

RUNNING HEAD: Cognitive Processes in Categorical and Associative Priming

Cognitive Processes in Associative and Categorical Priming:

A Diffusion Model Analysis

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Abstract

Cognitive processes and mechanisms underlying different forms of priming were investigated using a diffusion model approach. In a series of six experiments, effects of prime-target associations and of a semantic and affective categorical match of prime and target were analyzed for different tasks. Significant associative and categorical priming effects were found in standard analyses of RTs and error frequencies. Results of diffusion model analyses revealed that priming effects of associated primes were mapped on the drift rate parameter (v), while priming effects of a categorical match on a task-relevant dimension were mapped on the extra-decisional parameters (t_0 and d). These results support a spreading activation account of associative priming and an explanation of categorical priming in terms of response competition. Implications for the interpretation of priming effects and the use of priming paradigms in Cognitive Psychology and Social Cognition are discussed.

(141 Words)

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Sequential priming procedures play a major role in Cognitive Psychology and related disciplines. For example, priming techniques are used to assess associative structures in semantic memory (e.g., Collins & Loftus, 1975; Neely, 1977; Rosch, 1975), to analyze subliminal semantic processing (e.g., Draine & Greenwald, 1998; Klinger, Burton, & Pitts, 2000; Marcel, 1983), or to investigate the mental basis of attitudes, prejudice, and stereotyping (Blair & Banaji, 1996; Fazio, Sanbonmatsu, Powell, & Kardes, 1986; Wittenbrink, Judd, & Park, 1997, 2001a). With different sequential priming paradigms it has been shown that the processing of an irrelevant prime stimulus influences the processing of—or the responding to—a subsequently presented target stimulus. Typically, responses are faster and more accurate if prime and target are related.

Despite these similarities, there are also important differences between paradigms. First, relatedness of prime and target can be based on many dimensions, including semantic relatedness, associations, similarity, and others. We are primarily interested here in associative and semantic relations between prime and target. Items are semantically related when they belong to the same category and thus share semantic properties (e.g., *cat* and *cow* are mammals) or when they are functionally related (e.g., *broom* and *floor* are related because brooms are used to sweep floors). Items are considered to be associated when a large percentage of people give the target as the first word they think of in response to the prime (see Moss, Ostrin, Tyler, & Marslen-Wilson, 1995, for an elaborate discussion of the distinction between semantic and associative priming). In addition to the relatedness dimension, priming paradigms differ in the type of task that is to be performed on the targets: Most paradigms use the lexical decision task (Meyer & Schvaneveldt, 1971; Neely, 1977; see also Gaertner & McLaughlin, 1983; Wentura, 2000; Wittenbrink et al., 1997, 2001a), naming or pronunciation tasks (Meyer, Schvaneveldt & Ruddy, 1974; see also Bargh, Chaiken,

Raymond, & Hymes, 1996; Hermans, De Houwer, & Eelen, 1994), semantic or affective categorization tasks (e.g., De Houwer, Hermans, Rothermund, & Wentura, 2002; Fazio et al., 1986; Klinger et al., 2000), and verification tasks (Collins & Quillian, 1969; Meyer, 1970; see also Dovidio, Evans, & Tyler, 1986).

A structural taxonomy

In this regard it is helpful to introduce a structural taxonomy of priming *designs* that distinguishes between *semantic priming* and *response priming* (see also Wentura & Degner, 2010). In *semantic priming*, the relationship of interest (e.g., whether prime and target are associatively related or not) is varied orthogonally to the response categories: For example, in a semantic priming design using the lexical decision task, targets that are preceded by associatively related primes as well as targets that are preceded by unrelated primes require a word-response. By way of contrast, in *response priming* designs, primes are at the same time congruent or incongruent *to the target and to the response* that has to be given to the target. For example, in a typical response priming experiment using valent stimuli (i.e., affective priming), positive and negative target stimuli that have to be categorized according to their valence are preceded by positive or negative primes.

Accordingly, two dominant principles of explanation prevail: Effects in *semantic priming* designs are most often explained by a facilitation of target processing (see Spruyt, Hermans, De Houwer, & Eelen, 2002). For this kind of explanation, spreading activation in a semantic network is still a compelling metaphor (Collins & Loftus, 1975): The basic idea of the spreading activation account is that the processing of the prime stimulus activates its corresponding node in the semantic network and that this activation spreads through associative links to connected nodes. If prime and target are associated in semantic memory, the processing of the prime pre-activates the target node and thus facilitates the processing of the subsequently presented target. This process of speeded access to target information can be captured in terms of distributed memory models as well (see Masson, 1995). In a nutshell,

semantic relatedness should correspond to a similarity in the activation pattern of units in the model. Therefore the transition process from the prime-representing pattern to the target-representing pattern is faster in the case of related pairs compared to unrelated pairs.

We should hasten to add that effects found in semantic priming designs can also be due to so-called “post-lexical mechanisms” (Neely, 1991), especially if the lexical decision task is used. Different from mechanisms promoting target processing, post-lexical mechanisms refer to processes that depend on the retrieved semantics of the target stimuli, that is, information that can be assessed only after the orthographic information has been translated into semantic content. For example, Neely, Keefe, and Ross (1989) argued that “retrospective semantic matching” might contribute to the strength of priming effects. According to this account, the impression of a semantic match between prime and target facilitates word decisions because semantic matches typically only occur for word targets. Another post-lexical influence on priming effects was specified in the compound-cue model of Ratcliff and McKoon (1988). Starting from the assumption that lexical decisions are based on a familiarity estimation of the stimuli, with words yielding high and non-words yielding low familiarity values, Ratcliff and McKoon argued that familiarity estimations can also be influenced by the compound of prime and target, with related prime-target pairs yielding higher familiarity than unrelated pairs, thus facilitating a word decision. For some stimulus materials more specific hypotheses about post-lexical processes exist. If affectively valent materials are used, the affective match between prime and target might trigger an affirmative answer whereas a non-match might trigger a tendency to negate (Klauer & Stern, 1992). If the target-related task has explicitly or implicitly a “yes” vs. “no” character (e.g., like the lexical decision task: “yes, it is a word!” vs. “no, it is not a word”), the affirmative tendency (following an affective match) might facilitate a word response whereas a tendency to negate (following an affective mismatch) might interfere (Wentura, 2000).

Effects found in *response priming* designs are typically explained by response competition mechanisms (Kornblum, Hasbroucq, & Osman, 1990; De Houwer et al., 2002; Klauer & Musch, 2003; Klinger, et al., 2000; Wentura & Rothermund, 2003). Strictly speaking, response priming might work through response competition and response facilitation. We will use the former term “response competition” as a shortcut for both mechanisms. Similar as in response interference paradigms like the Stroop task (Stroop, 1935) and the flanker task (Eriksen & Eriksen, 1974), it is assumed that the irrelevant information (the prime) elicits a tendency to execute a certain response. If this pre-activated response is in accordance with the response required by the relevant information (the target), response execution is facilitated. Correspondingly, if the prime activates a response that conflicts with the response that is required for the target, response execution is delayed.

There is a crucial difference between accounts of priming that draw on a facilitation of target processing and those that are based on response competition. The former account assumes that priming operates at the stage of access to the target concept: The presentation of a related prime facilitates the encoding and identification of a subsequently presented target and thus speeds up the accessibility of (semantic) target attributes. This implies that this kind of priming should be operative for a wide variety of tasks (i.e., all tasks that require semantic identification of the target). Response competition accounts, however, assume that priming operates at later processing stages of response selection and execution; effects are thus only expected if the dimension on which prime and target are related is task relevant (i.e., in a response priming design), so that the prime pre-activates a response that is part of the response set of the task and thus can either be congruent or incongruent to the correct response (De Houwer et al., 2002; Klauer & Musch, 2003; Klinger et al., 2000; Wentura, 1999). The status of post-lexical mechanisms with regard to the stage of their influence on priming effects is less clear and might depend on the specific kind of post-lexical process that is assumed to mediate priming.¹

In sum, priming effects in semantic priming designs are typically explained by a facilitated access to the semantic target information on which response selection is based, whereas response priming is usually explained by a facilitation of (or interference with) response selection or execution. Importantly, however, it should be noted that there is a specific asymmetry with regard to the explanation of priming effects in semantic and response priming designs. Whereas, by virtue of the design, semantic priming effects cannot be explained by response competition, effects found with response priming designs can be explained by either or both of facilitation of target processing and response competition. Separating these mechanisms in response priming paradigms has therefore been an important research topic.

Problems of previous attempts to distinguish between mediating processes in priming designs

Previous attempts to distinguish between different underlying processes of priming effects in response priming designs have used various experimental manipulations to determine the nature of the underlying processes. Many of these manipulations involve the appropriate selection of another task that has to be performed on the target stimuli. For example, the pronunciation task can be used to eliminate influences of post-lexical and response competition effects on target responses because pronouncing the specific target word is not facilitated by the pre-activation of a naming response to a related prime, nor can it be facilitated by an increase in familiarity, nor can it be biased strategically by an evaluation of the semantic matching between prime and target. The finding of significant priming effects with the pronunciation task thus establishes a specific influence of facilitated target access processes on priming effects. Robust priming effects with the pronunciation task have repeatedly been demonstrated for associative prime-target pairs (e.g., Meyer et al., 1975; see Neely, 1991, for a review), whereas for categorically related prime-target pairs (e.g., affective priming), highly inconsistent results have been reported, including congruency, incongruency,

as well as null effects (e.g., Bargh et al., 1996; De Houwer & Randell, 2004; Glaser & Banaji, 1999; Hermans, De Houwer, & Eelen, 1994; Klauer & Musch, 2001; Schmitz & Wentura, in press; Spruyt, De Houwer, & Hermans, 2009; Spruyt, Hermans, De Houwer, & Eelen, 2002; Spruyt, Hermans, Pandelaere, De Houwer, & Eelen, 2004; Spruyt, Hermans, De Houwer, Vandromme, & Eelen, 2007; Wentura & Frings, 2008; see Klauer & Musch, 2003, and Wentura & Rothermund, 2003, for reviews).

Similarly, using a categorization task that is unrelated to the dimension for which category congruency effects are investigated (e.g., an animacy categorization task is used when testing for affective category priming) should eliminate response competition as a potential explanation of categorical priming effects (but see Schmitz & Wentura, in press). Moreover, since post-lexical mechanisms are most plausible for the lexical decision task (see above) this strategy should also eliminate post-lexical mechanisms. Categorical priming effects are typically eliminated in designs in which the task is to categorize the targets according to another dimension (e.g., De Houwer et al., 2002; Klinger et al., 2000; Klauer & Musch, 2002; but see Spruyt, De Houwer, Hermans, & Eelen, 2007; Schmitz & Wentura, in press).²

Manipulating the task that has to be performed on the targets has yielded many interesting results regarding the underlying processes and mediating mechanisms of associative and categorical priming effects. However, changing the task (or other experimental manipulations) might not only help to control the influence that specific processes have on responding, it might also influence the nature and quality of the processes themselves that are triggered by the stimuli of a particular priming study. Using a categorization task that is orthogonal to the dimension of interest in a categorical priming study might reduce or inhibit the processing of information regarding the task-irrelevant categories. For example, in the study by De Houwer and colleagues (2002) positive and negative targets that were preceded by positive or negative primes had to be categorized as

denoting a person (e.g., “friend” or “enemy”) or an object (e.g., “gift” vs. “garbage”). There was no indication of an affective priming effect (i.e., responses were not faster when prime and target matched in valence than when they differed in valence). This null result might indicate that processing of targets is not facilitated by valence-congruent primes. However, it might alternatively indicate that valence of stimuli is not automatically processed if it is completely irrelevant in the experimental context.

Evidence for such a qualitative change in the processing of the stimuli was reported in a recent ingenious study by Spruyt et al. (2007; see also Spruyt, De Houwer, & Hermans, 2009). In this study, an external cue (a colored frame surrounding the target picture) signaled whether an evaluation task (positive vs. negative) or a semantic categorization task (object vs. animal) had to be performed on the target. By varying the frequency of the different tasks within an experimental block, Spruyt and colleagues could show that categorical congruency effects depended more on the task context in a block than on the specific task that had to be executed in a particular trial. This finding highlights the fact that investigating categorical congruency effects in a semantic priming design might not yield a fair test of whether categorical congruency effects are mediated by processes that facilitate access to the target. Such a task might not only change the mechanism that translates a given process into a priming effect, it might also eliminate the (earlier) processing of the prime or its valence (Moors, Spruyt, & De Houwer, 2010).

The previous arguments have shown that task manipulations alone might not always yield an unambiguous conclusion about the underlying processes of priming and congruency effects. We therefore want to introduce a different route of testing: We decided to combine task manipulations with a diffusion model data analysis. This statistical method allowed us to analyze the influence of different types of priming on specific processing stages. Before we present our hypotheses and give an overview of the present studies, we first give a short

introduction to diffusion model data analysis and explain how this method can be used to identify the contribution of different types of processes to particular priming effects.

Diffusion Model Analysis

The rationale of the diffusion model. Diffusion models (Ratcliff, 1978; Ratcliff & McKoon, 2008; Ratcliff & Smith, 2004) provide a unique possibility to improve the understanding of cognitive processes underlying simple binary decisions. These models make use of the shape of response time distributions of correct responses and error responses, as well as the ratio of both, to estimate a set of parameters that are indicators for ongoing cognitive processes (Voss, Rothermund, & Voss, 2004). Diffusion model analyses have been applied successfully to data from many cognitive tasks such as recognition memory (e.g. Spaniol, Madden, & Voss, 2006), lexical decision (e.g., Ratcliff, Gomez, & McKoon, 2004), perceptual discrimination (e.g., Voss et al., 2004; Voss, Rothermund, & Brandtstädter, 2008), multiple categorization tasks (Klauer, Voss, Schmitz, & Teige-Mocigemba, 2007), and others (see Wagenmakers, 2009, for a recent review). To our knowledge, however, there is no study using a diffusion model approach to investigate the cognitive mechanisms underlying priming effects. Note, however, that a related, somewhat complementary approach to diffusion models was recently adopted by Balota, Yap, Cortese, and Watson (2008), who applied ex-Gaussian modeling to RT distributions from semantic priming experiments, using lexical decision and pronunciation tasks. We will give a more detailed description of this approach in the General Discussion.

The diffusion model belongs to the class of continuous sampling models (Ratcliff & Smith, 2004). Information accumulation within one trial is represented by a diffusion process running between two thresholds which stand for two alternative decisional outcomes (see Figure 1, for a graphical illustration of the information accumulation process and of the different parameters that are contained in the model). As soon as the diffusion process hits one of the thresholds the corresponding response is initiated. The duration of the diffusion

process is called decision time. The response time is divided into decision time and the duration of non-decisional processes which cannot be further decomposed by a diffusion model analysis (e.g., for a semantic categorization task it comprises both pre-decision encoding and post-decision initiation and execution of the selected response).

Diffusion model parameters. The diffusion process is characterized by several parameters. The drift rate (v) is the mean rate of information accumulation. Positive drift rates indicate that the evidence accumulation supporting the outcome represented by the upper threshold prevails, and vice versa. The drift represents the performance in a discrimination task: It is a measure of how fast information accumulates in the decisional process.

The distance between the two thresholds (a) represents decision strategies, with larger (smaller) values representing a more conservative (more liberal) strategy of decision making. The starting point of the information accumulation process (z) reflects an *a priori* decision bias. The closer the starting point lies to one threshold, the less information is needed for the corresponding decisional outcome.

Finally, the duration of all non-decisional processes is given by t_0 (sometimes denoted as T_{err}). This processes may include pre-decisional (preparatory) processes (e.g., directing of attention to the stimulus, activation of the correct task set) and post-decisional, response-related processes (i.e., translation of a decision in a motor action). Importantly, the t_0 parameter is conceptually independent of all processes of response *selection* (which are captured by the diffusion process). Thus, a late level-account of priming effects in terms of response competition which assumes that response *execution* is facilitated or delayed due to response preparation or interference would predict that priming effects map on this parameter.

The simple diffusion model with four parameters as described above can be extended to allow for variability in trial-to-trial performance within one experiment and participant. In this complete diffusion model, the drift rate is assumed to belong to a normal distribution with the mean v and the standard deviation s_v (or η). The starting point is supposed to be equally

distributed around z with the range s_z and the non-decisional component is assumed to be equally distributed around t_0 with the range s_t .

Mapping response tendencies with the diffusion model. With the standard diffusion model as described above it is not possible to map differences in the speed of response execution between the two types of responses of the task (i.e., the same duration of execution is assumed for correct and incorrect responses). Durations of response execution are mapped on t_0 independent of the chosen response. To solve this problem, Voss, Voss, and Klauer (2010) recently suggested mapping the duration of non-decisional processes separately for the two possible responses. Basically, different parameters $t_{0, lower}$ and $t_{0, upper}$ are applied to the two response alternatives. Thus, extra-decisional times may vary between response alternatives. For example, with the extended model it is possible to account for prime-congruent responses being executed faster than prime-incongruent responses in a classification task.

Technically, we still denote the mean duration of non-decisional processes (across both responses) as t_0 . Any difference between the non-decisional component corresponding to the lower threshold (incongruent response) and to the upper threshold (congruent response) is mapped by the new parameter d ($d = t_{0, lower} - t_{0, upper}$). If, for example, the upper threshold corresponds to the response that matches the prime, a positive value of d indicates that the prime speeds up the execution of a congruent response relative to an incongruent response.

Fitting the diffusion model to data. In a diffusion model analysis, parameters are estimated so that predicted response time distributions optimally fit empirical distributions (Ratcliff & Tuerlinckx, 2002). For this purpose, different optimization criteria have been suggested, like the Log-Likelihood statistic (e.g., Klauer, Voss, Schmitz, & Teige-Mocigemba, 2007), the Chi Square statistic (e.g. Ratcliff & Tuerlinckxs, 2002), and the Kolmogorov-Smirnov statistic (KS; e.g., Voss et al., 2004). We see two important advantages of the latter approach: Firstly, the KS statistic is not as strongly influenced by

outliers as the log-likelihood statistic is. Secondly, no binning of data is required, which is often problematic, especially for experiments with low trial numbers and/or low error rates. For the present analyses, the diffusion model was fitted to the individual response time distributions using the software *fast-dm* (Voss & Voss, 2007, 2008) which is based on the KS approach. In all analyses data were collapsed across target types (e.g., positive and negative, in the evaluation task). The upper (lower) threshold was assigned to correct (incorrect) responses. Thus, more positive drift rates always indicate a more efficient processing of the target. In the present models, the d -parameter maps the difference between positions of RT-distributions for correct responses and error responses. If primes influence the speed of response execution, larger (positive) values of d will emerge for congruent primes (i.e., the correct response is primed) and smaller (negative) values of d are expected for incongruent primes (i.e., the incorrect response is primed).

Due to a low number of errors, it was not possible to estimate a model with free starting point and with separate non-decisional parameters for correct and incorrect responses (Voss et al., 2010). For the same reason, the distance from the starting point to the lower threshold can also not be estimated with sufficient accuracy. We therefore decided to fix z to $a/2$ in all analyses. We decided to estimate separate t_0 parameters for correct and incorrect responses rather than estimating differences in the starting point of the decision process because such a difference in response execution times is what is predicted by response-conflict accounts of affective priming (e.g., De Houwer et al., 2002; Klinger et al., 2000; Klauer & Musch, 2002): If the prime already activates a corresponding response, this should reduce response execution times for correct responses (relative to incorrect responses) on congruent trials, but it should increase response execution times for correct responses (relative to incorrect responses) on incongruent trials. We cannot rule out on *a priori* grounds that semantic congruency effects might also affect the starting point of the diffusion process; we will address this issue again in the General Discussion. As will be seen, additional analyses in

which the starting point was left free to vary revealed that affective congruency effects did not map on the starting point, suggesting that affective priming is not mediated by response selection processes.

Drift rate (v), response-time constant (t_0), and response tendency parameter (d) were estimated separately for different prime types (i.e., congruent, incongruent, or neutral, while—for the sake of parsimony—the remaining parameters (a , s_z , s_v , and s_t) were assumed to be constant across conditions.

Overview and Hypotheses

The core interest of this paper is to investigate the influence of different types of priming on specific processing stages. Specifically, we compared associative priming and semantic priming for different types of tasks (categorization tasks and lexical decision task). The diffusion model allows us to estimate different parameters for processes that are related to either response selection or response execution. Some priming effects may be best explained by differences in the speed of target identification or in the accessibility of semantic target features. In the diffusion model framework, such effects will typically be mapped on the drift rate (v). Other forms of priming might operate at a later stage of information processing. In this case, priming facilitates or impedes the activation and execution of the correct motor program. Processes that are related to response-execution are captured by the response-time constant of the diffusion model (t_0). Post-lexical processes are not our main focus here³, but some aspects of our data can be used to rule out influences of these post-lexical mechanisms in the priming effects that we observed.

In line with previous findings, we expect that associative priming effects are—at least to some extent—based on a facilitation of early processing stages that are related to response selection: We assume that primes lead to a pre-activation of associated target concepts and their semantic attributes which should have an impact on the efficiency of the decision process. Information from pre-activated targets should be more readily accessible, that is, the

target concept and semantic target attributes should be processed and identified more readily. Therefore, we expect larger drift rates (v) for targets after associated compared to non-associated primes. Such associative priming effects are expected to be largely independent of the task that is to be performed on the targets as long as the task requires lexical or semantic target processing. For example, associative priming effects on the drift rate indicating more efficient target processing after associated primes are predicted for lexical decision and for semantic classification tasks alike.

As elaborated above, we expect that all types of response priming designs are primarily based on Stroop-like interference processes (De Houwer et al., 2002; Klinger et al., 2000; Klauer & Musch, 2002; Klauer, Musch, & Eder, 2005). We assume that such interference processes operate at the stage of response execution. According to this account, a prime from the same category as a following target might pre-activate the corresponding motor-response program. In this case, the primed response can be executed faster. If the prime belongs to the alternative response category, the execution of the correct response to the target should be slowed down due to response interference. Since these effects operate independently of the identification and classification of the target, they will be mapped onto the non-decisional RT component of the diffusion model. The non-decisional component should either be generally reduced by a categorical match between prime and target (lower values on t_0), or, more specifically, the primes should reduce (increase) the time that is needed in order to execute the matching (non-matching) response, leading to positive (negative) values for d in case of congruent (incongruent) primes.

Another possibility that cannot be ruled out *a priori* is that response priming effects influence the response selection process by biasing the decision process in the direction of the prime category. Such an effect would be mapped by the diffusion model on the starting point (z). As already mentioned above, we cannot estimate priming effects on t_0 , d , and z simultaneously (Voss et al., 2010). We therefore decided to estimate models with two non-

decisional components (t_0 and d) in which the starting point was fixed, but we also conducted additional analyses in which the starting point was estimated freely. The results of these additional analyses suggested that categorical priming does not have an influence on z (see below).

Response priming effects on the extra-decisional RT components are plausible only for (semantic or evaluative) categorization tasks and not for the lexical decision task, because the latter task implies response congruence (word-word) for related and unrelated prime/target pairs likewise. In the following studies we investigate empirically to which extent categorical congruency effects in *response priming* designs affect non-decisional components and drift rates. In principle, facilitated access for categories can be easily explained by reference to distributed memory models (see Masson, 1995): If we assume that a considerable part of an activation pattern represents valence, the transition of the prime-representing pattern to a target-representing pattern should be facilitated in the case of a valence match (and possibly hindered in the case of a non-match).

As outlined above, previous results were mixed with regard to categorical priming effects (e.g., affective congruency effects) in *semantic priming* designs (using, e.g., pronunciation or lexical decision instead of evaluation). Given the inconsistent findings reported in the literature, we think that it is an open question whether categorical priming effects that cannot be attributed to Stroop-like interference processes or post-lexical mechanisms can be found in a typical semantic priming design. Thus it is worthwhile to take the alternative route via diffusion model analysis. The task (i.e., evaluation) makes sure that valence is task-relevant. If part of the categorical priming effect in a response priming design is caused by facilitation of access to target information, the drift rate should be affected as well.

These hypotheses were tested with six experiments. In Experiments 1a and 1b effects of associative priming in a lexical-decision task (Exp. 1a) and of affective priming in

the evaluation task (Exp. 1b) were compared. In Experiments 2a and 2b, affective congruency and semantic congruency (person vs. object) of prime-target pairs were manipulated. Participants classified targets either according to their valence (Exp. 2a), or according to their semantic category membership (Exp. 2b). In Experiments 3a and 3b, the influence of semantic associations between prime and target was examined again in a lexical decision task (Exp. 3a) and in a semantic categorization task (living vs. non-living, Exp. 3b).

Experiments 1a and 1b

Experiment 1 compares cognitive processes of two typical priming paradigms: An associative priming study was realized with a lexical decision task (i.e., a semantic priming design; Exp. 1a), while an affective priming study was realized using the evaluation task (i.e., a response priming design; Exp. 1b). It is expected that associative priming with the lexical decision task influences the decision process by enhancing the accessibility of the target concept and its associated semantic attributes (parameter ν), while affective priming with the evaluation task operates primarily on the stage of response execution (parameters t_0 and d). It is an open question whether effects of target access (i.e., moderations of parameter ν) will be found in Experiment 1b as well (see above).

Method

Participants. Two independent samples of 30 undergraduate students of the University of Trier participated in the associative priming task (Exp. 1a, 22 female, age mean 23.4) and in the affective priming task (Exp. 1b, 15 female, age mean 24.6) for partial fulfillment of course requirements. Additionally, participants got small performance related financial rewards (see Procedure for details).

Materials. Primes and targets were adopted from Rothermund and Wentura (1998): For Experiment 1a, 96 German nouns were used as targets, and 96 other nouns, each of which was associatively related to one of the targets, were used as primes. Three prime stimuli were assigned to each target: One highly associated prime, one non-associated prime, and one

neutral prime (strings of 3 to 12 identical letters, e.g., “ccccc”). Each prime word was used as associated prime for one target and as non-associated prime for another target. Associations were taken from norm lists (Hager & Hasselhorn, 1994). Non-words were constructed from targets by replacing one letter (non-word trials were ignored in the following analyses; analyses including non-word trials are presented in Appendix A).⁴ Prime-target pairings were identical for all participants. For each participant, each target word was combined once with its associated prime, once with its non-associated prime, and once with a neutral prime, yielding a total of 288 prime-target trials plus an additional 288 trials that included the non-word targets. All trials were presented in an individually randomized sequence for each participant. For a practice block, an additional set of 16 associated prime-target pairs was used. Again, each target was combined with an associated, a non-associated, and a neutral prime, yielding 48 word trials, plus 48 trials with non-word targets.

For Experiment 1b, 48 positive and 48 negative German adjectives were used as targets (norms from Hager & Hasselhorn, 1994). Forty-eight positive and 48 negative nouns were used as primes (norms from Wentura, 1999). Prime-target pairs were constructed by assigning one congruent prime, one incongruent prime and one neutral prime (letter string) to each target. Each prime word was used as congruent prime for one target and as incongruent prime for another target. Pairings were identical for all participants. For each participant, each target was presented once with a congruent prime, once with an incongruent prime, and once with a neutral prime, yielding a total of 288 prime-target trials that were presented in an individually randomized sequence. For the practice block, additional adjectives (16 positive, 16 negative) and nouns (16 positive, 16 negative) were selected. Again, each target stimulus was presented once in each priming condition, yielding a total of 96 practice trials.

Design. The only theoretically relevant factor in Experiment 1 was prime type (Exp. 1a: associated, non-associated, neutral; Exp. 1b: affectively congruent, affectively incongruent, neutral). Additionally, the assignment of response keys (left or right) to the

response categories (Exp. 1a: word vs. non-word; Exp. 1b: positive vs. negative) was counterbalanced across participants.

Procedure. A diffusion-model analysis is only robust with a substantial number of error responses that allow for a reliable estimation of the RT distribution for error responses. Hence instructions strongly emphasized speed. Participants were repeatedly encouraged to respond as quickly as possible, even if this would increase their error rate up to 20%. Responses that were fast and correct were rewarded with 10 points and slow responses were penalized with a subtraction of 10 points in a game-like procedure. The distribution of the previous six correct RTs was used as an adaptive criterion for the categorization of a response as fast or slow. Responses that were below the first quartile or above the third quartile of this distribution were categorized as fast or slow, respectively. Participants earned 50 Euro Cents for every block of 72 trials that was finished with zero or more points and an error rate below 20%.

The experiments were implemented on an IBM-compatible Pentium computer, using a Turbo Pascal (Borland International Inc., Scotts Valley, CA) 7.0 program operating in text mode. Stimuli were presented in a white font on a black screen. The experiments were composed of 96 practice trials and 8 experimental blocks of 72 (Exp. 1a) or 36 (Exp. 1b) trials each. The first two trials of each block were regarded as warm-up trials. Each trial started with the presentation of a cue (***) at the center of the screen. After 500ms, the cue was replaced by the prime stimulus that was presented for 200ms. After an inter-stimulus interval of 50ms (SOA = 250ms) during which the screen was blank, the target was presented at the same location. The target remained on the screen until a response was given. Target stimuli had to be classified as word versus non-word (Exp. 1a), or as positive versus negative (Exp. 1b), by pressing a left key (D) or a right key (L) on a standard computer keyboard. Responses were registered to the nearest millisecond. Immediately after the response was registered, the

target was removed from the screen, and a new trial started after an inter-trial-interval of 300ms.

During the practice block, trial-wise performance feedback was provided, indicating whether a response was regarded as fast or slow, and the current account of points. In the experimental blocks, feedback was given only at the end of each block.

Results

Data pre-treatment. Speed instructions and rewarding of speeded responses were used to evoke a high error rate. However, the logic of payoffs (i.e., errors were not penalized up to a rate of 20%) seemed to have encouraged participants to make fast guesses in some trials to maximize the chance of winning the performance related reward. Accordingly, there was a large amount of fast outlier latencies which can bias parameter estimates from a diffusion model analysis (Ratcliff & Tuerlinckx, 2002). Therefore, a three-step procedure to identify outliers was performed: First, all latencies below 200ms were excluded. Second, latencies were eliminated starting from the lower edge of the individual RT distributions until the number of removed correct responses exceeded the number of removed error responses by three (cf. Ratcliff & Tuerlinckx, 2002). This was done to exclude latencies that were based on pure guessing. Third, from the remaining individual latency distributions values below (above) the first (third) quartile minus (plus) 1.5 inter-quartile-ranges were eliminated (outlier values; Tukey, 1977). This procedure led to an exclusion of 6.1% of trials (Exp. 1a) or 7.3 % of trials (Exp. 1b), respectively.

Latencies. Mean latencies from correct responses were entered in repeated measurement ANOVAs with the factor prime type (Exp 1a: associated, non-associated, neutral; Exp. 1b: congruent, incongruent, neutral). Table 1 shows the means and standard deviations for all conditions. In Experiment 1a (associative priming), there was a significant effect of prime type on mean latencies, $F(2,28) = 10.38, p < .001, \eta_p^2 = 0.43$. Planned contrasts revealed that responses in trials with associated primes ($M = 492\text{ms}$) were faster compared

to trials with non-associated primes ($M = 502\text{ms}$), $F(1,29) = 20.86$, $p < .001$, $\eta_p^2 = 0.42$.

Likewise, in Experiment 1b (affective priming), latencies were influenced by prime type, $F(2,28) = 3.88$, $p < .05$, $\eta_p^2 = 0.22$. Again, the contrast between congruent ($M = 546\text{ms}$) and incongruent ($M = 555\text{ms}$) trials was significant, $F(1,29) = 7.69$, $p = .01$, $\eta_p^2 = 0.21$.

Accuracy. Errors (%) are also presented in Table 1. For Experiment 1a, the error rate depended on prime type, with $F(2,28) = 18.00$, $p < .001$, $\eta_p^2 = 0.56$, for the global analysis and $F(1,29) = 33.63$, $p < .001$, $\eta_p^2 = 0.54$, for the contrast of associated ($M = 9.4\%$) and non-associated ($M = 14.4\%$) primes. For Experiment 1b, the main effect of priming missed significance, $F(2,28) = 2.68$, $p = .08$, $\eta_p^2 = 0.16$. Error rates did not differ significantly between congruent ($M = 14.8\%$) and incongruent ($M = 16.1\%$) trials, $F(1,29) = 1.69$, $p = .17$, $\eta_p^2 = 0.06$.

Diffusion model analyses. Response time distributions for correct responses and error responses were entered in diffusion model analyses using the *fast-dm* program (Voss & Voss, 2007; Voss et al., 2010). Parameter values were estimated individually for each participant. Drift rates (ν), non-decisional RT constants (t_0), and response-execution biases (d) were estimated separately for different prime-types. The remaining parameters (a , s_z , s_ν , and s_{t0}) were held constant between conditions. Table 2 shows the mean estimates for all parameters. Table B1 (Appendix B) presents effect sizes for all analyses reported below for the complete samples as well as for reduced samples excluding all data from participants for which the model had only a weak fit.

The three parameters that were allowed to vary between prime types (ν , t_0 , and d) were entered in separate repeated measurement ANOVAs. In Experiment 1a, only the drift rate (ν) was influenced by prime type, with $F(2,28) = 15.47$, $p < .001$, $\eta_p^2 = 0.53$, for the global analysis, and $F(1,29) = 32.02$, $p < .001$, $\eta_p^2 = 0.53$, for the contrast of associated ($M = 3.67$) vs. non-associated primes ($M = 2.96$), indicating a more efficient processing of targets following associated primes. For t_0 and d there were no significant effects of prime type, all $F < 1$.

Results were different in Experiment 1b. In this study, prime type did not influence the drift rates, $F < 1$. However, there was a significant effect on the RT constant (t_0), $F(2,28) = 6.85$, $p < .01$, $\eta_p^2 = 0.33$. Planned contrasts revealed that the non-decisional processes were faster in trials with congruent primes compared to trials with incongruent primes, $F(1,29) = 5.20$, $p < .05$, $\eta_p^2 = 0.15$. The analysis of the d -parameter failed to reach statistical significance, $F(2,28) = 2.37$; $p = .11$.

Table 2 also shows the fit-indices (p) provided by *fast-dm* (Voss & Voss, 2007). These p -values are the probabilities of the Kolmogorov-Smirnov-statistic, that is, they are measures for deviances of the empirical from the predicted RT distributions. In our case, the presented p values represent the product of the three different p values based on the comparison of empirical and predicted distributions for the three priming conditions. Although p cannot be interpreted as the exact probability of a statistical test⁵ it is nonetheless obvious that the values are very close to 1, indicating that the empirical distributions are reproduced very closely by the predicted distributions. A more thorough test of model fit is presented in Appendix B.

Between-experiments analyses. Our main hypotheses include the prediction of a double dissociation between different priming procedures and different diffusion model parameters. To test the differential effect of the two priming procedures on the different diffusion model parameters in a more straightforward manner, we entered data from Experiment 1a and Experiment 1b into combined 2 (experiment: associative priming [Exp. 1a] vs. affective priming [Exp. 1b]) x 3 (prime type: associated/congruent, non-associated/incongruent, neutral) ANOVAs for each of the diffusion-model parameters.

As expected, there was a significant experiment by prime type interaction in the analysis of drift rates, $F(1, 58) = 21.10$, $p < .001$, $\eta_p^2 = 0.27$, for the contrast of associated/congruent vs. non-associated/incongruent trials. As reported above, this interaction

reflects a significant priming effect on the drift rate in associative priming and the absence of such an effect in the case of affective priming.

For t_0 , there was an interaction of experiment with the contrast associated/congruent vs. neutral trials, $F(1,58) = 4.80$, $p < .05$, $\eta_p^2 = 0.08$, indicating a speeding of non-decisional processes for associated trials compared to neutral trials in associative priming but not for congruent compared to neutral trials in affective priming. The corresponding contrast (non-associated/incongruent vs. neutral trials) was not significant, $F < 1$, $\eta_p^2 < 0.01$.

For the d parameter, priming effects did not differ significantly between experiments, both $F(1,58) < 2.74$; $p > .10$, $\eta_p^2 < 0.05$, for the contrasts associated/congruent vs. neutral and non-associated/incongruent vs. neutral.

Discussion

With Experiment 1a and 1b, two different kinds of priming effects were realized: Experiment 1a revealed the effect of associative priming in a lexical decision task; in Experiment 1b the evaluation task was used to demonstrate an affective priming effect. Regarding latencies, priming effects in the two experiments were nearly identical (10ms vs. 9ms). To evaluate the absolute magnitude of these RT-based priming effects, it has to be taken into account that responses were given at the upper end of the of the speed spectrum due to high time pressure with latencies of about 500 ms. For error-rates, only in Experiment 1a robust priming effect emerged.

The diffusion-model analyses revealed different cognitive mechanisms underlying these priming effects: In the case of associative priming, effects were based on differences regarding the efficiency of response selection processes (drift-rate): If a target is pre-activated by an associated prime, it can be identified faster and it can be processed more efficiently. It should be noted that the associative priming effect that was mapped onto the drift rate in Experiment 1a could also be attributed to a post-lexical process. In particular, according to the compound cue model (Ratcliff & McKoon, 1988), familiarity information uptake should

be enhanced for associated prime-target pairs, which should also lead to an increase in drift rates. The present data do not allow us to disentangle influences of target processing and familiarity-based post-lexical effects for associative priming. We will address this issue again in the Discussion of Experiment 3b.

Affective priming effects with the evaluative decision task (Exp. 1b) were based on differences in the non-decisional components (t_0), indicating that response execution in the evaluation task was faster following congruent than incongruent primes. This finding fits with the response facilitation/interference account of affective priming effects in the evaluation task (e.g., De Houwer et al., 2002; Klinger et al., 2000; Klauer & Musch, 2002, 2003): According to this idea, the processing of the prime stimulus automatically pre-activates the corresponding response, which then either facilitates the execution of the target response in case of a match (congruent target), or interferes with the execution of the target response in case of a mismatch (incongruent target). The fact that the effect was mapped on t_0 in the present experiments indicates that response compatibility effects mainly affected the execution of correct responses. The lack of an effect on the d parameter indicates that the response compatibility effects were not reversed for error responses. We attribute this null finding at least in part to the fact that the RT component for error responses cannot be estimated very reliably due to the small number of errors.⁶ We postpone a detailed discussion of this finding, because we conducted two additional experiments with response priming designs (Exp.s 2a and 2b).

Experiment 1b is not the first study that reports evidence for a response competition account of affective priming. Previous studies provided this evidence indirectly by showing that affective congruency effects disappeared for tasks in which affective congruency was not confounded with response congruency between prime and target. The new aspect of our study is that it provided direct evidence for response competition effects in affective priming *within the evaluation task*. Such a demonstration is of major importance because it shows that

priming effects in the standard version of the paradigm (Fazio et al., 1986) are mediated by response competition rather than by a modulation of target processing. Second, by using the evaluation task, we can rule out that participants might not have attended to the valence of the stimuli (Spruyt, De Houwer, et al. 2007, Spruyt et al., 2009). Stimulus valence had to be processed because it was task relevant. Nevertheless, processing of a valent prime did not have an influence on the drift rate for (affectively congruent or incongruent) targets, indicating that affective congruency does not facilitate target processing. Affective congruency effects in the evaluation task thus have to be explained differently. The diffusion model analyses suggest that the basis of the effect lies in extra-decisional components of response facilitation and interference.

Experiments 2a and 2b

With Experiments 2a and 2b, categorical priming effects of affective and semantic congruency were analyzed more closely. As discussed above, in our view affective priming is a special case of a more general phenomenon. We expect that categorical priming effects—and this includes affective priming effects—are mediated by response competition processes that depend on the current task-set; that is, a categorical match of prime and target leads to speeded responses only if the dimension on which the match or mismatch between prime and target occurs is task-relevant (Klauer & Musch, 2002). To test this hypothesis, in Experiment 2, we manipulated semantic congruency (person vs. object) of prime-target pairs orthogonally to affective congruency within the same set of stimulus materials. In Experiment 2a, an evaluation task was used, while in Experiment 2b targets had to be classified as persons vs. objects. A priming effect of evaluative congruency was expected to occur only in the evaluation task, whereas an effect of semantic congruency was expected to occur only in the semantic categorization task. Like in Experiment 1b, we predicted that categorical priming effects were mapped on the non-decisional components (t_0 and/or d).

Method

Participants. Two independent samples of 32 undergraduate students of the University of Trier participated in Experiment 2a (24 female, age mean 22.3) and in Experiment 2b (28 female, age mean 20.8) for partial fulfillment of course requirements and a small performance related financial reward (see Procedure for details).

Materials. Two sets of 64 German nouns were chosen as primes and targets, respectively. Within both sets, one quarter of the stimuli (i.e., 16) were positive person-words (e.g., “mother”), negative person-words (e.g., “murderer”), positive object-words (e.g., “chocolate”), and negative object-words (e.g., “dirt”). Four prime stimuli (one of each category) were assigned to each target stimulus. Similarly, each prime word was assigned to four different target words (one of each category). Prime-target pairings were identical for all participants. For each participant, each target word and each prime word was presented four times, once for each priming condition (affective and semantic congruency [e.g., mother - friend], affective match/semantic mismatch [e.g., mother - diamond], affective mismatch/semantic match [mother - liar], affective and semantic mismatch [mother - weapon]), yielding a total of 256 prime-target trials that were presented in an individually randomized sequence. For the practice block, two additional sets of 8 nouns (2 of each category) were selected. Each target and prime stimulus was presented once in each priming condition, yielding a total of 32 practice trials.

Design. In both experiments, the design essentially comprised the repeated-measurement factors affective match (congruent vs. incongruent) and semantic match (congruent vs. incongruent). Additionally, the assignment of response keys to the response categories (Exp 2a: positive vs. negative; Exp 2b: person vs. object) was counterbalanced across participants.

Procedure. Procedural details of Experiment 2 were identical to Experiment 1b with regard to feedback, instructions and stimulus presentation. In Experiment 2, participants finished one block of 32 practice trials, and 8 blocks of 32 experimental trials. The only

difference between the procedures of Experiment 2a and 2b pertains to the task: In Experiment 2a stimuli had to be classified according to valence, whereas Experiment 2b required a semantic classification (person vs. object).

Results

Data pre-treatment. One participant had to be excluded from Experiment 2b, because she made no errors in one condition, which poses a problem for our diffusion model algorithm. For the remaining sample, the data pre-treatment procedure described above (see Experiment 1) led to an exclusion of 9.4% (Experiment 2a) or 8.1% (Experiment 2b) of all trials. The high number of outliers is due to the high rate of fast guesses that were provoked by the reward of fast responses (see Experiment 1 for details).

Latencies. Latencies from correct responses (see Table 3) were entered into 2 (affective match: congruent vs. incongruent) by 2 (semantic match: congruent vs. incongruent) repeated measurement ANOVAs, separately for Experiment 2a and 2b. In Experiment 2a, evaluation latencies from affectively congruent trials ($M = 502\text{ms}$) were shorter than latencies from incongruent trials ($M = 516\text{ms}$), $F(1,31) = 20.29$, $p < .001$, $\eta_p^2 = 0.40$. There was no significant main effect of semantic match and no significant interaction, both $F < 1$. Results from Experiment 2b revealed a significant effect for semantic match, $F(1,30) = 28.99$, $p < .001$, $\eta_p^2 = 0.49$, with faster semantic categorization responses for targets after semantically congruent primes ($M = 493\text{ms}$) than after semantically incongruent primes ($M = 508\text{ms}$). Affective match had no influence on latencies, $F < 1$ for main effect and interaction.

Error rates. The analyses of error rates revealed parallel results to the analyses of latencies (Table 3): Error rates were reduced in affective match trials ($M = 15.1\%$) compared to trials with affectively mismatching primes ($M = 18.8\%$) in the evaluation task (Experiment 2a), $F(1,31) = 6.33$, $p = .01$, $\eta_p^2 = 0.18$, and in semantic match trials ($M = 13.9\%$) compared to trials with semantically mismatching primes ($M = 17.6\%$) in the semantic categorization task

(Experiment 2b), $F(1,30) = 11.97$; $p < .01$; $\eta_p^2 = 0.29$. No other effects emerged in both experiments, all $F < 2.40$, $p > .12$.

Diffusion-model analyses. The diffusion model was fitted to individual response time distributions with the same specifications as reported for Experiment 1. Means and standard deviations of the resulting parameters are presented in Table 4 (see Table B1 for an overview of all effect sizes).

Drift rate (v), RT-constant (t_0), and response-execution bias parameter (d) were entered in separate 2 (affective match: congruent vs. incongruent) by 2 (semantic match: congruent vs. incongruent) repeated measurement ANOVAs. Results for Experiment 2a revealed a main effect of affective match on t_0 , $F(1,31) = 4.30$, $p < .05$, $\eta_p^2 = 0.12$, indicating faster response execution in affectively congruent trials. Effects on the execution bias parameter d revealed that affective-match had an opposite influence on RT constants of correct and error responses, $F(1,31) = 5.34$, $p < .05$, $\eta_p^2 = 0.15$. Conforming to our expectations, negative values of d (indicating a delay of correct responses) emerged in affectively incongruent trials. Although the drift rate is numerically larger for affectively matching pairs compared to non-matching pairs, this effect clearly misses the level of significance, $F(1,31) = 1.19$, $p = .28$, $\eta_p^2 = 0.04$. No other effects emerged for Experiment 2a, all $F < 1$.

For Experiment 2b, the predicted effects of semantic match on response-execution speed emerged for t_0 , $F(1,30) = 12.24$, $p = .001$, $\eta_p^2 = 0.29$, and for d , $F(1,30) = 12.71$, $p = .001$, $\eta_p^2 = 0.30$. These effects indicate (a) that responses were executed faster in the semantic match condition, and (b) that correct responses were executed faster than error responses for the semantic match condition, whereas error responses were executed faster than correct responses for semantically mismatching prime-target sequences. There were two further non-predicted marginally significant results: Firstly, analyses of drift rates revealed an affective match by semantic match interaction, $F(1,30) = 4.43$; $p = .04$; $\eta_p^2 = 0.13$.⁷ Secondly, affective

match also had an effect on d , $F(1,30) = 4.17$; $p=.05$; $\eta_p^2=0.12$.⁸ No other effects were significant, all $F < 2.25$, $p > .14$.

As already outlined in the introduction, we also tested whether the pattern of results remains stable in a model without response execution bias (d), in which instead the starting point was allowed to vary between conditions. (Unfortunately, the current data do not allow us to reliably estimate biases in the starting points (z/a) and response execution biases (d) simultaneously; Voss et al., 2010). For this purpose, data were reanalyzed with a diffusion model in which d was fixed to 0 and z was estimated for all conditions. Results revealed shorter non-decisional times (t_0) for affective match, $F(1, 31) = 12.53$; $p=.001$; $\eta_p^2=0.29$, in Experiment 2a, and for semantic match, $F(1, 30) = 22.83$; $p < .001$; $\eta_p^2=0.43$, in Experiment 2b. No other effects were significant in the analyses of z , v , and t_0 .

Between-experiments analyses. Differences between the diffusion model results from Experiment 2a and 2b were analyzed with separate 2 (experiment) x 2 (affective match) x 2 (semantic match) ANOVAs for the diffusion-model parameters. As expected, experiment had no influence in the analysis of drift rates, all $F(1,61) < 1.78$, $p > .18$, $\eta_p^2=0.03$. For t_0 , the interactions of semantic match and affective match with experiment were significant, experiment x semantic match: $F(1,61) = 5.06$, $p < .05$, $\eta_p^2=0.08$; experiment x affective match, $F(1,61) = 3.51$, $p < .05$ (one-tailed), $\eta_p^2=0.05$. For the d parameter there was a significant experiment x semantic-match interaction, $F(1,61) = 2.89$, $p < .05$ (one-tailed), $\eta_p^2=0.05$, while the experiment x affective match interaction did not reach significance, $F(1,61) = 1.53$; $p=.22$, $\eta_p^2=0.02$.

Discussion

In Experiment 2, the effects of affective match and semantic match between prime and target were analyzed for the evaluation task and for a semantic classification task (i.e., person vs. object classification). As predicted, only the task-relevant dimension had an influence on performance (De Houwer et al., 2002; Klauer & Musch, 2002; Klinger et al., 2000): In the

evaluation task, responses were faster in affective match trials, whereas semantic match had no influence. In the semantic classification task, only semantic match facilitated responses. Given that the very same stimulus materials were used in both tasks, the pattern of results cannot be attributed to any differences in semantic or affective overlap.

The diffusion-model analyses revealed that priming effects were mediated by the non-decisional components (t_0 and d): Response execution (t_0) was speeded for trials with a prime-target match on the task-relevant dimension. Results on the response-execution bias parameter (d) indicate that for the task-relevant congruent conditions, correct responses were executed faster than error responses, whereas for task-relevant mismatches, error responses were executed faster than correct responses (negative values of the d parameter in the incongruent conditions indicate a faster execution of erroneous responses). These results support the hypothesis that categorical priming effects are mediated by a pre-activation of the response that is associated with the prime by the current task-set.

It should be noted that the non-decisional components cannot reproduce the congruency effects that were found for the error rates, because these take influence only on latencies but not on response frequencies. A possible explanation of these error effects is that there may be effects on the starting point (z) in addition to the response execution effects (see General Discussion). Therefore, we repeated parameter estimates with an alternative model in which starting points z was allowed to vary (and with fixed d). These analyses, however, revealed no differences between priming conditions with regard to z . Apparently the difference in error frequencies between congruent and incongruent conditions also cannot be explained by biases in the starting point, and must be due to some other process that cannot easily be identified in the diffusion models we used. Taken together, the results support our assumption that categorical priming effects are largely based on the preparation of the prime response rather than on a decision bias.

In accordance with the results of Experiment 1b, we found no evidence of affective or semantic congruency effects on the drift rates. We thus conclude that categorical priming effects of affective and semantic congruency are not mediated by differences in target processing (spreading activation) but instead reflect effects of response facilitation and conflict (cf. also Hutchison, 2003).

Experiments 3a and 3b

In Experiment 3, we will further investigate the processes of associative priming. The findings from Experiment 1b, 2a, and 2b demonstrated that primes evoke response tendencies if they can be mapped onto the task-relevant response categories. Such response tendencies speed responses in congruent trials and slow down responses in incongruent trials. Experiment 1a suggested that in the case of associative priming another mechanism prevails: In this experiment the associative priming effect was located on the drift rate. This fits with our assumption that primes pre-activate closely associated targets, which are then processed more efficiently. A crucial difference between Experiment 1a (associative priming) and Experiments 1b, 2a, and 2b (categorical priming), however, relates to the type of task that was used. Whereas categorical priming effects were always investigated with classification tasks, associative priming effects were analyzed with a lexical decision task in Experiment 1a. To rule out that the different findings reflect different tasks rather than different types of prime-target relationships, two associative priming experiments were realized either with a semantic categorization task or a lexical decision task in Experiment 3. Experiment 3a is an associative priming experiment with the lexical decision task and thus a replication of Experiment 1a. Experiment 3b is an associative priming experiment with a semantic categorization task (living vs. non-living). We expect that associative priming effects should obtain (in RTs and errors) for both kinds of tasks, and that these associative priming effects should be captured by the drift rate for both types of task.

Using a semantic categorization task for the analysis of associative priming effects in Experiment 3b also allows us to rule out that a relatedness effect for associated primes is caused by a biasing of familiarity estimates due to compound cues (Ratcliff & McKoon, 1988). In contrast to the lexical decision task, decisions in a semantic categorization task cannot be based on familiarity estimates because this task contains only words as targets (and as primes). Similarly, processes of a post-lexical semantic matching cannot explain associative priming effects in a semantic categorization task because related and unrelated prime/target pairs are assigned to both responses of the categorization task with equal probability.

Method

Participants. In Experiments 3a and 3b, two independent samples of thirty-two undergraduate students (Exp 3a: 22 female, age mean 22.1; Exp. 3b: 22 female, age mean 22.6) of the University of Trier participated for partial fulfillment of course requirements and small performance related financial rewards (see Procedure of Experiment 1 for details).

Materials. A set of 64 pairs of associated German nouns was used. Half of the primes and targets belonged to the category "living" and half were "non-living". For half of the targets, the associated prime belonged to the same semantic category (e.g., lion-tiger, bread-butter), whereas for the other half of the targets, the associated prime belonged to the opposite semantic category (e.g., honey-bee, king-crown). The same set of target and prime words was also used to create the non-associated prime-target pairs. Again, for half of the non-associated prime-target pairs, prime and target belonged to the same semantic category (e.g., king-bee, honey-crown), whereas for the other half, prime and targets belonged to different semantic categories (e.g., lion-butter, bread-tiger). For Experiment 3a, pseudo-words were generated from all targets by replacing one letter. Prime-target pairs were identical for all participants. In Experiment 3a (lexical decision task), each target was presented once with its associated prime and once with its non-associated prime, yielding a

total of 128 trials plus an additional 128 non-word trials. In Experiment 3b (semantic categorization task), each target was presented twice with its associated prime and twice with its non-associated prime, yielding a total of 256 trials. The 256 trials of an experiment were presented in an individually randomized sequence for each participant. For the practice blocks, an additional set of eight associated prime-target pairs were used that were presented once or twice in each condition (associated, non-associated), yielding 32 practice trials.

Design. The design comprised the factors prime-target association (associated vs. non-associated) and prime-target match (congruent vs. incongruent). For data analysis, only the first factor (in the following denoted as prime type) was evaluated.⁹ Additionally, the assignment of response keys to response categories (Exp. 3a: word vs. non-word; Exp. 3b: living vs. non-living) was counterbalanced across participants.

Procedure. Procedural details regarding feedback and stimulus presentation parameters were identical to the previous experiments. The only difference concerns the required tasks, that is, a lexical decision in Experiment 3a and a living versus non-living classification in Experiment 3b.

Results

Data pre-treatment. The cleaning procedures described above led to an exclusion of 8.4% trials in Experiment 3a and 9.1% in Experiment 3b.

Latencies. Data were collapsed over congruent and incongruent prime-target pairs.¹⁰ Latencies of correct responses are presented in Table 5. In Experiment 3a (lexical decision task), responses in trials with associated primes were faster compared to trials with non-associated primes, $F(1,31) = 11.08, p < .01, \eta_p^2 = 0.26$. Similarly, in Experiment 3b (semantic classification), categorization responses for targets were also faster after associated primes than after non-associated primes, $F(1,31) = 30.24, p < .001, \eta_p^2 = 0.49$.

Error rates. Analyses of error rates also indicated an influence of prime type (Table 5): Responses were more accurate following associated primes than following non-associated

primes, with $F(1,31) = 10.51, p < .01, \eta_p^2 = 0.25$, and $F(1,29) = 9.56, p < .01, \eta_p^2 = 0.24$, respectively, for Experiments 3a and 3b.

Diffusion-model analyses. Results from the diffusion model analyses are presented in Table 6 (see Table B1 for an overview of all effect sizes). Parameters for drift rate (v), non-decisional-component (t_0), and response-execution bias (d) were entered in separate ANOVAs with the repeated measurement factor prime type (associated vs. non-associated) as independent variable.

As predicted, mean drift rates for trials with associated primes (lexical decision: 3.91; semantic classification: 3.73) exceeded drift rates for trials with non-associated primes (lexical decision: 3.42; semantic classification: 3.34), with $F(1,31) = 5.42, p < .05, \eta_p^2 = 0.15$, for Experiment 3a, and $F(1,31) = 6.71, p < .05, \eta_p^2 = 0.18$, for Experiment 3b. Additionally, in Experiment 3a there was a non-predicted effect of prime type on the t_0 parameter, $F(1,31) = 5.01, p < .05, \eta_p^2 = 0.14$, indicating a shorter duration of non-decisional processes in the associated condition. No other effects emerged, all $F(31) < 1.65; p > .20$.

Between-experiments analyses. We did not predict any differences between the diffusion model results from Experiment 3a and 3b. Confirming this prediction, separate 2 (experiment) x 2 (prime type) ANOVAs revealed only a main effect of association on the drift rate, $F(1,62) = 11.58, p < .001, \eta_p^2 = 0.16$. There were no interactions between experiment and prime type, with $F(1,62) = 2.37, p = .13, \eta_p^2 = 0.04$, for the d -parameter, and $F < 1$ for drift and $t_0, \eta_p^2 < 0.01$.

Discussion

In Experiment 3, associative priming effects from two different paradigms were analyzed, that is, the lexical decision task (Exp. 3a) and a semantic classification task (Exp. 3b). In both experiments, associated primes caused faster and more accurate responses. Confirming our predictions, the diffusion-model analysis indicated that behavioral effects are based on differences in drift rates, that is, the processing of targets was facilitated by the prior

presentation of an associated prime. This result supports a spreading activation account of associative priming: If a target is pre-activated by an associated prime, identification of the target and processing of its semantic features is facilitated independent of the task that is to be executed.

Results of Experiment 3b using a semantic categorization replicated the pattern of findings with the lexical decision task (Experiments 1a and 3a) very closely. To our knowledge, this is the first demonstration of associative priming effects with a semantic categorization task in the literature. The finding of associative priming effects with this kind of task is noteworthy for several reasons. Firstly, associative priming effects with this task cannot be easily attributed to post-lexical mechanisms. Because the task does not contain non-words, and associated and non-associated pairs are assigned to the two responses of the task with equal probability, responding cannot be biased by semantic matching processes (Neely et al., 1989), nor can the effects be due to differences in familiarity between associated and non-associated compounds of prime and target (Ratcliff & McKoon, 1988). Secondly, considering the results of the diffusion model analyses, we can be sure that the differences in the drift rate between associated and non-associated trials are due to an influence of the primes on the processing of the target, yielding strong support for a spreading activation account of associative priming. Of course, our findings do not rule out the possibility that under certain circumstances, associative priming effects can also be influenced by post-lexical or other mechanisms (e.g., strategic expectations). At least with regard to Experiment 3b, however, we can be fairly sure that this was not the case.

General Discussion

The goal of the present paper is to improve the understanding of the cognitive processes underlying different types of priming. For this purpose, data from different priming studies were entered in a diffusion model data analysis (Ratcliff, 1978). We argued that in the case of associative priming the target concept is pre-activated by spreading activation, which

facilitates identification of the subsequently presented target and increases the accessibility of its semantic features. In a diffusion model analysis, such an effect is mapped on the speed of information accumulation during the decision process, that is, on the drift rate. Categorical priming, on the other hand, might be based on different cognitive mechanisms: The diffusion model account was adopted to test whether the presentation of categorical matching (mismatching) primes enhances (impedes) the identification of the target and its semantic features (i.e., increasing/decreasing drift rate), or whether it influences the response execution stage. In the latter case, categorical match between prime and target should result in a speeded execution of the response that matches the prime. Such an effect would be mapped on the extra-decisional parameters of the diffusion model (t_0 and d).

To test these hypotheses, six priming experiments were conducted that were designed for a diffusion model analysis. In three experiments, associative priming effects were analyzed adopting either a lexical decision task (Exp.'s 1a, 3a) or a semantic categorization task (Exp. 3b). Robust associative priming effects emerged in the RT and error data of these experiments, regardless of the task. Diffusion model analyses revealed that these associative priming effects were mapped onto the drift rate parameter, indicating that associated primes facilitate information uptake during the processing of the target identity and its semantic features. Although we cannot rule out the possibility that this effect also reflects increased familiarity estimates of associated prime-target pairs ("compound cue model"; Ratcliff & McKoon, 1988) or effects of a post-lexical semantic matching (Neely et al., 1989) for Experiments 1a and 3a, we can rule out these explanations in case of Experiment 3b, in which a semantic categorization task was used to analyze associative priming effects.

Categorical congruency effects for affective and semantic categories (in response priming designs) were investigated in three additional experiments (evaluation task: Exp.'s 1b and 2a; semantic categorization: Exp. 2b). Congruency effects of the task-relevant semantic dimension were found for RTs in all experiments and somewhat weaker congruency effects

were obtained for the error data (significant only for Exp.'s 2a and 2b). In line with previous studies (De Houwer et al., 2002; Klauer & Musch, 2002; Klinger et al., 2000), Experiments 2a and 2b revealed that congruency effects were obtained only for the categories that constitute the relevant response categories of the current task, indicating that response facilitation and interference play an important role for the emergence of category congruency effects. Correspondingly, diffusion model analyses revealed that congruency effects were always mapped exclusively on the response constants (t_0 , d), indicating that congruent primes facilitate the extra-decisional processes whereas incongruent primes interfere with these processes. In contrast to the associative priming studies, none of these congruency effects was mapped on the drift rate, indicating that category congruency effects are not mediated by differences in the identification of a target or in the processing of its semantic features.

Importantly, the diffusion model analyses allowed us to separately estimate the mediating effects of decision-related (response selection) and decision-unrelated processes (response execution) in a response priming design although we used a task in which these effects are typically confounded, if the data are analyzed in terms of RT differences. The novel insight that is gained by the diffusion model analyses of categorical priming designs is that even when the congruency dimension of interest was task relevant and thus received full attention (evaluation task for affective congruency effects; semantic categorization task for semantic congruency effects), these congruency effects were mediated exclusively by response competition and not by a modulation of target identification and processing of its semantic features.

Cognitive Processes Underlying Associative Priming

Spreading activation. Drift rates were higher in trials with associated primes compared to trials with non-associated primes. Previous studies on lexical decision using a diffusion model analysis showed that drift rates for high-frequency words exceed drift rates for low frequency words (see Wagenmakers, 2009, for a review). It is assumed that drift rates

reflect the ease with which a word can be accessed and retrieved from memory. Short-term priming seems to ease the access to and retrieval of strongly associated target words from memory. Our findings thus provide additional support for an account of associative priming that is based on the ease of access to target information, either in its spreading activation version (Collins & Loftus, 1975) or in the version of distributed memory models (e.g., Masson, 1995).¹¹ We want to emphasize at this point that the finding of increased drift rates in case of related primes might be compatible with other approaches as well (e.g., compound cue model, Ratcliff & McKoon, 2003), at least for the lexical decision task.

Associative priming effects were also mapped on the drift rate in a semantic categorization task (Experiment 3b). This finding indicates that associative priming not only facilitates the retrieval of target concepts from a mental lexicon, but that it also facilitates the processing of semantic target features, which is necessary for the decision process in a semantic categorization task.

Earlier models of spreading activation mostly focused on the speed of word identification (e.g., Anderson, 1983); consequently such models make predictions with regard to response latencies but remain silent with regard to priming effects on accuracy. Our findings revealed, however, that associative priming effects were obtained not only on RTs but also on accuracies. The diffusion model analysis allows us to identify the underlying processes of both RT-based and accuracy-based associative priming effects within one analysis. The fact that both effects were explained by a single parameter, the drift rate (ν), indicates that a pre-activation of associated targets leads not only to a faster identification of the target's identity but also influences the percentage of correct and erroneous responses in different tasks. Apparently, a pre-activation of the target increases the probability that the target is more often identified correctly as a word or is more often categorized correctly in a semantic classification task compared to a condition in which the target is not pre-activated or a different concept has been pre-activated by the prime (unrelated priming condition).¹²

Additional processes. In Experiment 3a, non-decisional processes (t_0 parameter) were also speeded for associated primes. This effect was not predicted and did not emerge in Experiments 1a and 3b. A possible explanation of this effect is that associated prime-target pairs might foster affirmative responses (see Klauer & Musch, 2002; Wentura, 2000), which may generally accelerate responding. Alternatively, in the case of non-associated targets, a kind of orienting response might inhibit immediate responding and might entail a “double check” of the target, if two words are paired that do not fit semantically. However, the effect obtained in only one of three experiments, and further studies are needed to check for the robustness of this result.

Cognitive Processes Underlying Categorical Priming

Response competition. In line with previous findings, categorical priming effects were observed only if the dimension of interest was task-relevant (De Houwer et al., 2002; Klauer & Musch, 2002; Klinger et al., 2000). No congruency effects obtained for categories that could not be mapped onto the response categories of the task. Supporting the assumption that categorical priming reflects processes of response competition, the diffusion model analyses revealed that categorical priming effects are based on the duration of non-decisional processes (t_0 and d). In all three experiments (Exp. 1b, 2a, and 2b) there was a significant reduction of the duration of non-decisional components (t_0) for congruent compared to incongruent trials. For Experiments 2a and 2b, additional effects were found for d , indicating a relatively faster execution of correct responses in congruent trials and a faster execution of error responses in incongruent trials. However, the estimate for the non-decisional component for error responses (i.e., $t_0 + d/2$) may be quite unreliable, which can explain why effects of categorical priming were less robust for d compared to t_0 : Since we included all participants who made at least one error in each condition, it is possible that the estimate of the d parameter is sometimes based on only very few error responses. More reliable, and therefore more informative, is the estimate for the non-decisional component for correct

responses (i.e., $t_0-d/2$). This reasoning explains why response competition effects that were observed for categorical priming were distributed over t_0 and d .

As elaborated above, we expect that response priming takes place at a late stage of information processing, that is, during response execution. This view converges with previous experimental evidence (De Houwer et al., 2002; Klauer & Musch, 2002; Klauer et al., 2005; Klinger et al., 2000) and with recent electrophysiological studies that provided evidence for an activation of motor responses by the primes in categorical priming designs (Bartholow, Riordan, Saults, & Lust, 2009; Eder, Leuthold, Rothermund, & Schweinberger, 2012).

Another view of response priming is that primes influence the decision in the sense of a response bias in signal detection theory. In this case, prime-information enters the decisional process, either supporting or working against the target information. This latter account on response priming might be seen as standing between early target-access-based models and late response-based explanations. Unfortunately, with the present data we cannot empirically distinguish between these two accounts (i.e., prime influence on response execution vs. on response selection), because the diffusion model analysis tends to become unstable if the starting point z is estimated for RT distributions that contain only few error responses (see our discussion of additional processes in the following paragraph; cf. Voss et al., 2010).

Additional processes. Because prime effects were mapped on extra-decisional components, the response competition mechanism discussed above cannot explain any effects of prime type on error rates. Such effects are, however, not uncommon in categorical priming (e.g., Draine & Greenwald, 1998), and were also found in Experiments 2a and 2b of the present paper. This indicates that additional effects might contribute to categorical priming that could not be adequately mapped in the present analyses. Theoretically, there are three possible sources of error effects in the diffusion model: A reduced error rate might be based on (1) a higher drift rate, (2) more conservative response criteria (i.e. increased threshold

separation), (3) a response bias that facilitates the correct response (i.e., the starting point is moved towards the correct response). We will address these possibilities in turn.

One of the most important results of the present studies is that we found virtually no evidence for the first possible source of error effects in categorical priming, a difference in drift rates. Only in one experiment (i.e., Exp. 2b), there was a small interaction effect of prime types on drift rate: Drift was increased if prime and target matched affectively and semantically. Although this effect was found to be based on an extreme outlier value for one participant in the present study (see Footnote 6), it is possible that target processing might be facilitated if prime and target have many overlapping features (relatedly, Exp. 3a revealed that priming effects for associatively related prime/target pairs were somewhat stronger if these pairs also matched on an irrelevant semantic dimension; see Footnote 9). In this case, processes might become more similar to those in associative priming (see Carson & Burton, 2001; Masson, 1995). However, we would expect such an effect only in the case of multi-dimensional overlap, a case in which it is difficult—or even impossible—to exclude associations as a potential source of relatedness effects.

The second possibility to explain reduced error rates in compatible trials within a diffusion-model framework is the assumption of more conservative response criteria. To make the model more parsimonious (and thereby more robust), we decided to fix the threshold parameter across conditions. Therefore, we have no empirical test for such a mechanism. However, a more conservative response criterion would imply that the increased error rate is accompanied by slower responses. Therefore, the decreased latencies in compatible trials render this possibility less plausible.

Additionally, primes could influence error rates via the starting point: If one assumes that prime information pushes the starting point towards the corresponding threshold, this could explain reduced error rates and faster latencies. This mechanism can be described as a decision bias (see Voss et al., 2008, for an empirical demonstration of such a decision bias in

a motivational context) or—in the terminology of signal detection theory (Macmillan & Creelman, 2005)—as a response bias (which should not be confused with the response-execution bias discussed above). Such a mechanism can easily explain effects of categorical priming on error rates. Unfortunately, the present data did not allow us to reliably estimate starting points. Simulation studies from our own lab (Voss et al., 2010) indicated that results of the diffusion model were often instable and sometimes dramatically biased if there were very few errors (e.g., less than 5), and starting points were not fixed to $a/2$. Therefore, the present data is not appropriate for a reliable test of this decision-bias hypothesis. Nonetheless, we re-examined data of Experiment 2a and 2b with a model allowing for different starting points (see section Diffusion Model Analyses from Experiment 2). The results of these analyses suggested that starting points did not play a major role in explaining categorical priming effects.

Recently, diffusion models have been developed for flanker tasks (Hübner, Steinhauser, & Lehle, 2010; White, Ratcliff, & Starns, 2011). Flanker tasks are structurally similar to categorical priming tasks because flankers—as categorical primes—activate the same response set as the targets. In the proposed models, flanker effects were mapped on the drift rates, which seems to conflict with our predictions. However, the models that were used in these studies had only one parameter for the duration of extra-decisional processes which was applied for both congruent and incongruent flankers. Thus, the models did not allow the mapping of flanker congruency effects on response execution times, which might have forced a mapping of the effects onto the parameter that reflects decisional processes. Thus it might be helpful to re-analyze these data with models with more parameters in order to allow for a stronger test of which of the two processes underlies flanker effects (faster response selection vs. faster response execution). Of course, there are also important procedural differences between flanker and categorical priming paradigms that might also explain the differences in findings: Firstly, the simultaneous presentation of flanker and target stimuli might prevent

effects based on response preparation, because targets will usually be categorized faster than flankers (due to selective attention). Secondly, only a very small set of stimuli is typically used in flanker tasks, all of which are assigned to specific responses and that repeatedly occur also as targets during the task, which introduces episodic retrieval effects as an important additional source of flanker effects (see Rothermund, Wentura, & De Houwer, 2005; Frings, Rothermund, & Wentura, 2007) that is not present in a typical priming study.

The discussion of alternative mediating processes on the basis of the diffusion model did not yield a satisfactory answer to the question how the effects of categorical priming on error rates should be explained. Although our arguments revealed that these effects are probably not mediated by differences in drift rate, thresholds, or starting point, a positive answer of how these effects should be explained is still missing. A plausible explanation of this effect is that in some cases the response activation that is triggered by the prime is so strong that it elicits a response before the processing of the target is terminated. In such a case, the prime determines the response before target processing has reached a decision threshold. The diffusion model is incapable of explaining or modeling such an effect, because in this case, response selection and execution do not follow the idealized process model of a target-based decision process. Instead, such an effect should rather be modeled in terms of a simple race model (e.g., Bundesen, 1987), in which the prime response wins the race against the target response. It might be a worthwhile endeavor for future research to develop an expanded version of the diffusion model that includes the possibility of prime-based responding, e.g., by combining two independent diffusion processes. For the present purposes, however, it suffices to say that any categorical priming effect that is mediated by a direct, prime-based response selection and execution is fully compatible with a response competition account, and is completely unrelated to an explanation of categorical priming effects in terms of facilitated target processing.

Affective Priming—A Special Case?

In the discussion above we considered affective priming in the evaluation task as one example of congruency effects in categorization tasks. The diffusion model analyses suggested that affective priming is driven by the same underlying mechanism as semantic congruency effects in a semantic (non-affective) categorization task. However, the question remains whether there is something special in affective priming.

There is a growing body of studies demonstrating affective priming in non-affective tasks like the lexical decision task or the naming task (Bargh et al., 1996; Giner-Sorolla, Garcia, & Bargh, 1999; Hermans et al., 1994, 2001; Spruyt et al. 2002, 2004, 2007, 2009; Wentura, 2000; Wentura & Frings, 2008; Wittenbrink et al., 1997, 2001a). Obviously, the response competition model of affective priming that has been presented here cannot explain effects of affective congruency on non-affective tasks. Therefore, cognitive mechanisms that drive affective priming seem to vary between different tasks.

Spruyt, De Houwer, and colleagues (2007) highlight the role of (selective) attention to the valence dimension in affective priming. The authors expect affective priming effects to influence the encoding and processing of affectively congruent targets if, and only if, the experimental context encourages the participants to process valence (but see Werner & Rothermund, 2012, for evidence to the contrary). The absence of any differences in drift rates in the affective priming experiments (Exp. 1b and 2a) conflicts with this conception of affective priming. A crucial difference between the present studies and those of Spruyt, De Houwer et al. (2007), which might account for the difference in findings, lies in the nature of materials that were used in the studies. Whereas (positive and negative) words were used in our experiments, Spruyt and colleagues employed pictures in their experiments. In addition, participants had to name the category of the target picture rather than pressing an arbitrary key on the computer keyboard. These differences might account for the differences in findings, because picture processing might give rise to much stronger emotional experiences than reading of words, and naming of intrinsically valent response categories might further

contribute to the dominance of valence processing in the experiments of Spruyt and colleagues. Of course, it would be interesting to reanalyze the data of Spruyt with a diffusion model data analysis, provided that enough errors were committed to allow for a reliable estimate of parameters.

Comparison to other response time distributional analyses

As noted in the introduction, Balota and colleagues (2008) adopted a somewhat complementary approach to diffusion models for analyzing priming data that also investigates response time distributions rather than comparing average RTs or error frequencies¹³.

Whereas diffusion models proceed from an explicit model that predicts how parameters may change as a function of manipulations, an alternative approach is to fit an empirical RT distribution to a theoretical function that is known to capture important aspects of typical RT distributions and to explore how parameters of this function vary as a function of manipulations. The theoretical function used by the authors is the ex-Gaussian distribution with parameters μ , σ , and τ . The authors conducted several semantic priming experiments, employing different manipulations (SOA, target degradation, and masking). Since the two approaches—on the one hand diffusion models, on the other hand ex-Gaussian analysis—proceed from different theoretical vantage points, results are not easily comparable. The authors argue, however, that “if a variable has an isolated effect on the drift rate [i.e., if predictions were made from a diffusion model perspective—*added*], the most straightforward prediction [for the ex-Gaussian analysis—*added*] would be a change in μ , σ , and τ in the distribution” (p. 499). In fact, for the condition that is most similar to our experiments (i.e., lexical decision with a short SOA of 250 ms), Balota and colleagues report that associatively related primes led to a shift of the entire RT distribution (decrease in parameter μ in combination with a decrease in the standard deviation, parameter σ), suggesting that some kind of a “head start” mechanism like spreading activation might be responsible for associative priming effects. For other experimental conditions, priming effects mainly

affected only the μ parameter: It thus remains an open question whether these two approaches indeed suggest different conclusions with regard to the underlying mechanisms of priming effects. Nevertheless, it seems clearly a worthwhile endeavor to continue these two lines of modeling that go beyond simple analysis of mean RTs (see Mazke & Wagenmakers, 2009, for a further comparison of exGaussian and diffusion model analysis). In particular, it would be interesting to compare categorical and associative priming in order to see whether and how the two types of priming can also be dissociated with this kind of RT distribution analysis.

Some Methodological Caveats

Validity of the Diffusion Model Parameters. The diffusion model provides a theoretical framework to explain different effects of priming. However, one must be careful in the interpretation of diffusion model results. The most important caveat regards the validity of the model parameters: Only rarely will there be a one-to-one relationship between a model parameter and a single psychological process. Thus, it is possible that the observed pattern of results is compatible with other theoretical accounts as well. Although the diffusion model parameters are by no means a perfect measure of psychological processes, they are still much more specific than most other measures that are commonly used in experimental psychology (e.g., mean response times, error rates, psycho-physiological measures), and therefore provide much more detailed information regarding the underlying processes of experimental effects. For example, Voss and colleagues (2004) demonstrated that specific experimental manipulations were mapped on specific parameters. Such experiments strongly support the parameters' interpretational validity.

Another caveat regards the problem of identifying the d parameter, that is, the parameter mapping differences in speed of response *execution*. As described in detail by Voss et al. (2010), effects of d and z can mimic each other: It is difficult to show empirically whether differences in latencies between two response alternatives are based on different starting points or on different execution times. That is unfortunate, because these possibilities

represent different cognitive processes. However, effects of target accessibility (i.e., drift rate) cannot be mimicked by z or d . Therefore, our results clearly suggest that (a) associations increase target accessibility and (b) categorical match does not increase target accessibility. We can be less sure whether categorical match speeds response execution (as argued for in this paper) or biases response selection.

The same argument can be extended to some degree for other diffusion model parameters as well: Especially in the case of small sample sizes (as in the present experiments), there might be tradeoffs between parameters. For example, slow responses can be explained either by a conservative criterion or by a small drift rate. To disentangle the two possibilities, the diffusion model analysis uses information of the form of the RT distributions, and the percentage and speed of error responses. However, the smaller the distributions are, the less reliable results from the parameter estimation procedures will be. This will primarily add noise to the estimation procedure. However, for small sample sizes systematic biases in estimates cannot be excluded; this would be especially problematic, if biases for the estimates differ between conditions (e.g., estimates from one condition might be more stable because of higher error rates). We consider this problem to be small in our case, however, because differences in performance between conditions were rather small.

Material Effects in Priming Studies. A problem that is independent of the modeling approach arises from the stimulus selection (see Hutchison, Balota, Cortese, & Watson, 2008, for a discussion of material effects). We thus cannot rule out the possibility that priming effects are influenced by the materials used for our studies. The consistent distinction in the parameterization of categorical and associative priming effects that we observed across different experiments, using different materials and tasks, however, may render the possibility unlikely that these differences are due to confounds in the selected stimulus materials.

It is also important to note that we included associated prime-target pairs also for non-word trials (e.g., boy-girl) in the lexical decision task. This was done in order to avoid effects

of semantic matching. Since semantic matching might affect different parameters of the model, we decided to eliminate these effects in order to more clearly map the effects of spreading activation and response-based processes in associative and category priming onto specific parameters of the model. At the same time, however, this feature sets our study apart from many previous associative priming studies that used only unrelated prime-target pairs for non-word trials. Investigating the effects of semantic matching (and other post-lexical processes) on the different parameters in a diffusion model analyses thus remains to be investigated in future studies.

Finally, it should be noted that a relatively high proportion of related prime-target pairs (i.e., 50% of the word-word trials) was chosen in all our experiments in order to make associative and categorization priming experiments as similar as possible. Deviating from the 50% proportion would introduce strategic effects in the category priming experiments because the prime then would become predictive of the target response (Klauer, Rossnagel, & Musch, 1997). Using a large percentage of related prime-target pairs in the associative priming experiments, however, might trigger post-lexical processes. It should be noted, however, that the same pattern of associative priming effects and the respective parameter estimates obtained also in Experiment 3b, in which an influence of post-lexical processes can be ruled out due to the use of a categorization task. In addition, due to the short SOA that was used in all experiments (250 ms) it is highly unlikely that priming effects were influenced by strategic expectancies (active generation of related targets on the basis of the primes; Neely, 1977; see also Footnote 10).

Effect Sizes. The last methodological issue we want to highlight here regards effect sizes. In our experiments, average RT differences between related and unrelated (or between congruent and incongruent) prime-target pairs ranged between 10 ms to 20 ms. These differences are in the typical range for sequential priming effects: For example, Balota et al (2008) reported semantic priming effects between 13 ms and 40 ms for conditions using short

SOAs and undegraded targets in a lexical decision task (larger effects were found for longer SOAs and degraded targets). To evaluate the absolute sizes of RT differences in our studies, it has to be taken into account that our experimental setup elicited very fast response times (about 500 ms). We induced high time pressure to increase the number of errors, which was necessary for our modeling approach. By increasing response speed, absolute RT differences are somewhat reduced. Still, all predicted priming effects were significant for RTs in all reported experiments. A look at standardized effect sizes for the model parameters (Table B1) reveals large effect sizes for the predicted effects, and nearly zero effects on parameters that should not be influenced, especially for Experiment 1a and 1b, which employ standard priming designs. In the more complex Experiments 2 and 3, effects are somewhat weaker, but still of medium size.

Summary, Implications, and Conclusions

In this article, diffusion model analyses were used to enhance our understanding of cognitive processes underlying different forms of priming. In experiments with associated prime-target pairs, results showed effects on a drift parameter (v), indicating that associated primes improved the *accessibility* of targets and their semantic features. In experiments investigating the effects of a categorical match between prime and target, affective and semantic congruency effects were mapped onto non-decisional parameters (d and t_0) if, and only if, the dimension of the categorical match was relevant for the ongoing task.

Implications for models of associative and semantic memory. Our findings suggest that strongly associated concepts seem to be connected by specific links that allow a spreading of activation. On the other hand, such a network metaphor seems not well suited to model the relations between (not associated) exemplars of a semantic category. At least in our experiments, evidence did not support the view of such direct interconnections among the various members of a category. This may be due to various reasons: Activation within a superordinate category may be distributed among too many channels, leading to a fan effect

(Anderson, 1974), or the spread of activation may be confined to only the most dominant or prototypical exemplars of a category (e.g., Rosch, 1978; but see Wentura & Frings, 2005).

Alternatively, propagation of activation across multiple links (“mediated priming”, Balota & Lorch, 1986) might simply be too weak an effect in order to occur from exemplars via category nodes to other exemplars.

Implications for Social Cognition. Our results have shown that affective and semantic categorical congruency effects cannot be taken as evidence for direct associative links between social categories or attitude objects and other concepts. Instead, these congruency effects are most parsimoniously explained by the assumption that *in the context of a certain task*, irrelevant prime stimuli also become categorized automatically, which leads to response competition effects between primes and targets. Our results thus do not lend support to strong versions of semantic or affective network models in Social Cognition (e.g., Bower, 1981). This statement is not meant to deny the influence of prejudice and stereotypes on perception and judgment (see, e.g., Fiske, 1998, and Moskowitz, 2005, for reviews). We rather want to warn against a too simplistic theoretical explanation of these influences in terms of a semantic-affective associative network model. Given our findings, it seems unlikely that activation of a category leads to an automatic and global pre-activation of all information (affective and conceptual) that is related to this category. Instead, such an activation effect should occur only for highly specific and strong associates of a category concept. To explain the ubiquitous influence of prejudice and stereotypes on information processing, we assume that a combination of category and context is necessary to provide associations that are strong and specific enough to allow for an automatic spreading of activation to related attributes (e.g., Blair, 2002; Casper, Rothermund, & Wentura, 2010, 2011; Wittenbrink, Judd, & Park, 2001b).

Potential of diffusion model data analyses in Cognitive Psychology. Diffusion model data analyses provide an additional tool that allows a direct identification and separation of

different underlying processes of priming effects. A major advantage of such an analysis of priming effects is that it allows separating and identifying underlying processes even in the absence of experimental manipulations that are often used to control or eliminate certain influences. By identifying processes statistically rather than experimentally, one can rule out the possibility that experimental manipulations might have influenced or changed the relevant processes under investigation.

The present study extended the use of diffusion model data analyses to sequential priming paradigms. The separation of influences that are mediated at the level of target processing and response competition was a major finding of our study. This dissociation between priming effects located at the stage of target processing and response execution might also provide a useful key towards a better understanding of priming effects in other areas of Cognitive Psychology for which different theoretical explanations have been brought forward. For example, processing- and response-level explanations represent alternative accounts of Negative Priming effects (e.g., Rothermund, Wentura, & De Houwer, 2005; Houghton & Tipper, 1994). Tse, Hutchison, and Li (2011) recently published a study in which inhibition-based and retrieval-based negative priming effects could be dissociated with distributional analyses (i.e., conditions fostering inhibition led to a shift of the complete RT distribution whereas under conditions that strengthened retrieval processes NP effects were increased for the later parts of the RT distribution). On the basis of the diffusion model, we would expect that inhibition-based effects should map onto decision-related parameters (drift rate or starting point) whereas negative priming effects that are based on a retrieval of distractor-response bindings should affect response-related parameters (t_0 or d). A combination of experimental and statistical methods should shed additional light on the underlying processes and mechanisms in this paradigm as well.

References

- Anderson, J. R. (1974). Retrieval of propositional information from long-term memory. *Cognitive Psychology*, *6*, 451-474.
- Balota, D. A., & Lorch, R. F. (1986). Depth of automatic spreading activation: Mediated priming effects in pronunciation but not in lexical decision. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *12*, 336-345.
- Balota, D. A., Yap, M. J., Cortese, M. J., & Watson, J. M. (2008). Beyond mean response latency: Response time distributional analyses of semantic priming. *Journal of Memory and Language*, *59*, 495-523.
- Bargh, J. A., Chaiken, S., Raymond, P., & Hymes, C. (1996). The automatic evaluation effect: Unconditional automatic attitude activation with a pronunciation task. *Journal of Experimental Social Psychology*, *32*, 104-128.
- Bartholow, B. D., Riordan, M. A., Sauls, J. S., & Lust, S. A. (2009). Psychophysiological evidence of response conflict and strategic control of responses in affective priming. *Journal of Experimental Social Psychology*, *45*, 655-666.
- Blair, I. V. (2002). The malleability of automatic stereotypes and prejudice. *Personality and Social Psychology Review*, *6*, 242-261.
- Blair, I. V., & Banaji, M. R. (1996). Automatic and controlled processes in stereotype priming. *Journal of Personality and Social Psychology*, *70*, 1142-1163.
- Bower, G. H. (1981). Mood and memory. *American Psychologist*, *36*, 129-148.
- Bundesen, C. (1987). Visual attention: Race models for selection from multielement displays. *Psychological Research*, *49*, 113-121.
- Carson, D. R., & Burton, A. M. (2001). Semantic priming of person recognition: Categorical priming may be a weaker form of the associative priming effect. *The Quarterly Journal of Experimental Psychology A: Human Experimental Psychology*, 1155-1179.

- Casper, C., Rothermund, K., & Wentura, D. (2010). Automatic stereotype activation is context dependent. *Social Psychology, 41*, 131-136.
- Casper, C., Rothermund, K., & Wentura, D. (2011). The activation of specific facets of age stereotypes depends on individuating information. *Social Cognition, 29*, 393-414.
- Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. *Psychological Review, 82*, 407-428.
- Collins, A. M., & Quillian, M. R. (1969). Retrieval time from semantic memory. *Journal of Verbal Learning and Verbal Behavior, 8*, 240-247.
- De Houwer, J., Hermans, D., Rothermund, K., & Wentura, D. (2002). Affective priming of semantic categorisation responses. *Cognition & Emotion, 16*, 643-666.
- De Houwer, J., & Randell, T. (2004). Robust affective priming effects in a conditional pronunciation task: Evidence for the semantic representation of evaluative information. *Cognition and Emotion, 18*, 251-264.
- Dovidio, J. F., Evans, N., & Tyler, R. B. (1986). Racial stereotypes: The contents of their cognitive representations. *Journal of Experimental Social Psychology, 22*, 22-37.
- Draine, S. C., & Greenwald, A. G. (1998). Replicable unconscious semantic priming. *Journal of Experimental Psychology: General, 127*, 286-303.
- Eder, A., Leuthold, H., Rothermund, K., & Schweinberger, S. R. (2012). Automatic response activation in sequential affective priming: An LRP study. *Social Cognitive and Affective Neuroscience, 7*, 436-445.
- Eriksen, B. A., & Eriksen, C. W. (1974). Effects of noise letters upon the identification of a target letter in a nonsearch task. *Perception & Psychophysics, 16*, 143-149.
- Fazio, R. H., Sanbonmatsu, D. M., Powell, M. C., & Kardes, F. R. (1986). On the automatic activation of attitudes. *Journal of Personality and Social Psychology, 50*, 229-238.

- Fiske, S. T. (1998). Stereotyping, prejudice, and discrimination. In D. T. Gilbert, S. T. Fiske, G. Lindzey, D. T. Gilbert, S. T. Fiske & G. Lindzey (Eds.), *The handbook of social psychology, Vols. 1 and 2 (4th ed.)*. (pp. 357-411). New York, NY US: McGraw-Hill.
- Frings, C., Rothermund, K., & Wentura, D. (2007). Distractor repetitions retrieve previous responses to targets. *Quarterly Journal of Experimental Psychology*, *60*, 1367-1377.
- Gaertner, S. L., & McLaughlin, J. P. (1983). Racial stereotypes: Associations and ascriptions of positive and negative characteristics. *Social Psychology Quarterly*, *46*, 23-30.
- Giner-Sorolla, R., García, M. T., & Bargh, J. A. (1999). The automatic evaluation of pictures. *Social Cognition*, *17*, 76-96.
- Glaser, J., & Banaji, M. R. (1999). When fair is foul and foul is fair: Reverse priming in automatic evaluation. *Journal of Personality and Social Psychology*, *77*, 669-687.
- Hager, W., & Hasselhorn, M. (Eds.). (1994). *Handbuch deutschsprachiger Wortnormen (Handbook of norms for German words)*. Goettingen: Hogrefe.
- Hermans, D., De Houwer, J., & Eelen, P. (1994). The affective priming effect: Automatic activation of evaluative information in memory. *Cognition & Emotion*, *8*, 515-533.
- Hermans, D., De Houwer, J., & Eelen, P. (2001). A time course analysis of the affective priming effect. *Cognition & Emotion*, *15*, 143-165.
- Houghton, G., & Tipper, S. P. (1994). A model of inhibitory mechanisms in selective attention. In D. Dagenbach & T. H. Carr (Eds.), *Inhibitory processes in attention, memory, and language* (pp. 53-112). San Diego, CA: Academic Press.
- Hübner, R., Steinhauser, M., & Lehle, C. (2010). A dual-stage two-phase model of selective attention. *Psychological Review*, *117*(3), 759-784.
- Hutchison, K. A. (2003). Is semantic priming due to association strength or feature overlap? A microanalytic review. *Psychonomic Bulletin & Review*, *10*, 785-813.

- Hutchison, K. A. (2007). Attentional control and the relatedness proportion effect in semantic priming. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *33*, 645-662.
- Hutchison, K. A., Balota, D. A., Cortese, M. J., & Watson, J. M. (2008). Predicting semantic priming at the item level. *The Quarterly Journal of Experimental Psychology*, *61*, 1030-1066.
- Klauer, K. C., & Musch, J. (2001). Does sunshine prime loyal? Affective priming in the naming task. *The Quarterly Journal of Experimental Psychology A: Human Experimental Psychology*, *54A*, 727-751
- Klauer, K. C., & Musch, J. (2002). Goal-dependent and goal-independent effects of irrelevant evaluations. *Personality and Social Psychology Bulletin*, *28*, 802-814.
- Klauer, K. C., & Musch, J. (2003). Affective priming: Findings and theories. In J. Musch & K. C. Klauer (Eds.), *The psychology of evaluation: Affective processes in cognition and emotion* (pp. 7-49). Mahwah, NJ: Lawrence Erlbaum Associates, Publishers.
- Klauer, K. C., Musch, J., & Eder, A. B. (2005). Priming of semantic classifications: Late and response related, or earlier and more central? *Psychonomic Bulletin and Review*, *12*, 897-903.
- Klauer, K. C., Roßnagel, C., & Musch, J. (1997). List-context effects in evaluative priming. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *23*(1), 246-255.
- Klauer, K. C., & Stern, E. (1992). How attitudes guide memory-based judgments: A two-process model. *Journal of Experimental Social Psychology*, *28*, 186-206.
- Klauer, K. C., Voss, A., Schmitz, F., & Teige-Mocigemba, S. (2007). Process components of the Implicit Association Test: A diffusion-model analysis. *Journal of Personality and Social Psychology*, *93*(3), 353-368.

- Klinger, M. R., Burton, P. C., & Pitts, G. S. (2000). Mechanisms of unconscious priming: I. Response competition, not spreading activation. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *26*, 441-455.
- Kornblum, S., Hasbroucq, T., & Osman, A. (1990). Dimensional overlap: Cognitive basis for stimulus-response compatibility—A model and taxonomy. *Psychological Review*, *97*, 253-270.
- Macmillan, N. A., & Creelman, C. D. (2005). *Detection theory: A user's guide (2nd ed.)*. Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers.
- Marcel, A. J. (1983). Conscious and unconscious perception: Experiments on visual masking and word recognition. *Cognitive Psychology*, *15*(2), 197-237.
- Masson, M. E. J. (1995). A distributed memory model of semantic priming. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *21*, 3-23.
- Matzke, D., & Wagenmakers, E.-J. (2009). Psychological interpretation of the ex-Gaussian and shifted Wald parameters: A diffusion model analysis. *Psychonomic Bulletin & Review*, *16*, 798-817.
- Meyer, D. E. (1970). On the representation and retrieval of stored semantic information. *Cognitive Psychology*, *1*(3), 242-299.
- Meyer, D. E., & Schvaneveldt, R. W. (1971). Facilitation in recognizing pairs of words: Evidence of a dependence between retrieval operations. *Journal of Experimental Psychology*, *90*, 227-234.
- Meyer, D. E., Schvaneveldt, R. W., & Ruddy, M. G. (1974). Functions of graphemic and phonemic codes in visual word-recognition. *Memory & Cognition*, *2*, 309-321.
- Moors, A., Spruyt, A., & De Houwer, J. (2010). In search of a measure that qualifies as implicit: Recommendations based on a decompositional view of automaticity. In B. Gawronski & K. B. Payne (Eds.), *Handbook of implicit social cognition: Measurement, theory, and application* (pp. 19-37). NY: Guilford Press.

- Moskowitz, D. S. (2005). Unfolding interpersonal behavior. *Journal of Personality, 73*(6), 1607-1632.
- Moss, H. E., Ostrin, R. K., Tyler, L. K., & Marslen-Wilson, W. D. (1995). Accessing different types of lexical semantic information: Evidence from priming. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 21*, 863-883.
- Neely, J. H. (1977). Semantic priming and retrieval from lexical memory: Roles of inhibitionless spreading activation and limited-capacity attention. *Journal of Experimental Psychology: General, 106*, 226-254.
- Neely, J. H. (1991). Semantic priming effects in visual word recognition: A selective review of current findings and theories. In D. Besner & G. W. Humphreys (Eds.), *Basic processes in reading: Visual word recognition* (pp. 264-336). Hillsdale, NJ : Lawrence Erlbaum Associates, Inc.
- Neely, J. H., Keefe, D. E., & Ross, K. L. (1989). Semantic priming in the lexical decision task: Roles of prospective prime-generated expectancies and retrospective semantic matching. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 15*, 1003-1019.
- Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review, 85*, 59-108.
- Ratcliff, R., & McKoon, G. (1988). A retrieval theory of priming in memory. *Psychological Review, 95*, 385-408.
- Ratcliff, R., & McKoon, G. (2008). The diffusion decision model: Theory and data for two-choice decision tasks. *Neural Computation, 20*, 873-922.
- Ratcliff, R., & Smith, P. L. (2004). A comparison of sequential sampling models for two-choice reaction time. *Psychological Review, 111*, 333-367.
- Ratcliff, R., & Tuerlinckx, F. (2002). Estimating parameters of the diffusion model: Approaching to dealing with contaminant reaction and parameter variability. *Psychonomic Bulletin and Review, 9*, 438-481.

- Ratcliff, R., Gomez, P., & McKoon, G. (2004). A diffusion model account of the lexical decision task. *Psychological Review*, *111*, 159-182.
- Rosch, E. (1975). Cognitive representations of semantic categories. *Journal of Experimental Psychology: General*, *104*, 192-233.
- Rosch, E. (1978). Principles of categorization. In E. Rosch & B. B. Lloyd (Eds.), *Cognition and categorization* (pp. 27-48). Hillsdale, NJ: Erlbaum.
- Rothermund, K., & Wentura, D. (1998). Ein fairer Test für die Aktivationsausbreitungshypothese: Untersuchung affektiver Kongruenzeffekte in der Stroop-Aufgabe. [An unbiased test of a spreading activation account of affective priming: Analysis of affective congruency effects in the Stroop task]. *Zeitschrift für Experimentelle Psychologie*, *45*, 120-135.
- Rothermund, K., Wentura, D., & De Houwer, J. (2005). Retrieval of incidental stimulus-response associations as a source of negative priming. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *31*, 482-495.
- Schmitz, M., & Wentura, D. (in press). Evaluative priming of naming and semantic categorization responses revisited: A mutual facilitation explanation. *Journal of Experimental Psychology: Learning, Memory, and Cognition*.
- Spaniol, J., Madden, D. J., & Voss, A. (2006). A diffusion model analysis of adult age differences in episodic and semantic long-term memory retrieval. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *32*, 101.
- Spruyt, A., De Houwer, J., & Hermans, D. (2009). Modulation of automatic semantic priming by feature-specific attention allocation. *Journal of Memory and Language*, *61*, 37-54.
- Spruyt, A., De Houwer, J., Hermans, D., & Eelen, P. (2007). Affective priming of nonaffective semantic categorization responses. *Experimental Psychology*, *54*, 44-53.
- Spruyt, A., Hermans, D., Houwer, J. D., & Eelen, P. (2002). On the nature of the affective priming effect: Affective priming of naming responses. *Social Cognition*, *20*, 227-256.

- Spruyt, A., Hermans, D., De Houwer, J., Vandromme, H., & Eelen, P. (2007). On the nature of the affective priming effect: Effects of stimulus onset asynchrony and congruency proportion in naming and evaluative categorization. *Memory & Cognition, 35*, 95-106.
- Spruyt, A., Hermans, D., Pandelaere, M., De Houwer, J., & Eelen, P. (2004). On the replicability of the affective priming effect in the pronunciation task. *Experimental Psychology, 51*, 109-115.
- Stroop, J. R. (1935). Studies of interference in serial verbal reactions. *Journal of Experimental Psychology, 18*, 643-662.
- Tse, C.-S., Hutchison, K. A., & Li, Y. (2011). Effects of contextual similarity and target-repetition proportion on negative priming in rt distributional analyses. *Journal of Experimental Psychology: Human Perception and Performance, 37*, 180–192.
- Tukey, J. W. (1977). *Exploratory data analysis*. Reading, MA: Addison-Weasley.
- Voss, A., & Voss, J. (2007). Fast-dm: A free program for efficient diffusion model analysis. *Behavior Research Methods, 39*, 767.
- Voss, A., & Voss, J. (2008). A fast numerical algorithm for the estimation of diffusion model parameters. *Journal of Mathematical Psychology, 52*, 1-9.
- Voss, A., Rothermund, K., & Brandtstädter, J. (2008). Interpreting ambiguous stimuli: Separating perceptual and judgmental biases. *Journal of Experimental Social Psychology, 44*, 1048-1056.
- Voss, A., Rothermund, K., & Voss, J. (2004). Interpreting the parameters of the diffusion model: An empirical validation. *Memory & Cognition, 32*, 1206.
- Voss, A., Voss, J., & Klauer, K. C. (2010). Separating response tendency and decision biases: Arguments for an additional parameter in Ratcliff's diffusion model. *British Journal of Mathematical and Statistical Psychology, 63*, 539-555.

- Wagenmakers, E.-J. (2009). Methodological and empirical developments for the Ratcliff diffusion model of response times and accuracy. *European Journal of Cognitive Psychology, 21*, 641-671.
- Wentura, D. & Degner, J. (2010). A practical guide to sequential priming and related tasks. In B. Gawronski & B. K. Payne (Eds.), *Handbook of implicit social cognition: Measurement, theory, and applications*. New York: Guilford.
- Wentura, D. (1999). Activation and inhibition of affective information: Evidence for negative priming in the evaluation task. *Cognition & Emotion, 13*, 65-91.
- Wentura, D. (2000). Dissociative affective and associative priming effects in the lexical decision task: Yes versus no responses to word targets reveal evaluative judgment tendencies. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 26*, 456-469.
- Wentura, D., & Frings, C. (2005). Repeated Masked Category Primes Interfere With Related Exemplars: New Evidence for Negative Semantic Priming. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 31*(1), 108-120.
- Wentura, D., & Frings, C. (2008). Response-bound primes diminish affective priming in the naming task. *Cognition and Emotion, 22*, 374-384.
- Wentura, D., & Rothermund, K. (2003). The “meddling-in” of affective information: A general model of automatic evaluation effects. In J. Musch & K. C. Klauer (Eds.), *The psychology of evaluation: Affective processes in cognition and emotion* (pp. 51-86). Mahwah, NJ: Lawrence Erlbaum Associates, Publishers.
- Werner, B., & Rothermund, K. (2012). Attention please: No affective priming effects in a valent/neutral-categorization task. *Manuscript submitted for publication*.
- White, C. N., Ratcliff, R., & Starns, J. J. (2011). Diffusion models of the flanker task: Discrete versus gradual attentional selection. *Cognitive Psychology, 63*(4), 210-238.

Wittenbrink, B., Judd, C. M., & Park, B. (1997). Evidence for racial prejudice at the implicit level and its relationship with questionnaire measures. *Journal of Personality and Social Psychology, 72*, 262-274.

Wittenbrink, B., Judd, C. M., & Park, B. (2001a). Evaluative versus conceptual judgments in automatic stereotyping and prejudice. *Journal of Experimental Social Psychology, 37*, 244-252.

Wittenbrink, B., Judd, C. M., & Park, B. (2001b). Spontaneous prejudice in context: Variability in automatically activated attitudes. *Journal of Personality and Social Psychology, 81*, 815-827.

Footnotes

¹ By definition, post-lexical processes are not mediated by influencing the encoding and identification of the target stimulus. However, according to the compound cue model, post-lexical effects that are instantiated by the compound of prime and target influence the very process of familiarity information sampling that leads to the word/non-word decision and is also driven by the target word. Post-lexical semantic matching effects, on the contrary, are assumed to bias responses by a different route than the target, that is, by a strategic biasing of word/non-word responses.

² To our knowledge, associative priming effects have not yet been investigated with semantic categorization tasks because response competition is not a problem with the more typical tasks that are used to analyze associative priming (lexical decision, pronunciation). Nevertheless, it would also be interesting to analyze associative priming effects with semantic categorization tasks in order to control for post-lexical influences (see our Exp. 3b below).

³ Although not the focus of this paper, the diffusion model might also be used to investigate the influence of post-lexical processes on priming effects. Depending on the nature of these processes, effects should be mapped onto different parameters of the model: Familiarity-based effects of associated prime/target pairs (“compound cue effects”) in the lexical decision task can be expected to be mapped onto the drift rate. Priming effects due to post-lexical semantic matching that are mediated by an activation of a specific response should instead be mapped onto the extra-decisional parameters of the model (d , t_0).

⁴ Non-words were also either related or unrelated to primes. Thus, there was no increased portion of non-word responses for unrelated targets, which should eliminate semantic matching strategies.

⁵ Because the form of the predicted CDFs is adapted post-hoc to the individual data sets, the KS test becomes more liberal, that is, given the null hypothesis is true, values of $p < .05$ will be achieved in less than 5% of tests.

⁶ The precision of the estimates for the non-decisional component for error responses is lower than the precision of all other parameters, because it depends exclusively on the leading edge of the error distribution, which in some cases comprises only a few responses.

⁷ For one participant, the estimate for the drift in affectively and semantically congruent trials ($v = 7.36$) was a far-out value (i.e., this value was more than 3 inter-quartile ranges above the third quartile of the distribution of drift rates; Tukey, 1977). If this participant was excluded from the analysis, the interaction was no longer statistically significant, $F(1,29) = 3.21$; $p = .08$; $\eta_p^2 = 0.10$.

⁸ For two participants, estimates for the d -parameter were far-out values (i.e., more than 3 inter-quartile ranges above the 3 quartile of the according distributions of d -parameters; Tukey, 1977) for at least one condition. If these participants were excluded from the analysis, the effect of affective match was no longer significant, $F(1,28) = 2.58$; $p = .12$; $\eta_p^2 = 0.08$, while the effect of semantic match remained unaffected, $F(1,28) = 10.95$; $p < .01$; $\eta_p^2 = 0.28$.

⁹ If the factor semantic match (congruent vs. incongruent) was included in the analyses, we had to exclude too many participants, who made no error in one condition, because the parameter estimation of the diffusion-model analyses are unstable with low error rates.

¹⁰ Additional analyses including categorical prime-target match as an additional factor revealed the following results: For Experiment 3a, the main effect of association was qualified by an association by categorical match interaction, with $F(1,31) = 13.83$; $p = .001$; $\eta_p^2 = 0.31$ for the latency analysis, and $F(1,31) = 5.85$; $p < .05$; $\eta_p^2 = 0.16$ for the error analysis, indicating in both cases stronger effects of association in the match condition. No main effects of categorical match emerged in the RT and error analyses, both $F < 1$. In Experiment 3b, there were main effects of categorical match, with $F(1,31) = 35.31$; $p < .001$; $\eta_p^2 = 0.53$ for the latency analysis and $F(1,31) = 17.63$; $p < .001$; $\eta_p^2 = 0.36$, for errors, indicating a better performance in match trials that conceptually replicated the findings of Experiment 2b. Interactions were not significant, both $F(1,31) < 1.51$; $p > .22$. As pointed out above, we could not investigate these effects further with the diffusion model analysis because of the low error rates.

¹¹ Although we used a short SOA in all our experiments that should eliminate strategic expectation-based processes, a recent study by Hutchison (2007) revealed that for participants high in attentional control, expectancy-based processes might also play a role in associative priming at a short SOA (267 ms). It should be noted, however, that differences in the predictiveness of the primes were highly salient in the study by Hutchison (2007; for example, predictive and non-predictive primes were presented in different colors), which might have increased the influence of strategic processes in this study.

¹² An anonymous reviewer pointed out that equating the drift rate with target activation might be problematic for diffusion model accounts that claim constancy of drift over decision time because target activation might increase with the time the target is on screen, which would lead to an increasing drift rate. Certainly, activation will increase rapidly during *encoding* (reflecting an extra-decisional process that is mapped onto the t_0 parameter); the activation

level after encoding will be higher for primed compared to unprimed targets. Once, the decisional phase has started, we assume a constant activation level and drift rate (note that the decisional phase takes less than 100ms, as is evident from the difference of latencies and non-decisional processes).

¹³ We thank an anonymous reviewer for making us aware of this work.

Table 1

Means (*M*) and standard deviations (*SD*) of correct latencies (ms) and error rates (%). Data from Experiment 1.

Exp.	Prime	Latencies		Errors	
		M	SD	M	SD
1a	associated	492	53	9.4	5.2
	non-associated	502	53	14.4	5.3
	neutral	497	58	11.6	5.7
1b	congruent	546	56	14.8	5.5
	incongruent	555	57	16.1	5.5
	neutral	550	56	16.4	5.9

Table 2

Means (*SDs* in parentheses) of estimates for the diffusion model parameters and for the fit index (p). If parameters were fixed across conditions, the value is only presented in the top row of the corresponding experiment (results from Experiment 1).

Exp.	Prime	a	v	t_0	d	s_z	s_v	s_{t0}	p
1a	associated	0.72 (0.13)	3.67 (1.03)	0.411 (0.041)	0.008 (0.023)	0.21 (0.20)	0.64 (0.59)	0.14 (0.05)	.99 (.02)
	non-associated	-	2.96 (0.80)	0.414 (0.036)	0.009 (0.025)	-	-	-	-
	neutral	-	3.30 (1.02)	0.414 (0.041)	0.010 (0.021)	-	-	-	-
1b	congruent	0.77 (0.11)	2.46 (0.58)	0.426 (0.035)	-0.031 (0.037)	0.34 (0.13)	0.36 (0.20)	0.17 (0.04)	.99 (.07)
	incongruent	-	2.52 (0.64)	0.437 (0.032)	-0.022 (0.040)	-	-	-	-
	neutral	-	2.53 (0.77)	0.441 (0.037)	-0.007 (0.039)	-	-	-	-

Table 3

Means (*M*) and standard deviations (*SD*) of correct latencies (ms) and error rates (%). Data from Experiment 2.

Task	Affective P/T-relation	Semantic P/T-relation	Latencies		Errors	
			M	SD	M	SD
Evaluation (Exp. 2a)	match	match	502	63	15.4	6.7
	match	mismatch	502	55	14.8	7.8
	mismatch	match	516	62	19.0	8.3
	mismatch	mismatch	516	56	18.6	8.7
Semantic classification (Exp. 2b)	match	match	492	51	13.3	4.9
	match	mismatch	508	47	18.3	5.9
	mismatch	match	494	47	14.6	5.0
	mismatch	mismatch	508	47	16.9	7.6

Table 4

Means (SDs in parenthesis) of estimates for the diffusion model parameters and for the fit index (p). If parameters were fixed across conditions, the value is only presented in the top row of the corresponding experiment (Results from Experiment 2).

Aff. P/T- relation	Sem. P/T- relation	a	v	t_0	d	s_z	s_v	s_{t0}	p
Evaluation (Exp. 2a)									
match	match	0.70 (0.13)	3.13 (1.00)	0.418 (0.040)	0.002 (0.023)	0.31 (0.15)	0.65 (0.49)	0.15 (0.05)	.94 (.07)
match	mismatch	-	3.12 (1.22)	0.417 (0.038)	-0.001 (0.028)	-	-	-	-
mismatch	match	-	2.89 (0.99)	0.423 (0.041)	-0.014 (0.030)	-	-	-	-
mismatch	mismatch	-	2.94 (1.02)	0.423 (0.038)	-0.014 (0.038)	-	-	-	-
Semantic classification (Exp. 2b)									
match	match	0.69 (0.10)	3.42 (0.94)	0.415 (0.038)	0.008 (0.016)	0.29 (0.13)	0.50 (0.33)	0.16 (0.05)	.94 (.05)
match	mismatch	-	2.99 (0.77)	0.420 (0.036)	-0.007 (0.020)	-	-	-	-
mismatch	match	-	3.08 (0.67)	0.411 (0.033)	-0.002 (0.015)	-	-	-	-
mismatch	mismatch	-	3.26 (1.13)	0.422 (0.037)	-0.009 (0.018)	-	-	-	-

Table 5

Means (*M*) and standard deviations (*SD*) of correct latencies (ms) and error rates (%). Data from Experiment 3.

Task	Prime	Latencies		Errors	
		M	SD	M	SD
Lexical decision (Exp. 3a)	associated	516	60	10.2	6.8
	non-associated	527	67	14.1	7.0
Semantic classification (Exp. 3b)	associated	500	68	13.5	7.0
	non-associated	511	66	16.2	7.0

Table 6

Means (SDs in parenthesis) of estimates for the diffusion model parameters and for the fit index (p). If parameters were fixed across conditions, the value is only presented in the top row of the corresponding experiment (results from Experiment 3).

Task	Prime	a	v	t_0	d	s_z	s_v	s_{t0}	p
Lexical decision (Exp. 3a)	associated	0.73 (0.20)	3.91 (1.21)	0.433 (0.039)	0.009 (0.028)	0.27 (0.17)	0.77 (0.70)	0.16 (0.06)	.99 (.02)
	non- associated	-	3.42 (1.26)	0.442 (0.043)	0.016 (0.030)	-	-	-	-
Semantic classification (Exp. 3b)	associated	0.71 (0.20)	3.73 (1.48)	0.416 (0.040)	-0.002 (0.035)	0.31 (0.19)	0.89 (0.66)	0.17 (0.04)	.97 (.12)
	non- associated	-	3.34 (1.14)	0.421 (0.040)	-0.012 (0.032)	-	-	-	-

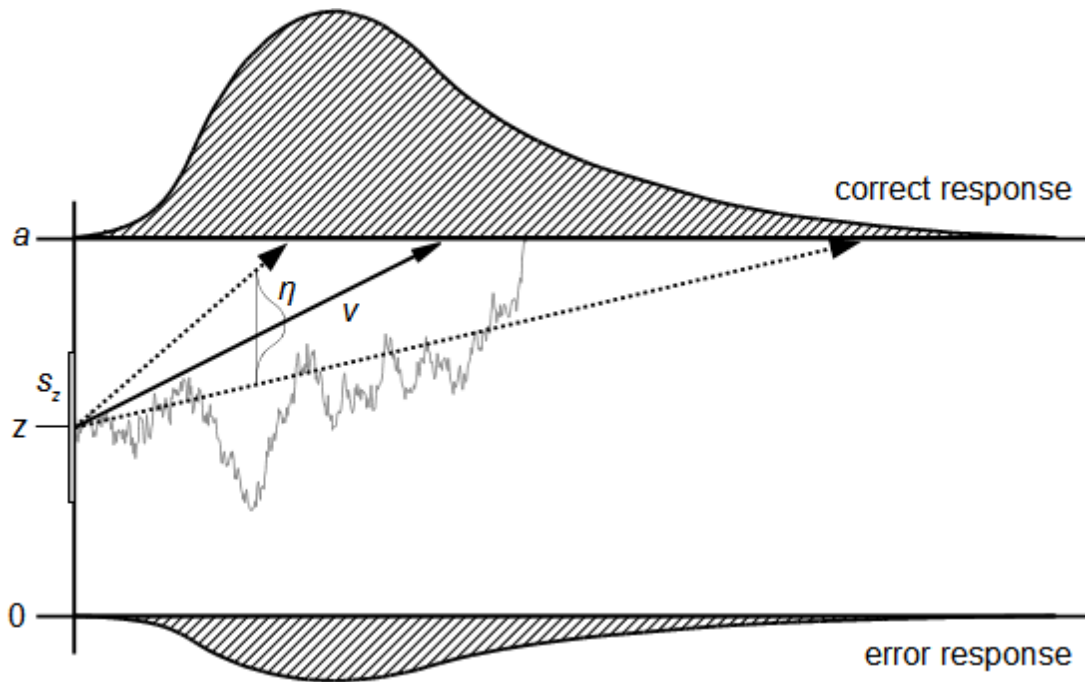


Figure 1

The Diffusion Model. The diffusion process starts in each trial of an experiment from the interval s_z around z and is driven by a constant drift with mean v and standard deviation s_v . The diffusion process is assumed to be noisy, that is, random noise is added to the drift rate, resulting in different process paths in each trial of an experiment. The gray line depicts a sample path for the diffusion process. The diffusion process terminates as soon as the upper threshold (a) or the lower threshold (0) is reached. Then, the decision phase is completed and the response linked to the threshold is initiated. Predicted distributions for decision times are sketched outside the thresholds.

Appendix A: Diffusion Model Analyses of Lexical Decision Data including the non-word trials

The diffusion model analyses of the lexical decision experiments (Exp. 1a and Exp. 3a) reported in the main part of this paper are based on responses only from trials with "word" targets. Non-word trials were ignored because we had no hypothesis whether associations would help or impede correct rejections. Here, we will report results from diffusion model analyses of the complete data sets including non-word trials. Parameters were estimated for a model with the upper threshold used for "word" responses and the lower threshold used for "non-word" responses, thus yielding positive drift rates for word trials and negative drift rates for non-word trials. Drift and response-time constant were estimated as a function of target type (word vs. non-word) and prime type (Exp. 1a: associated, non-associated, or neutral; Exp. 3a: associated vs. non-associated). The response-tendency-parameter d was estimated only in dependency of prime type (and not of target type), because this parameter refers to differences in the speed of response execution of responses connected to the lower vs. upper threshold, and is thus conceptually independent of target type.

Results from Experiment 1a are presented in Table A1. The observed pattern replicates the findings reported above: Effects of prime-association reveal themselves in increased drift rates for word trials. An 2 (target type) by 3 (prime type) ANOVA of drift rates revealed main effects of target type, $F(1,29) = 897.65, p < .001, \eta_p^2 = 0.97$, and of prime type, $F(2,28) = 10.99, p < .001, \eta_p^2 = 0.44$. These effects were qualified by a significant interaction, $F(2,28) = 4.12, p < .05, \eta_p^2 = 0.23$, indicating that drift is influenced by prime in word trials, $F(2,28) = 12.41, p < .001, \eta_p^2 = 0.47$, but not in non-word trials, $F(2,28) = 1.11, n.s., \eta_p^2 = 0.07$. The analysis of the response time constant suggested that non-decisional processes take longer in the case of non-word-trials than in word trials, $F(1,29) = 40.74, p < .001, \eta_p^2 = 0.58$. There was also an effect of prime on t_0 , $F(2,28) = 6.23, p < .01, \eta_p^2 = 0.31$, indicating slower non-decisional processing after neutral primes (e.g., "ffffff"), compared to word primes.

Confirming our hypothesis, prime-target association however did not influence the duration of non-decisional processes, with $F(2,28) = 1.19$, *n.s.*, $\eta_p^2=0.04$, for the contrast of associated vs. non-associated primes, and $F < 1$, $\eta_p^2=0.00$, for the interaction of this contrast with target type. As expected, the d parameter is also independent of the prime type, $F < 1$.

The same pattern of results emerges for Experiment 3a (Table A2): Drift rate differs significantly between target types, $F(1,31) = 616.15$, $p < .001$, $\eta_p^2=0.95$, but is not influenced by prime type, $F(1,31) = 1.96$, $p = .17$, $\eta_p^2=0.06$. However, there is a prime by target interaction, $F(1,31) = 4.57$, $p < .05$, $\eta_p^2=0.13$. Analyses within the target types show that drift for word trials is influenced by prime type, $F(1,31) = 5.06$, $p < .05$, $\eta_p^2=0.14$, whereas prime type has no influence on drift for non-words, $F < 1$. Like in Experiment 1a, the non-decisional component t_0 was larger for non-words, $F(1,31) = 40.64$, $p < .001$, $\eta_p^2=0.57$, but it did not differ substantially between trial with associated or non-associated primes, $F < 1$. The prime by target interaction also failed to reach statistical significance, $F(1,31) = 3.13$, $p = .09$, $\eta_p^2=0.09$. There was no effect of prime on the d -parameter, $F < 1$.

Table A1

Mean parameter values (*SD* in parenthesis) of the diffusion model estimated from data from Experiment 1a, including the non-word trials. If parameters were fixed across conditions, the value is only presented in the top row of both trial types.

Prime	a	v	t_0	d	s_z	s_v	s_{t0}	p
Word Trials								
associated	0.85 ^a (0.10)	3.11 (0.79)	0.396 (0.036)	0.028 ^a (0.023)	0.40 ^a (0.11)	0.24 ^a (0.15)	0.03 ^a (0.01)	.65 ^a (.18)
non-associated	-	2.57 (0.70)	0.394 (0.034)	0.024 ^a (0.023)	-	-	-	-
Neutral	-	2.81 (0.84)	0.397 (0.033)	0.027 ^a (0.030)	-	-	-	-
Non-Word Trials								
associated	0.85 ^a (0.10)	-2.31 (0.61)	0.417 (0.043)	0.028 ^a (0.023)	0.40 ^a (0.11)	0.24 ^a (0.15)	0.03 ^a (0.01)	.65 ^a (.18)
non-associated	-	-2.45 (0.52)	0.416 (0.037)	0.024 ^a (0.023)	-	-	-	-
Neutral	-	-2.28 (0.84)	0.429 (0.046)	0.027 ^a (0.030)	-	-	-	-

^aThe identical values are valid for word and non-word trials

Table A2

Mean parameter values (*SD* in parenthesis) of the diffusion model data from Experiment 3a, including the non-word trials. If parameters were fixed across conditions, the value is only presented in the top row of both trial types.

Prime	<i>a</i>	<i>v</i>	<i>t</i> ₀	<i>d</i>	<i>s</i> _z	<i>s</i> _v	<i>s</i> _{t0}	<i>P</i>
Word Trials								
Associated	0.90 (0.15)	2.91 (0.87)	0.404 (0.038)	0.021 (0.025)	0.38 ^a (0.14)	0.31 ^a (0.24)	0.03 ^a (0.01)	.88 ^a (.10)
non-associated	-	2.58 (0.91)	0.410 (0.043)	0.024 ^a (0.027)	-	-	-	-
Non-Word Trials								
Associated	0.90 ^a (0.15)	-2.11 (0.61)	0.442 (0.049)	0.021 (0.025)	0.38 ^a (0.14)	0.31 ^a (0.24)	0.03 ^a (0.01)	.88 ^a (.10)
non-associated	-	-2.07 (0.77)	0.438 (0.049)	0.024 ^a (0.027)	-	-	-	-

^aThe identical values are valid for word and non-word trials

Appendix B: Model fit of diffusion model analyses

Model Fit was analyzed with two strategies: Firstly, a large Monte-Carlo simulation study was conducted to get exact probabilities for significant model misfit and, secondly, match of predicted and empirical response-time quartiles and error rates are presented graphically.

Monte-Carlo-Simulation

Method. From the Parameter values of each participant of each experiment, 1000 datasets were simulated using the *construct-sample* routine of *fast dm* (Voss & Voss, 2007) with high precision of calculation (precision =4). Then, parameters were re-estimated with *fast-dm*. This allowed getting empiric distributions of model fit (as given by the *p*-values) for "true" models, i.e. models that were based on data following a diffusion process. From the resulting distributions of fit indices the 5% percentiles (or the 1% percentiles) were used as critical values for the evaluation of fit indices from the empiric models. Whenever model fit from the analysis of the real data was worse than this critical value, we assumed that the diffusion model cannot account for the data.

Results. In the 6 experiments there were in total 187 participants; consequently, 187.000 datasets were generated and re-analyzed, which took about 850 hours of processor time. Using an alpha level of .05, model fit from the 17 of 187 participants (9%) was suspicious (number of bad-fitting models: Exp 1a: 1; Exp. 1b: 0; Exp. 2a: 5; Exp. 2b: 5; Exp. 3a: 3; Exp. 3b: 3). Only two models (1 %) showed a significant misfit when alpha was set to .01 (both from Exp. 3b). The numbers of detected mismatches roughly fits the number to be expected for perfect models; thus overall fit is assumed to be good.

Re-analyses of parameters. Parameters were re-analyzed excluding data from the 17 participants for which a misfit on the 5% level was found. Table B1 shows the effect sizes of priming effects for the complete samples and for the reduced samples (excluding data from models with "bad fit"). As can be seen, the pattern of results is very similar.

Table B1

Effect sizes (η_p^2) for the effects of prime on the diffusion model parameters for the complete samples and for reduced samples (participants with bad fitting models excluded).

	Complete Sample	Reduced Sample
Experiment 1a		
<i>N</i>	30	29
Effect <i>v</i>	.53***	.51***
Effect <i>t</i> ₀	.03	.03
Effect <i>d</i>	.01	.01
Experiment 1b		
<i>N</i>	30	30
Effect <i>v</i>	.02	.02
Effect <i>t</i> ₀	.33**	.33**
Effect <i>d</i>	.15	.15
Experiment 2a		
<i>N</i>	32	27
Effect <i>v</i> (<i>affective match</i>)	.04	.01
Effect <i>v</i> (<i>semantic match</i>)	.00	.01
Effect <i>t</i> ₀ (<i>affective match</i>)	.12*	.19*
Effect <i>t</i> ₀ (<i>semantic match</i>)	.00	.00
Effect <i>d</i> (<i>affective match</i>)	.15*	.21*
Effect <i>d</i> (<i>semantic match</i>)	.01	.05
Experiment 2b		
<i>N</i>	31	26
Effect <i>v</i> (<i>affective match</i>)	.00	.00
Effect <i>v</i> (<i>semantic match</i>)	.02	.01
Effect <i>t</i> ₀ (<i>affective match</i>)	.01	.00
Effect <i>t</i> ₀ (<i>semantic match</i>)	.29**	.38***
Effect <i>d</i> (<i>affective match</i>)	.12 ⁺	.11 ⁺
Effect <i>d</i> (<i>semantic match</i>)	.30**	.28**
Experiment 3a		
<i>N</i>	32	29
Effect <i>v</i>	.15*	.12 ⁺
Effect <i>t</i> ₀	.14*	.21*
Effect <i>d</i>	.03	.02
Experiment 3b		
<i>N</i>	32	29
Effect <i>v</i>	.18*	.14*
Effect <i>t</i> ₀	.05	.05
Effect <i>d</i>	.05	.06

⁺ $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$

Graphical analysis of model fit

For a graphical analysis of model fit, the observed percentage of correct responses and the three quartiles of the observed RT-distributions of correct responses were compared with the corresponding values from the predicted RT distributions. In Figure B1 observed (empiric) statistics are plotted against predicted statistics for all conditions of all experiments, that is, each symbol represents the distribution of one participant in one condition. As can be seen, the majority of data points lie close to the line of perfect congruency. Most important, there seems to be no systematic bias in the predicted distributions.

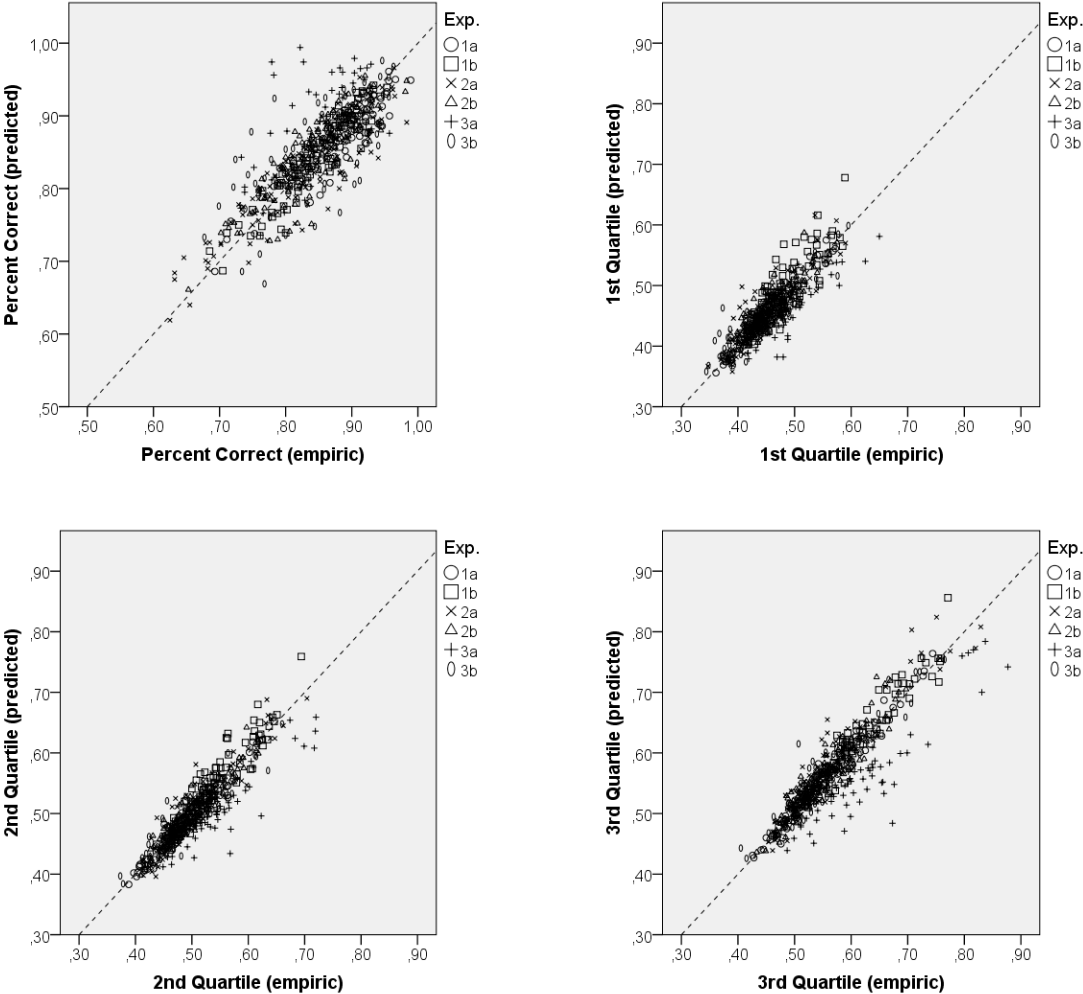


Figure B1. The figure displays the relation of the empiric vs. predicted statistics (top left: percent correct; top right: first quartile; bottom left: second quartile; bottom right: third quartile) from all conditions of all experiments.