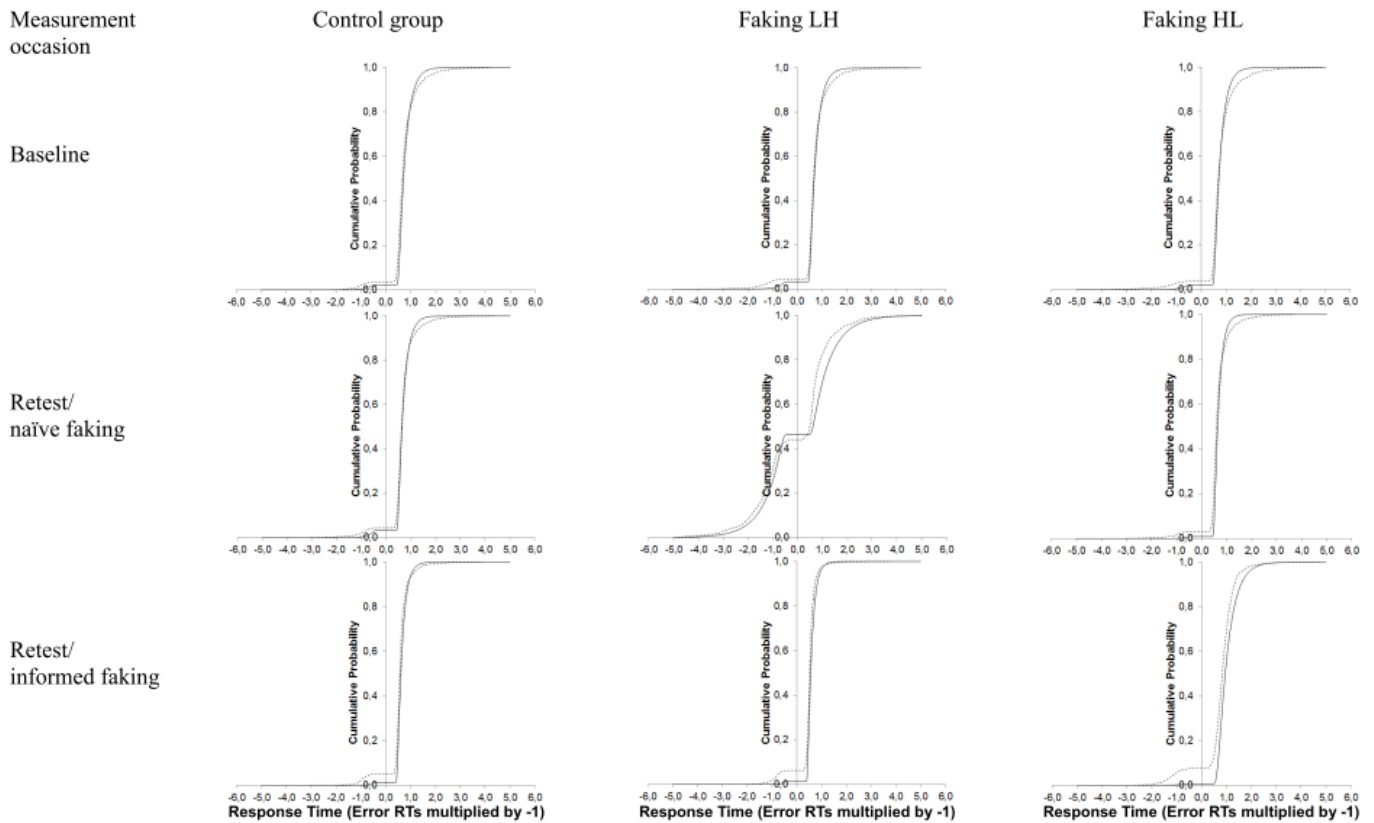
There are two relevant disadvantages. First, from the users’ perspective, analyzing IAT results with diffusion models is a comparably time-consuming and complex procedure. The data preparation and analyses have to be executed in a thorough manner. Especially when comparing diffusion model analyses with the computation of the traditional IAT  $D$  measure, it is obvious that the latter represents a much simpler and less time-consuming procedure. Second, the technique of using diffusion model analyses to interpret IAT results is somewhat limited in so far as the new IAT effects that can be decomposed cannot yet separate faking- and construct-related variance in the IAT under all faking conditions.

However, replacing the traditional  $D$  measure with  $IAT_v$ ,  $IAT_a$ , and  $IAT_{t_0}$  to analyze the IAT nevertheless offers three clear and relevant advantages. First, although diffusion model analyses are more complex to implement, note that they also deliver much more information. In particular, on the one hand, they allow users to have a closer look at the cognitive processes behind the execution





**Figure 3** ■ Example of a graphical model display. The overlaid predicted (parameter-based) and observed (empirical) cumulative distribution functions (cdfs) for all experimental groups and measurement occasions in the compatible IAT phase. Continuous lines represent predicted cdfs. Dashed lines represent observed cdfs. The plotted functions are joint distributions of correct and incorrect responses. Negative values on the X-axis are latencies of error responses (multiplied by -1) and are plotted on the left side. Positive values on the X-axis are latencies of correct responses and are plotted on the right side. Copyright 2016 by the Psychonomic Society. All rights reserved. Used with permission.



of an IAT with and without faking intentions. On the other hand, under specific faking circumstances, they even allow users to separate the faking-related variance from the construct-related variance to a certain extent. Note that the  $D$  measure that is traditionally used to interpret IAT results is not even intended to separate faking- and construct-related variance at all. Second, the IAT effects that can be decomposed with diffusion model analyses might provide some first indications of faking. Third, they can also help researchers learn about the faking process itself, which will aid the understanding of faking, and we hope will one day help in correcting for it. These advantages are not provided when the traditional IAT  $D$  measure is used. When confronted with the fakeability of the IAT and its use in socially sensitive areas, which make faking possible and likely, diffusion model analyses clearly represent a step in

the right direction.

Summing up, diffusion model analyses represent a useful tool that can be applied to analyze IAT effects. Besides the investigation of faking in IAT effects that can be decomposed from the parameters of diffusion model analyses, many more applications of diffusion models in IATs are thinkable. For example, comparing (faked) IAT effects that can be decomposed from diffusion model analyses between younger and older participants would be interesting as reaction times and errors depend on age (Endrass, Schreiber, & Kathmann, 2012).

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**Table 1 ■** Between- and Within-Group Comparisons from Repeated-Measures ANOVAs on the *D* measure (top) and on *IAT<sub>v</sub>*, *IAT<sub>a</sub>*, and *IAT<sub>t0</sub>* (bottom).

Measurement Occasion	<i>D</i> Measure			<i>IAT<sub>v</sub></i>			<i>IAT<sub>a</sub></i>			<i>IAT<sub>t0</sub></i>		
	Control group	Faking LH	Faking HL	Control group	Faking LH	Faking HL	Control group	Faking LH	Faking HL	Control group	Faking LH	Faking HL
	<i>M</i> ( <i>SD</i> )	<i>M</i> ( <i>SD</i> )	<i>M</i> ( <i>SD</i> )	<i>M</i> ( <i>SD</i> )	<i>M</i> ( <i>SD</i> )	<i>M</i> ( <i>SD</i> )	<i>M</i> ( <i>SD</i> )	<i>M</i> ( <i>SD</i> )	<i>M</i> ( <i>SD</i> )	<i>M</i> ( <i>SD</i> )	<i>M</i> ( <i>SD</i> )	<i>M</i> ( <i>SD</i> )
Baseline	0.36 <sub>a1</sub> (0.38)	0.27 <sub>a1</sub> (0.46)	0.09 <sub>a1</sub> (0.47)	-0.55 <sub>a1</sub> (0.99)	-0.41 <sub>a1</sub> (0.95)	-0.42 <sub>a1</sub> (1.04)	-0.06 <sub>a1</sub> (1.12)	0.13 <sub>a1</sub> (0.62)	-0.01 <sub>a1</sub> (0.47)	0.04 <sub>a1</sub> (0.12)	0.00 <sub>a12</sub> (0.07)	0.00 <sub>a1</sub> (0.09)
Retest/ naïve faking	0.31 <sub>b1</sub> (0.43)	-0.23 <sub>a2</sub> (0.56)	0.41 <sub>b2</sub> (0.55)	-0.40 <sub>a1</sub> (1.01)	0.87 <sub>b2</sub> (1.21)	-1.30 <sub>c2</sub> (1.46)	0.13 <sub>a1</sub> (0.91)	0.17 <sub>a1</sub> (0.92)	-0.14 <sub>a1</sub> (1.01)	0.02 <sub>a1</sub> (0.10)	-0.05 <sub>a1</sub> (0.19)	0.02 <sub>a1</sub> (0.10)
Retest/ informed faking	0.33 <sub>c1</sub> (0.37)	1.04 <sub>a3</sub> (0.25)	-0.79 <sub>b3</sub> (0.68)	-0.75 <sub>ab1</sub> (1.17)	-1.30 <sub>b3</sub> (1.76)	-0.12 <sub>a1</sub> (1.35)	-0.29 <sub>a1</sub> (0.72)	0.37 <sub>a1</sub> (1.16)	-1.33 <sub>b2</sub> (2.06)	0.06 <sub>a1</sub> (0.06)	0.07 <sub>a2</sub> (0.13)	0.01 <sub>a1</sub> (0.16)

*Note.* Faking LH represents the faking condition in which low scores were faked first and then high scores were faked; faking HL represents the faking condition in which high scores were faked first and then low scores were faked; different alphabetic subscripts indicate significant differences between experimental groups (i.e., columns); different numeric subscripts identify significant differences between measurement occasions (i.e., rows) at  $p < .05$ . The content of the left part of this table was reprinted from Röhner, Schröder-Abé, and Schütz (2013) with the permission from Elsevier and was published in 2013. The content of the right part of this table: Copyright 2016 by the Psychonomic Society. All rights reserved. Used with permission.

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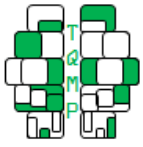
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