Part III

Methods for Tracing Physiological, Neurological, and Other Concomitants of Cognitive Processes

6

Analyzing Response Times to Understand Decision Processes

WOLFGANG GAISSMAIER, MARIO FIFIC, and
JÖRG RIESKAMP

The central aim of contemporary research in cognitive psychology is the isolation of plausible cognitive mechanisms that are engaged in judgment and decision making. Given that a solely behavioral approach is unable to deal with some empirical phenomena, researchers have gradually begun exploring the cognitive principles underlying decision making. When two cognitive models predict the same outcome at the behavioral level, assuming completely different mechanisms, it becomes obvious that research focus should shift from testing the outcome to testing actually assumed processes (Anderson, 1990).

Most of the time, the cognitive processes underlying decision making are hidden from direct observation. With process tracing – an approach that has been explored in great detail – it is possible to monitor the information search process as it takes place during decision making. For instance, information can be represented by the use of a computerized information board where information is hidden behind boxes but can be acquired by clicking on the boxes. This provides high experimental control about what information people search for and in what order, allowing us to make strong inferences about the cognitive models describing the decision process (e.g., Bröder, 2000, 2003; Maule, 1994; Newell & Shanks, 2003; Newell, Weston, & Shanks, 2003; Payne, Bettman, & Johnson, 1988, 1993; Rieskamp & Hoffrage, 1999, 2008). However, the application of process tracing techniques might change the decision strategies that people apply, limiting the conclusions one can draw.

In less controlled experimental settings researchers often only monitor the final decision. Typically, when the task is displayed, participants deliberate about the best response and then make a final decision. An observable output could be a simple verbal response or the pressing of a decision button. For more than 50 years, the predominant interest in testing models of decision making lay in the analysis of the choices made in such tasks. Rarely, the main research focus was directed to an alternative observable aspect, namely, how long a person took to make a decision, that is, the response time. Yet response times provide another noninvasive pathway to understanding the cognitive process underlying decision making (e.g., Busemeyer & Townsend, 1993). The neglect of response time analysis in the judgment and decision making literature is somewhat surprising considering that it is an established, standard approach in cognitive psychology. In general, cognitive psychologists have used both choice probabilities and response times to test assumptions of cognitive models (e.g., Ashby, 2000; Ashby & Maddox, 1994; Heath, 1992; Lamberts, 1998, 2000; Link, 1992; Nosofsky & Palmeri, 1997; Ratcliff, 1978; Smith, 1995). The response time approaches to process decomposition date even earlier, to the latter half of the 19th century, starting with the work of Donders (1868) and Wundt (1880), and flourished with the development of the information processing approach (e.g., Sternberg, 1966, 1969).

In this chapter, we will follow the lead of prominent scientists in various areas of cognitive psychology and use a response time analysis as the main methodological tool to infer the mental processes underlying judgment and decision making. We argue that studying response time could enhance our understanding of the cognitive processes underlying decision making. In the present work we will focus on how the analysis of response time can be used to test different cognitive strategies for making *probabilistic inferences*. In such tasks people have to infer which of several alternatives has the highest criterion value on the basis of various cues. We will report conclusions from a few studies that have investigated memory-based probabilistic inferences (e.g., Bröder & Gaissmaier, 2007; Bröder & Schiffer, 2003; Juslin, Olsson, & Olsson, 2003; Persson & Rieskamp, 2009). Finally we will present advanced techniques in response time analysis and illustrate their advantages.

RESPONSE TIME ANALYSIS FOR TESTING PROCESS MODELS OF PROBABILISTIC INFERENCES

In a probabilistic inference task participants have to compare objects and decide which of, for instance, two objects scores higher on a criterion. Each of the two objects has several attributes ("cues"), which the participants can use to make their inferences. For example, assume that participants have to decide which of two stocks will perform best in the future. Let us assume that participants can use only two cues to make such an inference, for instance, the companies' past investments and recent returns. The central question is how the information of the two cues is processed and combined to form a final decision.

There are many cognitive models that have been suggested to predict probabilistic inferences (e.g., Bergert & Nososfsky, 2007; Dougherty, Gettys, & Ogden, 1999; Gigerenzer & Goldstein, 1996; Hammond, 1990; Juslin & Persson, 2002; Lee & Cummins, 2004; Payne et al., 1988; Rieskamp, 2006; Rieskamp & Hoffrage, 1999, 2008; Rieskamp & Otto, 2006). These include, among others, connectionist models (Gluck & Bower, 1988), exemplar models (Juslin & Persson, 2002), sequential sampling models (Lee & Cummins, 2004; Wallsten & Barton, 1982), and procedural strategies (Gigerenzer, Todd, & the ABC Research Group, 1999; Payne et al., 1993).

In the present chapter we will not discuss the response time predictions that can be derived from all the models mentioned above. Instead, for illustration purposes we will only focus on how response times can be used to test two prototypical inference strategies suggested by *the strategy approach*. This illustration, however, can be generalized to a variety of cognitive models. The strategy approach assumes that people are equipped with a repertoire of different strategies to make inferences. The different inference strategies can be differentiated by two aspects of processing, namely, the amount of information used and the way information is processed. The strategy approach has its roots in the information processing theory concerning these two critical processes.

Regarding the amount of information, the critical question is whether the processing is exhaustive or self-terminating. In the self-terminating case, processing stops as soon as the gathered information, for instance, from one single cue, provides enough evidence for the final decision. By contrast, in the exhaustive case, processing continues until all available information has been gathered regardless of the evidence that had been accumulated. Concerning the way information is processed, one basic question is whether the processing of information operates in a serial or parallel fashion. In serial processing, information from each cue is processed sequentially, one cue at a time. By contrast, in parallel processing, information from both cues is gathered simultaneously.

The first prototypical strategy that we consider is a noncompensatory lexicographic one, of which the take-the-best heuristic (Gigerenzer & Goldstein, 1996) is an example. The strategy predicts limited and serial processing of information. Take-the-best assumes that people compare objects cue-wise, starting with the most valid cue with regard to predicting the criterion, and stopping as soon as one cue is found that discriminates between the two objects. That is, a person using take-the-best first searches for the most valid cue, which is the best discriminating cue between two objects on a criterion. If this cue discriminates, the person does not search further and makes a decision. Otherwise, searching for cues (in order of validity) continues until a discriminating cue is found. Therefore, when take-the-best finds the first (i.e., most valid) discriminating cue, it stops searching and makes a decision based on that cue alone, while all the remaining cues are ignored.

In contrast, compensatory strategies, such as the weighted additive strategy (WADD), assume that all available information is processed in serial fashion (e.g., Gigerenzer & Goldstein, 1996; Payne et al., 1988). WADD assumes that each cue is weighted (usually by the validity of the cue), and that a decision maker calculates the sum of all weighted cue values when choosing between two alternatives. A decision maker chooses the alternative with the largest weighted sum. A simplified version of WADD is the Tally decision strategy. For Tally it is assumed that a decision maker also calculates the sum of the cue values for each alternative but weights each cue equally. The alternative with the largest sum is selected. In the case of a tie, the person has to guess. The idea of Tally goes back to Dawes' (1979) work on unit-weight models, showing that it is often better to rely on robust equal weights than to try to differentiate the predictive accuracy of the various cues. Because less valid cues can overrule more valid cues, WADD and Tally are compensatory strategies. Note that a limited information search is in principle possible even for compensatory strategies (see Bergert & Nosofsky, 2007; Dieckmann & Rieskamp, 2007; Persson & Rieskamp, 2009).

In contrast to the strategy approach to probabilistic inferences, alternative models often do not assume serial processing of information. For instance, similarity-based models (e.g., exemplar models), which are also compensatory, assume that all available information is processed and that similarity computations are processed in a parallel manner (e.g., Juslin & Persson, 2002; Nosofsky & Bergert, 2007).

It is important to note that mean response time predictions, which can be derived from each of the above decision strategies, can provide a sufficient statistic to differentiate between the models. When information is processed in a serial manner, it can be predicted that inference strategies that rely on a limited self-terminating information search will lead to shorter response times than strategies that rely on an exhaustive search. When information is processed in a parallel fashion one would expect shorter response times than if it is processed in a serial manner.

However, a mean response time analysis allows for differentiation between the models only under limited conditions. For example, it is possible that different variants of parallel information processing models can also predict an increase in response time as a function of the number of compared attributes n (Townsend & Ashby, 1983; Townsend & Wenger, 2004a, p. 1011). The rationale for this is that parallel models can exhibit a decrease in processing resources as n increases. For example, as the number of compared cues increases, it is possible that less and less of the available resources are devoted to each comparison, in turn making the overall decision time longer and longer. This leads to the mimicking dilemma (e.g., Townsend, 1969, 1971, 1972; Townsend & Ashby, 1983). The dilemma states that, based only on a mean response time analysis, it is impossible to distinguish between serial and parallel information processing. In the following we will report how models can be tested against each other when assuming serial processing of information. Thereafter we will discuss how models can be tested against each other when additionally assuming parallel processing.

EMPIRICAL EVIDENCE AND A TEST OF DIFFERENT MODELS OF PROBABILISTIC INFERENCES ASSUMING SERIAL INFORMATION PROCESSING

In this section we present empirical evidence for the application of specific inference strategies on the basis of response times. We divide the results into two sections, depending on how information was presented to the participants. First, we illustrate the approach for an inference situation in which all information was presented to participants simultaneously, employed by Bergert and Nosofsky (2007). This is defined as "inferences from givens". Thereafter, we show evidence for probabilistic inferences where a person has to retrieve the relevant cues from memory to make a decision, as studied by Bröder and Schiffer (2003, 2006), Bröder and Gaissmaier (2007), and Persson and Rieskamp (2009). This is defined as "inferences from memory".

Inferences from Givens

In the task used by Bergert and Nosofsky (2007), participants were presented with pictures of bugs that could be described by six attributes/cues, such as length of the antennae, body texture, shape of the tail, and so forth. Participants had to decide which of the two bugs was more poisonous based on those cues. Bergert and Nosofsky tested generalized models of take-the-best and WADD, which they did by relaxing some of the model assumptions while at the same time preserving the core components of the stricter original versions (see Bergert & Nosofsky, 2007, for details).

These generalized versions of the models indeed provided a superior fit compared to the stricter versions, even when taking their increased complexity into account. However, although these models differ strongly in the spirit of the underlying processes they assume, they are formally identical in their predictions of choice probabilities. The authors concluded that choice data were not sufficient to tell take-the-best and WADD models apart, and that the response time data could provide an additional source of information for testing the models against each other.

To maximize the difference between take-the-best and WADD predictions, Bergert and Nosofsky (2007) constructed stimulus pairs of objects (hereafter, item types) for which the two models made diverging response time predictions. The idea was to create two kinds of item types in which the stimuli would differ on every cue (Figure 6.1). The first item type had positive cues for one alternative and negative cues for the other. Therefore the first object was favored by all cues and when applying WADD a quick decision for this alternative should result. In contrast, for the second item type, the cues favored different alternatives, so that some

Objects	Cue 1	Cue 2	Cue 3	Cue 4	Cue 5	Cue 6
Item type 1						
A	1	1	1	1	1	1
B	0	0	0	0	0	0
Item type 2						
C	1	0	0	1	0	1
D	0	1	1	0	1	0

FIGURE 6.1 Two different item types (pairs of objects) that generate different response time predictions from a compensatory and a noncompensatory inference strategy. The compensatory strategy predicts faster decisions for inferential choices between A and B and slower response times for choices between C and D. The noncompensatory strategy predicts identical response times for both pairs of objects.

cues were in favor of the first object and others were in favor of the second. For this item type the application of WADD should require some additional time to compute which of the two alternatives has a larger weighted sum of evidence.

In contrast to WADD's prediction, the noncompensatory strategy take-the-best, which relies on only a single discriminating cue, made identical predictions for both item types. This is because when using take-the-best, every cue provides sufficient information to discriminate between the two alternatives. Thus, the take-the-best strategy should lead to an equally fast decision for both item types. Bergert and Nosofsky found that the results of response time analysis largely supported take-the-best over WADD. Less than a quarter of their participants could be classified as WADD decision makers.

Inferences from Memory

In a paradigm involving memory-based inferences people make inferences based on information that has to be retrieved from memory. In experiments run by Bröder and Schiffer (2003, 2006), a hypothetical criminal case was employed involving 10 suspects in a murder: A famous singer was murdered near a pool, presumably by one of his former girlfriends. The participants were asked to help find the murderer. The basic idea of these experiments was to separate the acquisition of knowledge about the suspects from making inferences about them, so that knowledge had to be retrieved from memory when making decisions.

Each experiment consisted of four phases. First, in an anticipation learning paradigm, participants acquired knowledge about the individual cue patterns of 10 suspects, which differed on four cues (e.g., type of jacket). A portrait and a name of a suspect appeared on the screen, and participants had to reproduce the cue values with appropriate feedback. To prevent participants from prematurely making inferences during learning, a cue hierarchy was established only in a second phase when they were informed about the evidence (cues) witnessed at the site of the crime and about its relative importance. In the third phase, consisting of complete paired comparisons of all suspects, participants had to decide which suspect was most likely to be the murderer. Importantly, only the names of the suspects and their portraits were displayed. To decide between the two suspects, participants had to retrieve the cue values from memory. After this decision phase, a final memory test assessed the stability of cue memory.

Bröder and Gaissmaier (2007) reanalyzed the data of Bröder and Schiffer (2003, 2006), focusing on response times. They also investigated the strategies described above, namely, take-the-best, WADD, and Tally, but in addition they included a baseline guessing model. Recall that the lexicographic take-the-best heuristic assumes that participants sequentially retrieve cues describing the suspects in the order of their validity and stop searching as soon as a discriminating cue is found. Therefore, the first (i.e., most valid) discriminating cue determines when take-the-best stops searching and decides. Take-the-best assumes serial processing of information, so that the response time should monotonically increase with the number of cues that have to be retrieved until this first discriminating cue is found (Figure 6.2).

Cue 1	1	0	1	1	1	1	1	1
Cue 2			0	1	0	0	0	0
Cue 3					1	0	1	1
Cue 4							0	1
	Item Type 1		Item Type 2		Item Type 3		Item Type 4	

Position of best discriminating cue

FIGURE 6.2 Four different item types differing with regard to the position of the first discriminating cue.

To derive response time predictions Bröder and Gaissmaier (2007) assumed serial and exhaustive information processing for WADD and Tally. Accordingly, when Tally is used for making memory-based inferences, it is assumed that all cues need to be retrieved and summed up and the alternative with the larger sum should be selected. A person who applies WADD also has to retrieve all cue values, but in addition to Tally's steps all cue values have to be weighted by their validity. It is assumed that, due to this additional weighting process, people who apply WADD should need the most time for their decisions. In contrast to Bergert and Nosofsky (2007), Bröder and Gaissmaier (2007) assumed that both WADD and Tally require, at least in a strict sense, searching for all cues in an unspecified order. Response times should therefore not depend on which cue is the first discriminating cue. In contrast, for someone who uses the noncompensatory take-the-best strategy the response times should depend on the first discriminating cue that is retrieved from memory. If the first cue retrieved from memory discriminates between the two alternatives a quick decision can be made. In general, response time predicted by take-the-best should be an increasing function of the number of cues that have to be retrieved from memory. Finally, a person who makes random decisions does not need to retrieve any information and therefore should decide most quickly. The response times of guessers should not vary with the position of the first discriminating cue. In sum, on average, WADD should be slower than Tally, and guessing should be quickest overall. The response times of take-the-best depend on the number of cues retrieved from memory.

Following these ideas Bröder and Gaissmaier (2007) re-examined five of Bröder and Schiffer's (2003, 2006) experiments to determine whether the strategy classification analysis was in line with a response time analysis. For this purpose they split the participants into four groups with identical strategy classifications on the basis of their inferences. Of all participants 198 were classified as using take-the-best, 90 as using WADD, 83 as using Tally, and 44 as guessing. For each participant, Bröder and Gaissmaier computed the outlier-robust median response time for each of the four item types (see Figure 6.2), depending on the position of the first discriminating cue. These individual response time medians were entered in the subsequent analyses and averaged across participants.

The mean response times for each strategy group are shown in Figure 6.3. The response times followed the predicted pattern and supported the assumption of sequential search: Participants classified as using take-the-best showed a robust increase in response time depending on the position of the best discriminating cue, while this increase was much less pronounced for participants who were classified as using WADD or Tally. The increase was absent for participants classified as guessers. WADD users generally needed more time than Tally users, which was expected, given that Tally users only have to count evidence, while WADD users also have to calculate the sum of weighted evidence. Participants with predominantly nonsystematic guessing behavior generally needed less time than all the others. In sum, the analysis shows that the response times of the participants were in line with the strategies they were using, classified according to their choice behavior. Thus, both the response time analysis and the analysis of participants' choices led to the same conclusion about people's decision processes.

Learning of Cue Validities and Inference Strategies

Bröder and Gaissmaier (2007) showed that both the response time and choice probability analyses conformed to the prevalence of take-the-best in Bröder and

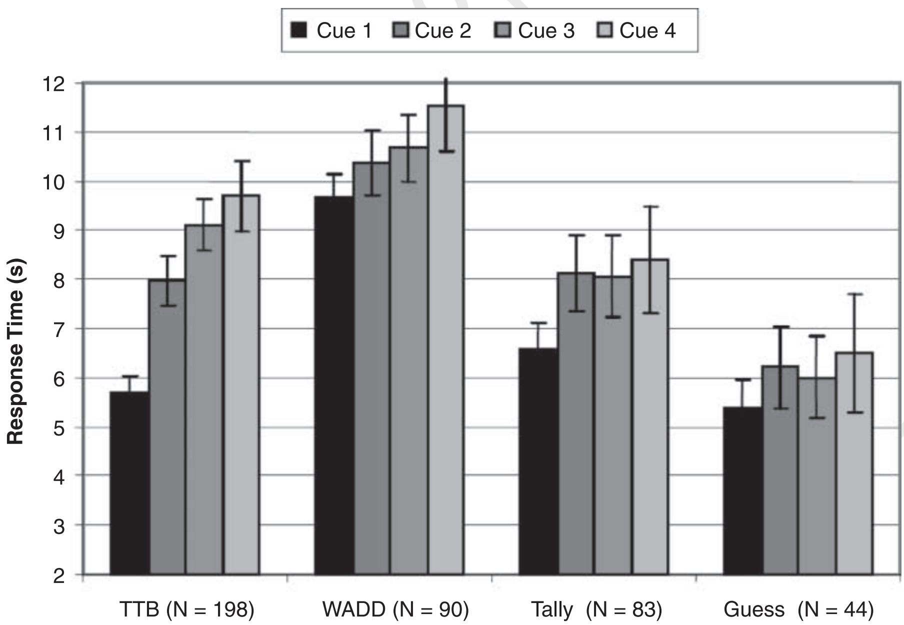

FIGURE 6.3 Mean response times in seconds (and standard errors) as a function of best discriminating cue and outcome-based strategy classification on the combined data from Bröder and Schiffer (2003, 2006). TTB = take-the-best, WADD = weighted additive strategy.

Schiffer (2003, 2006). One of the remaining questions, however, was whether the prevalence of take-the-best was induced by the experimental requirements. For instance, in Bröder and Schiffer's (2003) experiments, participants were given the rank order of cue validities. This procedure might have fostered the selection of take-the-best, which requires this information. In contrast, if participants had to learn the validities of the cues, this might lead them to use other inference strategies, such as Tally, which does not require any cue validities. Persson and Rieskamp (2009) tested the models of probabilistic inferences in experiments in which cue validities had to be learned. The authors conducted a choice probability analysis and a response time analysis to evaluate the conclusions drawn from each analysis alone.

The experimental procedure of Persson and Rieskamp (2009) was very similar to the one used by Bröder and Schiffer (2003). However, in Persson and Rieskamp's experiment the participants had to make inferences about the stage of an illness of 15 hypothetical patients. Each patient was described by four symptoms (i.e., cues) that could be either present or absent. In the first, memorization phase, participants had to learn all cue values by heart. In the second, learning phase, participants started to compare a subset of patients to learn the validities of the cues. In the learning phase, participants received feedback about which patient was in a more severe stage of the disease. Finally, in the test phase, they had to infer which of two patients (from the remaining subset of patients) was at a more severe stage of the disease. This final test phase was used to classify the strategies that people were using.

Persson and Rieskamp (2009) conducted two experiments that varied the type of feedback in the learning phase. In the first experiment, the participants simply received dichotomous feedback about whether their choice was correct or wrong. In the second experiment, the participants received additional continuous feedback, that is, they were informed about the stage of the disease. In turned out that two strategies were best in predicting participants' inferences. In the first experiment, the inferences of the majority of participants (60%) were best predicted by take-the-best. In contrast, in the second experiment with continuous feedback the inferences of the majority (64%) were best described by the compensatory WADD. Apparently, providing continuous feedback about the criterion induced the use of a strategy that could also predict this criterion, such as a compensatory strategy.

Persson and Rieskamp (2009) additionally performed a response time analysis to confirm the results of their strategy classification analysis, similar to Bröder and Gaissmaier (2007). However, due to lower statistical power they only differentiated two item types, namely, items where the most valid cue discriminated and items where it did not discriminate. Participants classified as using take-the-best should make quicker decisions for the first item type than for the second type. Indeed, this was exactly what was found: If the most valid cue discriminated, participants who were classified as using take-the-best required 8.1 s for their decisions (median response times), but 9.6 s for the second item type.

For the compensatory strategies Tally and WADD, Persson and Rieskamp (2009) assumed that the response time should be a function of the difference between each alternative's cue sums. The underlying rationale for this prediction relies on the idea that people will not literally execute a strategy step by step when its prediction can easily be foreseen. For example, if one alternative has only positive cue values and the other has only negative cue values, someone applying WADD does not need to determine the exact score for each alternative. Instead, the person can foresee WADD's prediction and make a corresponding choice. In contrast, if some cues favor one alternative and some cues favor the other, the decision maker cannot simply foresee WADD's prediction and has to compute the alternatives' scores, which will take some time. Accordingly, the larger the difference between the alternatives' scores, the faster a decision should be made. When Tally is applied and both alternatives have the same score, a slow response time is expected (cf. Bergert & Nosofsky, 2007; see also Figure 6.1).

When examining the response times for participants classified as using WADD or Tally, Persson and Rieskamp (2009) considered all items where the sum of cue values differed for the two alternatives so that Tally could discriminate between the alternatives, in comparison to those items where the cue sums were the same and Tally could not discriminate. For the first group of items the average difference between the two scores determined by WADD for the alternatives was 3.5, as opposed to the second group with an average difference of 2.3. Therefore, participants assigned to Tally or WADD should have a faster response time for the first as opposed to the second group of items.

In line with these predictions, Tally users made their inferences with a median response time of 3.6 s for the first group of items compared to 5.7 s for the second group. Note that the response times for participants using Tally were much faster than for those assigned to take-the-best. This is surprising, when assuming serial information processing for Tally and take-the-best (Gigerenzer & Goldstein, 1996). Take-the-best searches on average for fewer cues and therefore one would expect people to apply take-the-best faster than Tally. This finding can be explained in two ways. First, it could be that trying to retrieve the cues in the correct order is cumbersome, which slows take-the-best down, while Tally does not have to order cues in any fashion. Second, one could argue that Tally can be processed rather quickly if one does not assume a serial search process, but a parallel one. The current data do not allow us to tell precisely.

The participants assigned to WADD made their inferences with an average median response time of 5.7 s for the first group of items compared to 8.4 s for the second group. Replicating Bröder and Gaissmaier's (2007) results, the response times of WADD users were larger compared to Tally users, which can be expected when considering that WADD requires a specific weighting of cues that Tally ignores. Thus, overall, the response times of the participants assigned to the different strategies were consistent with the strategies' predicted response times.

The reported studies illustrate how a response time analysis can be used to validate the inference that had been made on a pure analysis of people's choices. The goal of the reported response time analyses was to find convergent evidence for the processes assumed to underlie memory-based probabilistic inferences. For memory-based decisions, process tracing techniques cannot be applied. Therefore, response times were analyzed to validate the idea of a sequential cue search in inference processes and as an independent source of support for the outcome-based strategy classification method. In this manner, Bergert and Nosofsky (2007), Bröder and Gaissmaier (2007), and Persson and Rieskamp (2009) tried to answer the call that models should ideally aim to be testable with different kinds of data (e.g., Jacobs & Grainger, 1994). When assuming serial processing of information, this leads to specific response time predictions for the various inference strategies. These tests led to convergent evidence for the interpretations that were drawn on the analysis of participants' choices.

PARALLEL PROCESSING OF INFORMATION

Bröder and Gaissmaier (2007) and Persson and Rieskamp (2009) tested different inference strategies against each other by assuming serial processing of information. Yet when examining memory-based inferences, it is natural to assume that the information could also be processed in a parallel fashion. Of course, when information is processed in parallel, different response time predictions could result. The key idea of this section is to introduce the processing order (serial and parallel) as an additional basis for comparison. The processing order is more frequently referred to as a *mental architecture*. Interestingly, the class of parallel models can also predict an increase in response time as a function of the number of compared attributes n (Townsend & Ashby, 1983; Townsend & Wenger, 2004a, p. 1011). This leads to the mimicking dilemma (e.g., Townsend, 1969, 1971, 1972; Townsend & Ashby, 1983), so that it is impossible to distinguish between serial and parallel decision strategies based only on examining mean response times.

In the next part we will review and recommend the application of a powerful theory-driven methodology for testing response time predictions. This methodology has evolved over the past several decades and is able to avoid most, if not all, model-mimicking challenges. The systems factorial technology (SFT) methodology is being developed to diagnose the type of processing architecture that underlies performance in different cognitive tasks – for example, whether information processing is serial or parallel, and exhaustive or self-terminating (e.g., Schweickert, 1985; Schweickert, Giorgini, & Dzhafarov, 2000; Townsend & Ashby, 1983; Townsend & Nozawa, 1995; Townsend & Wenger, 2004b). The key to the SFT methodology is twofold: SFT is a nonparametric methodology, and the SFT diagnostic properties are achieved by exploration of a survivor interaction contrast (SIC) function, which is calculated from the data. By judging the overall shape of the SIC function, it is possible to uniquely identify serial versus parallel processing and exhaustive versus self-terminating information search. Previously, the SFT method has been employed for a variety of cognitive tasks: stimulus detection where the task is to detect the presence or absence of a stimulus (Townsend & Nozawa, 1995), visual and memory search tasks, (e.g., Egeth & Dagenbach, 1991; Fific, Townsend, & Eidels, 2008; Sung, 2008; Townsend & Fific, 2004; Wenger & Townsend, 2001, 2006), face perception tasks (Fific, 2006; Ingvalson & Wenger, 2005), classification (Eidels, Townsend, & Pomerantz, 2008; Fific, Nosofsky, & Townsend, 2008), and global–local perception tasks (Johnson, Blaha, Houpt, & Townsend, 2009).

Constructing Specific Experimental Designs for a Response Time Analysis Using the SFT Methodology

The standard approach that we reported above compresses data by averaging and then plots the mean or median response times as a function of the number of discriminating cues or the number of memorized items. This approach is able to distinguish exhaustive versus self-terminating information search processes when assuming serial processing of data. However, when assuming that information can also be processed in parallel, the standard approach reaches its limit and cannot distinguish when information search stops. For this purpose SFT was developed. To achieve more diagnostic power with SFT than with the standard approach, the data are not averaged but instead plotted as a function, namely, a survivor function. A survivor function is a probability function that tells us the survival rate of some components of interest, after some time t. Instead of converting a dataset into a single response time mean value, each dataset is converted into a survivor function, which can easily be done using standard statistical software packages. The additional information, contained in the shape of the survivor function, provides more diagnostic power than a single response time value. SFT utilizes the SIC function, and in the next section we will provide a short tutorial on how diagnostic information can be obtained from calculating SIC functions.

A Guide to Calculating Survivor Function

The *survivor function* S for a random variable T (which in the present case corresponds to the time of processing) is defined as the probability that the process T takes greater than t time units to complete: $S(t) = P(T > t)$. Note that for time-based random variables, when $t = 0$ it is the case that $S(t) = 1$; and as t approaches infinity it is the case that $S(t)$ approaches zero. Slower processing is associated with greater values of the survivor function across the time domain.

The survivor function is estimated from the data using the following procedure:

1. Determine the response time bin size. A bin size corresponds to an interval on a response time scale; usually one can use 10 ms. Divide the time scale into equal-sized bins, up to the maximum single response time observed.
2. Count the total number of observed single response times that fall in each bin. This step generates a frequency distribution.
3. Divide each frequency of observations in each bin by the total number of observations. This will produce a relative frequency distribution, that is, an empirical probability density function.
4. Calculate the empirical CDF (cumulative distribution function) $F(t)$ by accumulating the empirical probabilities (from Step 3) from the lowest to the highest valued bin.
5. Calculate an empirical survivor function by subtracting the value of $F(t)$ from 1, that is, calculate $S(t) = 1 - F(t)$. This step generates an empirical survivor distribution function $S(t)$, which converges to the real survivor

function for a sufficient amount of data (for more details see appendix in Townsend, Fific, & Neufeld, 2007).

How can SFT be applied to a probability inference task as described above? For instance, the task could be to infer which of two suspects is more likely to be a murderer (cf. Bröder & Gaissmaier, 2007). For simplicity let us assume that only two cues are available. The research question is whether people process cues in serial or in parallel fashion, and whether people make their inferences on the basis of one or two processed cues. The number of cues defines the number of processes, which in our case is two. In addition we assume that, via experimental control, we can manipulate whether these two processes take place or not, that is, we can turn them off or on. The question is whether doing so is sufficient to infer processing order and stopping rule. The answer is no. Decades of research on this problem have indicated that we will readily confuse parallel and serial processing orders (e.g., Townsend, 1969, 1971, 1972; Townsend & Ashby, 1983). To infer correct decision strategies we need additional manipulation. Let us define the first factor as the first cue comparison, and the second factor as the second cue comparison. Then each factor (defined as a single cue comparison process) needs to have at least two levels, orthogonally combined – a so-called "double factorial design" (as used in a 2×2 ANOVA; see Table 6.1). We will omit the detailed explanation of why this design permits correct inferences about the underlying decision strategy, because of the abstract nature of the mathematical proofs (e.g., Townsend & Nozawa, 1995). However, it is important to note that with this design the different decision strategies will exhibit different data patterns of mean response times and, more importantly, their corresponding survivor functions.

How are the levels of each factor defined in a double factorial design? Usually they are defined as the saliency of the cue. Saliency manipulation should affect the overall speed of the two cue comparison processes: One level should correspond to a manipulation that speeds up the processing of a cue, and the other level should correspond to a manipulation that slows down a cue comparison. It is possible to choose between different types of manipulations to produce such speeding up or slowing down, which can depend on whether the task requires

TABLE 6.1 Experimental conditions of two factors corresponding to the processing of two cues. Each process is manipulated at two levels of saliency, fast (F) and slow (S). In the experiment this defines four different experimental conditions. In the FS condition, for instance, the first cue is highly salient and can be processed quickly; the second cue has low salience and is processed slowly. This experimental setup is called the double factorial paradigm.

		Second cue	
		Fast	*Slow*
First cue	Fast	FF	FS
	Slow	SF	SS

inferences from givens or from memory. For the case of probabilistic inferences, salience of a cue could be defined as the difference between rates of cue retrieval from memory: The candidate manipulations could be presentation frequency, familiarity, or similarity between the cues. We assume that the larger the saliency, the faster the cue comparison. When two processes are involved, factorially combined with saliency levels, the SIC function is defined as follows:

$$\mathrm{SIC}(t) = [S_{\mathrm{SS}}(t) - S_{\mathrm{SF}}(t)] - [S_{\mathrm{FS}}(t) - S_{\mathrm{FF}}(t)] \tag{6.1}$$

Here S_{FS} indicates the survivor function for the condition where the first cue comparison was of high salience (thus F, for fast), and the second cue comparison was of low salience (thus S, for slow). One can compute the survivor functions associated with each of the four types of factorial combinations of cues and saliency levels, which we denote $S_{\mathrm{SS}}(t)$, $S_{\mathrm{SF}}(t)$, $S_{\mathrm{FS}}(t)$, and $S_{\mathrm{FF}}(t)$. Because processing is presumably slower for low-saliency (S) than for high-saliency (F) cue comparisons, the following should hold: $S_{\mathrm{SS}}(t) = S_{\mathrm{SF}}(t)$, $S_{\mathrm{FS}}(t) = S_{\mathrm{FF}}(t)$, for all time t (Townsend & Nozawa, 1995).

As illustrated in Figure 6.4, different mental architectures and decision strategies yield distinct predictions of the form of the SIC function. To understand why this is the case we need to consult Equation (6.1). Equation 6.1 determines the difference of two differences (in brackets). The different decision strategies (Figure 6.4) predict that the difference between the terms in brackets (Equation 6.1) should change at a different rate across time. This then leads to different SIC shapes. If processing is *serial and self-terminating*, then the value of the SIC is equal to zero at all time values (Figure 6.4A). For instance, if only the first cue is processed, denoted by a left subscript in Equation 6.1, then the cognitive process terminates on a first cue and makes a final decision. This implies for Equation 6.1 that the terms in the left and right brackets become identical, and they cancel each other out. The definition of take-the-best closely corresponds to a serial self-terminating mental architecture. If cues are ordered and searched according to their validity, from the highest to the lowest, the processing should terminate on recognition of the first cue and should not continue any further.

For *serial exhaustive processing*, the SIC is negative at early values of time but positive thereafter, with the total area spanned by the negative portion of the function equal to the total area spanned by the positive portion (i.e., the area bounded by the SIC function below the x-axis should be equal to the area bounded by the SIC function above the x-axis) (Figure 6.4B). The predicted SIC function crosses the x-axis only once. The intuition is that the serial exhaustive model predicts that a total decision time, for each term in Equation 6.1, is a sum of two cue comparisons. As there are more slow (S) than fast (F) comparisons (in the following conditions: SS, SF, FS, FF), each S(t) function in Equation 6.1 should appear more stretched over time. Imagine that the SIC function is made of rubber. Then stretching corresponds to elongating this object to the right. So, when the predictions for each condition are combined in Equation 6.1, the resulting function "weaves" around the x-axis.

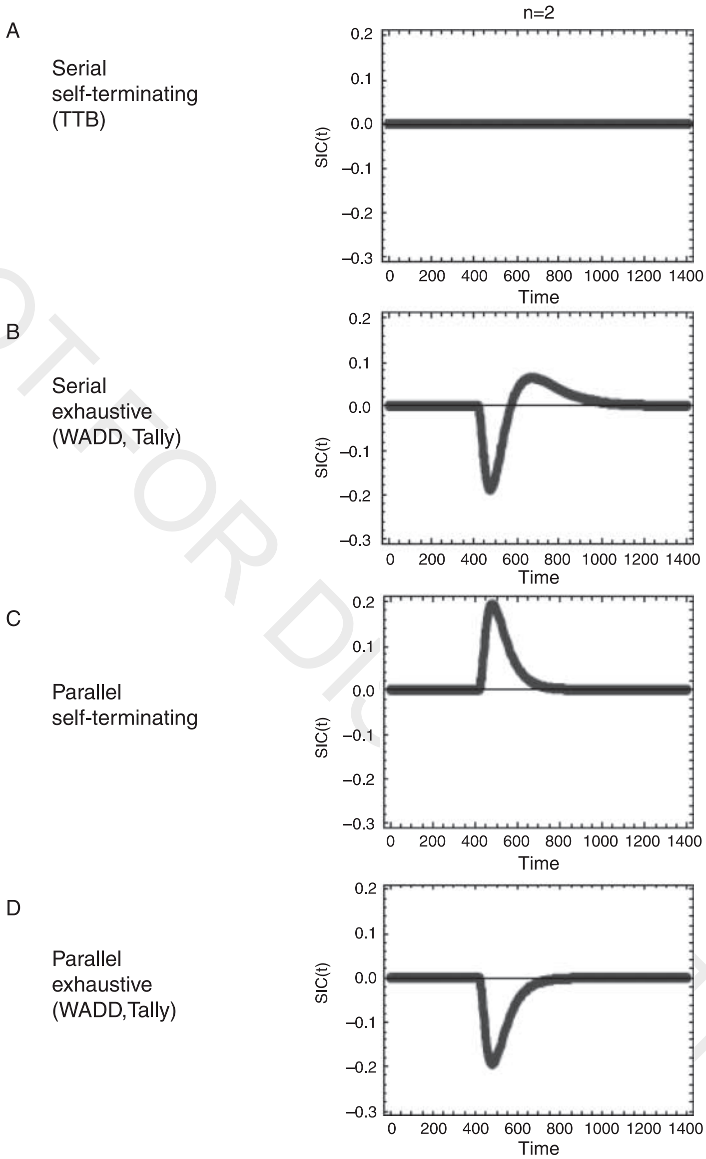

FIGURE 6.4 Survivor interaction contrast (SIC) functions for different mental architectures (serial, parallel) combined with stopping rules (terminating, exhaustive). The comparable decision-making strategies (take-the-best (TTB), Tally, WADD) are given in parentheses.

We do not expect take-the-best to exhibit this type of SIC function, except if processing is conducted on all cues in serial fashion. This is possible only if the processing of the first cue did not provide a basis for an overall decision. By contrast, for both WADD and Tally, exhaustive processing of both cues appears most likely.

If processing is *parallel self-terminating*, then the value of the SIC is positive at all values of t (Figure 6.4C). The intuition here is that the left bracket term is always larger than the right bracket term in Equation 6.1, for all time points t. This is because in the condition SS, described by $S_{SS}(t)$, the processing cannot self-terminate quickly because both processes are slow. Hence, the survival rate is higher for the left bracket term than for the right bracket term, for all time t. Although this model makes distinct predictions in comparison to take-the-best, WADD, or Tally, it is a very representative model of human cognition involved in visual and perceptual domains.

Finally, for *parallel exhaustive processing*, the SIC function is negative at all values of t (Figure 6.4D). The intuition here is that the left bracket term is always smaller than the right bracket term in Equation 6.1, and this is due to the parallel exhaustive stopping rule: The cognitive system always waits for the longest component to be accomplished and then makes a final decision. Because both terms in the left bracket $[S_{SS}(t) - S_{SF}(t)]$ have at least one slow component that determines total time, this difference tends to be very small. In contrast, the discrepancy in the right-hand bracket is larger, thus the outcome is a negative SIC function, for all time t. This SIC function is also a likely candidate for both WADD and Tally, but not for take-the-best.

In Figure 6.5 we display four representative observed SIC functions from two different studies that employed a memory search task and a face categorization task (Townsend & Fific, 2004). In both studies we manipulated two processes and their saliency levels (F and S) and factorially combined them. These four empirical SIC functions revealed four distinct underlying cognitive processes. In one of the studies, the face study, the task was to categorize displayed faces into two groups, based on processing of two features. The faces in the two groups did not share facial features, but some of them appeared similar. Less similar ones appeared more salient than the more similar, thus slow and fast levels were determined by facial feature similarity. Given that no features were shared between groups, the participants could terminate processing on recognition of either of the two face features (eyes and lips). Figure 6.5A shows a SIC function of a participant who processed both features in parallel but chose to stop on positive recognition of either eyes or lips. Panel B shows a participant who exhibited a serial self-terminating SIC function. In short, this participant based his or her decision on positive recognition of a single face feature only, namely, the eyes. This participant ignored the lips feature, although it was informative and could support the overall decision. We classify this performance as a noncompensatory decision strategy. Obviously the eyes were more informative than the lips. The participant elected to attend only to the eyes and terminated the decision on positive recognition. Note that the slight variability of the SIC function exhibited for the short response times was due to response latency noise.

Figures 6.5C and 6.5D display the SIC functions showing serial exhaustive and parallel exhaustive processing, taken from the short-term memory study of Townsend and Fific (2004). The participant in Panel C processed both items in a sequential manner. The participant in Panel D processed both memorized items in parallel but waited for the completion of both before making an overall decision.

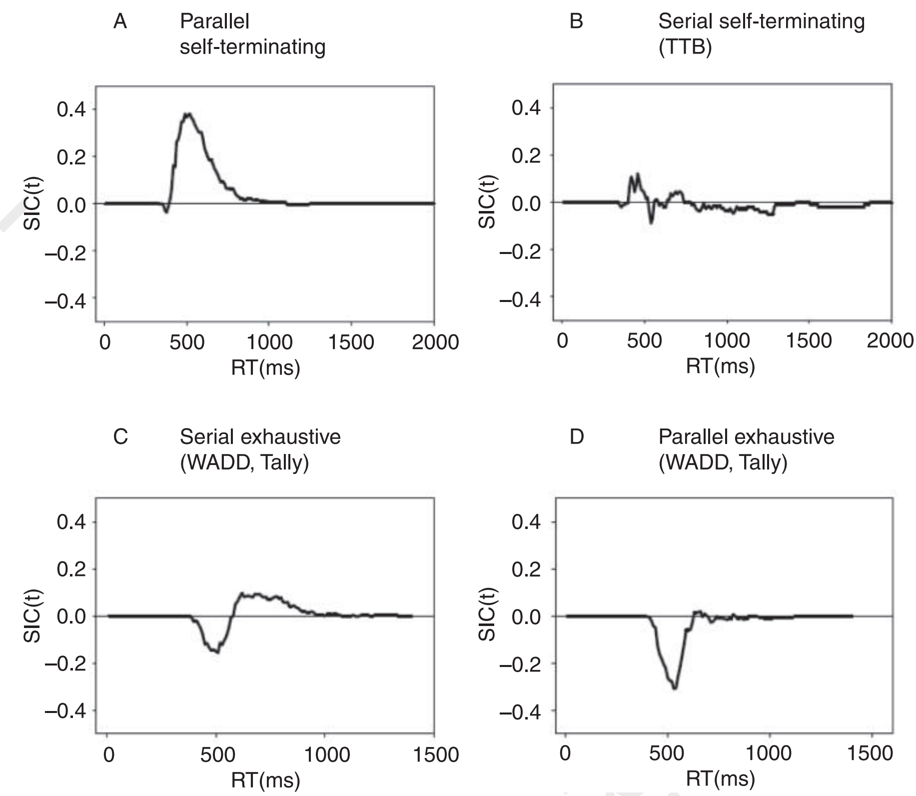

FIGURE 6.5 SIC functions of four participants observed in two different studies. Panels A and B are taken from a face categorization study, where subjects learned to classify faces based on a previously memorized set of two features (eyes and lips; Fific & Townsend, 2009). Panels C and D are from a short-term memory search study (Townsend & Fific, 2004), where subjects had to process two memorized items before making a decision. RT = response time.

In the memory study, the stopping rule for memory search was necessarily exhaustive. It is important to note that both participants' SIC functions conformed to the exhaustive stopping rule and thus validated the methodology. The SFT approach that we described here with two cues could be extended to multiple processes of, for instance, three or four cues.

CONCLUSIONS

In this chapter, we argued that response times are a valuable resource for testing process models of judgment and decision making. Decisions and judgments are the result of the processing of information. Cognitive models of decision making imply different types of information processing that lead to a decision. Very generally one can differentiate two aspects of information processing: the scope of information search (self-terminating vs. exhaustive) and the type of information processing (serial vs. parallel). These two aspects can be found in different combinations in a variety of models. Despite different processing assumptions, however, these models often cannot be distinguished by the decisions they predict, leading to an identification problem (cf. Anderson, 1990).

We have illustrated that response time analyses can help to solve this identification problem. Bergert and Nosofsky (2007) were able to distinguish between two different models based on response time analyses. These models were formally identical but very different in the spirit of the underlying process assumptions. Moreover, the response time analyses of both Bröder and Gaissmaier (2007) and Persson and Rieskamp (2009) supported the assumption of self-terminating, serial cue search in memory-based decision making, at least for a substantial proportion of their participants. The results demonstrate the usefulness of response time analyses as a method for tracing processes that are not directly observable. The analysis of response times can therefore provide valuable information on whether the interpretations drawn from an analysis of participants' decisions alone appear valid.

To tackle the issue of serial versus parallel information processing we introduced the SFT methodology. It provides a detailed assessment of the scope of information search (self-terminating vs. exhaustive) and the type of information processing (serial vs. parallel). We outlined the main properties of SFT and suggested how it could be applied in comparisons of different types of decision making strategies, such as noncompensatory strategies and compensatory strategies, thereby extending the scope of such inquiries. We hope to have shown convincingly that analyzing response times is a fruitful endeavor that can foster an understanding of cognitive processes underlying people's judgments and decisions.

RECOMMENDED READING LIST

- Bröder and Gaissmaier (2007) showed how response time analyses can provide convergent evidence for assumptions about information search in memory-based decision making.
- Fific, Nosofsky, and Townsend (2008) extended the systems factorial technology (SFT), which can diagnose the types of information processing architectures (serial, parallel, or coactive) and stopping rules (exhaustive or self-terminating), to foundational issues in multidimensional classification.
- Persson and Rieskamp (2009) tested an exemplar-based approach to predicting people's inferences from memory against the strategy-based approach and used response time analyses to confirm strategy classifications.

REFERENCES

Anderson, J. R. (1990). *The adaptive character of thought*. Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.

Ashby, F. G. (2000). A stochastic version of general recognition theory. *Journal of Mathematical Psychology*, *44*, 310–329.

Ashby, F. G., & Maddox, W. T. (1994). A response time theory of separability and integrality in speeded classification. *Journal of Mathematical Psychology*, *38*, 423–466.

Bergert, F. B., & Nosofsky, R. M. (2007). A response-time approach to comparing generalized rational and take-the-best models of decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *331*, 107–129.

Bröder, A. (2000). Assessing the empirical validity of the “take-the-best” heuristic as a model of human probabilistic inference. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *26*, 1332–1346.

Bröder, A. (2003). Decision making with the “adaptive toolbox”: Influence of environmental structure, intelligence, and working memory load. *Journal of Experimental Psychology: Learning Memory, and Cognition*, *29*, 611–625.

Bröder, A., & Gaissmaier, W. (2007). Sequential processing of cues in memory-based multiattribute decisions. *Psychonomic Bulletin and Review*, *14*, 895–900.

Bröder, A., & Schiffer, S. (2003). Take the best versus simultaneous feature matching: Probabilistic inferences from memory and effects of representation format. *Journal of Experimental Psychology: General*, *132*, 277–293.

Bröder, A., & Schiffer, S. (2006). Stimulus format and working memory in fast and frugal strategy selection. *Journal of Behavioral Decision Making*, *19*, 361–380.

Busemeyer, J. B., & Townsend, J. T. (1993). Decision field theory: A dynamic-cognitive approach to decision making in an uncertain environment. *Psychological Review*, *100*, 432–459.

Dawes, R. M. (1979). The robust beauty of improper linear models in decision making. *American Psychologist*, *34*, 571–582.

Dieckmann, A., & Rieskamp, J. (2007). The influence of information redundancy on probabilistic inferences. *Memory and Cognition*, *35*, 1801–1813.

Donders, F. C. (1868). Over de snelheid van psychische processen. Onderzoekingen gedaan in het Physiologisch Laboratorium der Utrechtsche Hoogeschool: 1868–1869. *Tweede Reeks*, *2*, 92–120.

Dougherty, M. R. P., Gettys, C. F., & Ogden, E. E. (1999). MINERVA-DM: A memory processes model for judgments of likelihood. *Psychological Review*, *106*, 180–209.

Egeth, H. E., & Dagenbach, D. (1991). Parallel versus serial processing in visual search: Further evidence from subadditive effects of a visual quality. *Journal of Experimental Psychology: Human Perception and Performance*, *17*, 550–559.

Eidels, A., Townsend, J. T., & Pomerantz, J. R. (2008). Where similarity beats redundancy: The importance of context, higher-order similarity, and response assignment. *Journal of Experimental Psychology: Human Perception and Performance*, *34*, 1441–1463.

Fific, M. (2006). *Emerging holistic properties at face value: Assessing characteristics of face perception*. Unpublished doctoral dissertation, Indiana University, Bloomington.

Fific, M., Nosofsky, R. M., & Townsend, J. T. (2008) Information-processing architectures in multidimensional classification: A validation test of the systems factorial technology. *Journal of Experimental Psychology: Human Perception and Performance*, *34*, 356–375.

Fific, M., Townsend, J. T., & Eidels, A. (2008). Studying visual search using systems factorial methodology with target-distractor similarity as the factor. *Perception and Psychophysics*, *70*, 583–603.

Gigerenzer, G., & Goldstein, D. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review*, *103*, 650–669.

Gigerenzer, G., Todd, P. M., & the ABC Research Group (1999). *Simple heuristics that make us smart*. New York: Oxford University Press.

Gluck, M. A., & Bower, G. H. (1988). From conditioning to category learning: An adaptive network model. *Journal of Experimental Psychology: General*, *117*, 227–247.

Hammond, K. R. (1990). Functionalism and illusionism: Can integration be usefully achieved? In R. M. Hogarth (Ed.), *Insights in decision making: A tribute to Hillel J. Einhorn* (pp. 227–261). Chicago: University of Chicago Press.

Heath, R. A. (1992). A general nonstationary diffusion model for two choice decision making. *Mathematical Social Sciences*, *23*, 283–309.

Ingvalson, E. M., & Wenger, M. J. (2005). A strong test of the dual mode hypothesis. *Perception and Psychophysics*, *67*, 14–35.

Jacobs, A. M., & Grainger, J. (1994). Models of visual word recognition – Sampling the state of the art. *Journal of Experimental Psychology: Human Perception and Performance*, *20*, 1311–1334.

Johnson, S. A., Blaha, L. M., Houpt, J. W., & Townsend, J. T. (2009). Systems factorial technology provides new insights on global-local information processing in autism spectrum disorders. *Journal of Mathematical Psychology*, *54*, 53–72.

Juslin, P., Olsson, H., & Olsson, A. C. (2003). Exemplar effects in categorization and multiple-cue judgment. *Journal of Experimental Psychology: General*, *132*, 133–156.

Juslin, P., & Persson, M. (2002). PROBabilities from EXemplars (PROBEX): A “lazy” algorithm for probabilistic inference from generic knowledge. *Cognitive Science*, *26*, 563–607.

Lamberts, K. (1998). The time course of categorization. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *24*, 695–711.

Lamberts, K. (2000). Information–accumulation theory of speeded categorization. *Psychological Review*, *107*, 227–260.

Lee, M. D., & Cummins, T. D. R. (2004). Evidence accumulation in decision making: Unifying the “take the best” and “rational” models. *Psychonomic Bulletin and Review*, *11*, 343–352.

Link, S. W. (1992). *The wave theory of difference and similarity*. Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.

Maule, A. J. (1994). A componential investigation of the relation between structural modelling and cognitive accounts of human judgement. *Acta Psychologica*, *87*, 199–216.

Newell, B. R., & Shanks, D. R. (2003). Take the best or look at the rest? Factors influencing “one-reason” decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *29*, 53–65.

Newell, B. R., Weston, N. J., & Shanks, D. R. (2003). Empirical tests of a fast-and-frugal heuristic: Not everyone “takes-the-best”. *Organizational Behavior and Human Decision Processes*, *91*, 82–96.

Nosofsky, R. M., & Bergert, F. B. (2007). Limitations of exemplar models of multi-attribute probabilistic inference. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *33*, 999–1019.

Nosofsky, R. M., & Palmeri, T. J. (1997). An exemplar-based random walk model of speeded classification. *Psychological Review*, *104*, 266–300.

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *14*, 534–552.

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge: Cambridge University Press.

Persson, M., & Rieskamp, J. (2009). Inferences from memory: Strategy- and exemplar-based judgment models compared. *Acta Psychologica*, *130*, 25–37.

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*, 59–108.

Rieskamp, J. (2006). Perspectives of probabilistic inferences: Reinforcement learning and an adaptive network compared. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *32*, 1371–1384.

Rieskamp, J., & Hoffrage, U. (1999). When do people use simple heuristics, and how can we tell? In G. Gigerenzer, P. M. Todd, & the ABC Research Group (Eds.), *Simple heuristics that make us smart* (pp. 141–167). New York: Oxford University Press.

Rieskamp, J., & Hoffrage, U. (2008). Inferences under time pressure: How opportunity costs affect strategy selection. *Acta Psychologica*, *127*, 258–276.

Rieskamp, J., & Otto, P. E. (2006). SSL: A theory of how people learn to select strategies. *Journal of Experimental Psychology: General*, *135*, 207–236.

Schweickert, R. (1985). Separable effects of factors on speed and accuracy: Memory scanning, lexical decision, and choice tasks. *Psychological Bulletin*, *97*, 530–546.

Schweickert, R., Giorgini, M., & Dzhafarov, E. (2000). Selective influence and response time cumulative distribution functions in serial–parallel task networks. *Journal of Mathematical Psychology*, *44*, 504–535.

Smith, P. L. (1995). Psychophysically principled models of visual simple reaction time. *Psychological Review*, *102*, 567–591.

Sternberg, S. (1966). High speed scanning in human memory. *Science*, *153*, 652–654.

Sternberg, S. (1969). The discovery of processing stages: Extensions of Donder's method. In W. G. Koster (Ed.), *Attention and performance II* (pp. 276–315). Amsterdam: North-Holland.

Sung, K. (2008). Serial and parallel attentive visual searches: Evidence from cumulative distribution functions of response times. *Journal of Experimental Psychology: Human Perception and Performance*, *34*, 1372–1388.

Townsend, J. T. (1969). Mock parallel and serial models and experimental detection of these. In *Proceedings of the Purdue Centennial Symposium on Information Processing* (pp. 617–628). West Lafayette, IN: Purdue University Press.

Townsend, J. T. (1971). A note on the identifiability of parallel and serial processes. *Perception and Psychophysics*, *10*, 161–163.

Townsend, J. T. (1972). Some results concerning the identifiability of parallel and serial processes. *British Journal of Mathematical and Statistical Psychology*, *25*, 168–199.

Townsend, J. T., & Ashby, F. G. (1983). *The stochastic modeling of elementary psychological processes*: Cambridge: Cambridge University Press.

Townsend, J. T., & Fific, M. (2004). Parallel versus serial processing and individual differences in high-speed search in human memory. *Perception and Psychophysics*, *66*, 953–962.

Townsend, J. T., Fific, M., & Neufeld, R. W. J. (2007). Assessment of mental architecture in clinical/cognitive research. In T. A. Treat, R. R. Bootzin, & T. B. Baker (Eds.), *Psychological clinical science: Papers in honor of Richard M. McFall*. (pp. 223–258) Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Townsend, J. T., & Nozawa, G. (1995). Spatio-temporal properties of elementary perception: An investigation of parallel, serial, and coactive theories. *Journal of Mathematical Psychology*, *39*, 321–359.

Townsend, J. T., & Wenger, M. J. (2004a). A theory of interactive parallel processing: New capacity measures and predictions for a response time inequality series. *Psychological Review*, *111*, 1003–1035.

Townsend, J. T., & Wenger, M. J. (2004b). The serial–parallel dilemma: A case study in a linkage of theory and method. *Psychonomic Bulletin and Review*, *11*, 391–418.

Wallsten, T. S., & Barton, C. (1982). Processing probabilistic multidimensional information for decisions. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *8*, 361–384.

Wenger, M. J., & Townsend, J. T. (2001). Faces as Gestalt stimuli: Process characteristics. In M. J. Wenger & J. T. Townsend (Eds.), *Computational, geometric, and process perspectives on facial cognition: Contexts and challenges*, Scientific Psychology Series (pp. 229–284). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Wenger, M. J., & Townsend, J. T. (2006). On the costs and benefits of faces and words: Process characteristics of feature search in highly meaningful stimuli. *Journal of Experimental Psychology: Human Perception and Performance*, *33*, 755–779.

Wundt, W. (1880). *Grundzüge der physiologischen Psychologie* [Foundations of physiological psychology] (2nd ed.). Leipzig: Engelmann.