

## ACTIVATION-STATE REPRESENTATION OF MODELS FOR THE REDUNDANT-SIGNALS-EFFECT

HANS COLONIUS  
*Universität Oldenburg*

JAMES T. TOWNSEND  
*Indiana University*

**ABSTRACT.** The redundant signals effect (RSE) refers to the fact that subjects generally respond faster to simultaneously presented redundant targets than to single targets in a detection task where they are required to monitor two or more information sources. Based on the notion of an activation state representation, a unifying formal framework for the various response time models developed for the RSE is presented. Prospects for testing between different model classes are discussed and illustrated by some first results.

### 1. INTRODUCTION: THE REDUNDANT SIGNALS EFFECT

Consider a task requiring people to monitor two (or more) information sources ("channels") for the presence of a target signal requiring a particular speeded response. A common finding is that people respond faster (or more accurately) when signals are presented simultaneously on both channels than when a signal is presented on a single channel alone. This has been referred to as the *redundant signals effect* (RSE), or the *redundant targets effect*. For example, when signals are presented on two modalities, visual and auditory, say, responses to such bimodal stimuli tend to be faster than responses to unimodal stimuli (an effect also known as *intersensory facilitation*). The experimental literature on the RSE is voluminous and the results depend on whether or not the stimuli are presented within the same modality, the nature of the stimulus materials, and other contextual factors. Many different explanations of the RSE have been suggested over the years, some of them in terms of formalized quantitative models, others more informal (for a recent review, see Townsend & Nozawa, 1995).

The purpose of this paper is to provide a unifying formal framework within which most theoretical approaches to the RSE can be embedded. Apart from yielding a common language to describe the various theoretical approaches, such

---

*Key words and phrases.* Redundant signals effect, separate activation model, coactivation model, channel interaction, race model.

*Acknowledgment.* The authors are grateful to Ehtibar Dzhafarov and an anonymous reviewer for comments and suggestions. This research was supported by a German-American Collaborative Research Award sponsored by the American Council of Learned Societies (ACLS) and by Deutscher Akademischer Austauschdienst (DAAD). Support was also provided by U.S. National Science Foundation Grant BNS 9112813 to the second author.

*Address for correspondence.* Hans Colonius, Institut für Kognitionsforschung, Universität Oldenburg, D-26111 Oldenburg, Germany. Email: colonius@psychologie.uni-oldenburg.de

a framework may help point to techniques required to differentiate among various models and to make evident where model mimicking or excessive generality, relative to certain experimental domains, makes hypothesis testing difficult or impossible (cf. Townsend & Ashby, 1983; Dzhafarov, 1993).

The central concept of our framework is the notion of a *time-dependent activation state* representing the momentary effect of a signal within one or several channels. The motivation for this notion relates to a basic distinction between models of *separate activation* and models of *coactivation* as introduced by Miller (1982). In the former, presentation of the stimuli triggers the buildup of activation in each sensory channel separately. A response is initiated as soon as activation reaches a criterion level of activation in either channel. These models are commonly called "race models," because the response to a redundant signal is produced by the winner of the race between two (or more) stochastic response activation processes (Meijers & Eijkman, 1977; Raab, 1962). The RSE is explained by statistical facilitation, i.e., the mean of the winner's time is at most as large as the mean of either of the racers. Alternatively, *coactivation* models allow activation from different channels to combine over time in satisfying a *single* criterion for response initiation. Responses to redundant signals will be especially fast, because two sources feed activation into satisfying a single criterion level of activation.

While the distinction between separate and coactivation models makes sense at an intuitive level, the above characterization of the separate activation and the coactivation models allows for rather broad realizations of specific stochastic mechanisms within both classes of models. As in certain other fundamental distinctions, such as parallel vs. serial processing (see, e.g., Townsend, 1990), our analyses below will show that any attempt at empirically distinguishing between the two hypotheses hinges upon specific additional assumptions being made in either case, and experimental manipulations based on those assumptions.

The next section introduces some notation and gives a more explicit definition of separate activation and coactivation models for the RSE. In Section 3, the formal framework of an activation state representation is developed. Section 4 discusses some special cases within this framework, while Section 5 considers prospects for testability of these model classes and presents some first results. Finally, Section 6 reviews evidence for the localization of the RSE from some psychophysiological studies.

## 2. BASIC ASPECTS OF SEPARATE ACTIVATION AND COACTIVATION

Let  $\mathcal{X}, \mathcal{Y}$  be two different sets of stimuli, e.g., from two different modalities, visual and auditory, say. The elements of  $\mathcal{X}$  (respectively,  $\mathcal{Y}$ ) can be defined in a given experimental condition either as target or as non-target (distractor) stimuli. For brevity, in this section we will only consider the case without distractors, i.e., where non-target stimuli will not be presented. For target stimuli  $X \in \mathcal{X}$  and  $Y \in \mathcal{Y}$ , let  $T_X$  and  $T_Y$  denote (random) trigger times for response initiation by the sensory channels corresponding to  $\mathcal{X}$  and  $\mathcal{Y}$ , respectively<sup>1</sup>. According to the

<sup>1</sup>By an abuse of language, we will often refer to  $\mathcal{X}$  and  $\mathcal{Y}$  as channels.

separate activation point of view, response time in the redundant target condition is defined by

$$RT_{XY} = \min(T_X, T_Y). \quad (1)$$

For simplicity, we disregard any residual components of the response time here. Note that (1) implies the existence of a bivariate distribution function  $P[T_X \leq s, T_Y \leq t]$  with  $s, t \geq 0$ . Thus, in separate activation models, the observable RT distribution in the redundant target condition is

$$\begin{aligned} P[RT_{XY} \leq t] &= P[\min(T_X, T_Y) \leq t] \\ &= 1 - P[T_X > t, T_Y > t]. \end{aligned} \quad (2)$$

This equation implies that the underlying bivariate distribution  $P[T_X \leq s, T_Y \leq t]$  is unobservable under the given experimental conditions except at the points  $(t, t)$ . Thus, it is impossible to test for stochastic independence of the trigger times  $T_X$  and  $T_Y$  without adding further assumptions. One assumption commonly made in separate activation models is referred to as *context independence* by Colonius (1990) or as *perceptual separability* by Ashby and Townsend (1986) (see also Luce, 1986b, p. 128ff). In a context independent separate activation model, the distribution of the trigger time  $T_X$  (resp.,  $T_Y$ ) is the same in the single target condition and in the redundant target condition. Technically, context independence equates the single target distribution  $F_X(t) = P[T_X \leq t]$  with the redundant target marginal distribution  $P[T_X \leq t, T_Y \leq \infty]$  (analogously, for  $T_Y$ ). Under this condition, separate activation models predict the following inequality, as first observed by Miller (1982):

$$\max(F_X(t), F_Y(t)) \leq P[RT_{XY} \leq t] \leq F_X(t) + F_Y(t). \quad (3)$$

It should be emphasized that, under context independence, this inequality is valid no matter whether the trigger times are stochastically independent or not. In fact, stochastic independence occurs when  $P[RT_{XY} \leq t]$  equals  $F_X(t) + F_Y(t) - F_X(t)F_Y(t)$ , while the upper and the lower bound in (3) represent the cases of maximal positive and maximal negative stochastic dependence between the trigger times  $T_X$  and  $T_Y$  with fixed given marginals, also known as Fréchet bounds (see Colonius, 1990). Ulrich and Giray (1986) and Colonius (1986, 1990) studied the influence of stochastic dependence on the RSE. The predicted RSE is greater if the trigger times are negatively correlated, because in this case a large latency in one channel tends to be compensated by a small latency in the other channel.

Inequality (3) has been found violated in many empirical studies. In particular, response times in the redundant target condition often are faster than allowed by the upper bound (e.g., Miller, 1982, 1986; Diederich & Colonius, 1987; Westendorf & Blake, 1988; Mordkoff & Yantis, 1993). This prompted the development of so-called coactivation models. As Miller (1991) notes, coactivation models have so far been defined primarily by default, i.e., as models that produce faster detection of redundant targets than race models or, more specifically, than race models under context independence. As mentioned in the introductory section, one way to conceive of coactivation is in terms of a combination of activations across channels with a single criterion to be satisfied for response initiation.

A prominent example of a mathematical coactivation model is the *Poisson superposition* model (cf., Diederich & Colonius, 1991; Schwarz, 1989). Let  $X(t)$  and  $Y(t)$  denote the number of Poisson counts that occur by time  $t$  in the channel processing  $X$  and  $Y$ , respectively. The RT distribution in the redundant target condition is defined by the first-passage time associated with the superposition of the Poisson counters, that is,

$$RT_{XY} = \inf\{t : X(t) + Y(t) > c\}, \quad (4)$$

where  $c$  is the shape parameter of the gamma distribution associated with the superposed Poisson processes. Thus, by definition, the response time is the *greatest lower bound* (infimum) of the set of all time points  $t$  where the summed counters exceed the criterion  $c$ . Townsend and Nozawa (1995) have developed general coactivation models that include the Poisson model as special case. Other types of coactivation models are based on the concept of random walk (e.g., Smith, 1990) or on the superposition of certain diffusion processes (Diederich, 1992, 1995; Schwarz, 1994). Superposition models have fared much better in accounting for RSE data than separate activation models, both at the level of central tendencies (means, medians) and at the level of variance of the RT distributions.

### 3. ACTIVATION STATE REPRESENTATIONS

The counters in the Poisson superposition model presented in Equation 4 provide a simple example of an activation state representation for a coactivation type model where the momentary effect of a signal within a sensory channel is captured by time-dependent random variables,  $X(t)$  and  $Y(t)$ . However, the concept of a time-dependent state of activation initiates a much more general approach that will be outlined in this section. In particular, it encompasses separate activation type models. For example, a slight modification of the first-passage time of Equation 4 yields an activation state representation for a separate activation type of model. Defining

$$RT_{XY} = \inf\{t : \max\{X(t), Y(t)\} > c\} \quad (5)$$

provides an activation state formulation for the redundant target response time defined in Equation 1 with, in the Poisson case, gamma-distributed trigger times racing against each other.

A more elaborate view of how sensory information in the channels develops over time involves the idea of interactions occurring among the channels. For example, in the *interactive race model* recently proposed by Mordkoff and Yantis (1991), separate sensory channels begin exchanging information about the identity of the element being processed in either channel (e.g., whether it is a target or a non-target) as soon as any channel has partially identified its signal. Given specific experimenter-determined signal contingencies, processing time in a given channel may be speeded up either by increasing the level of activation or by lowering the response initiation criterion in the redundant target conditions. Of course, inhibitory interactions across channels could also occur in such models.

It is interesting to note that the occurrence of channel interactions implies the existence of at least two functionally and, most likely, also morphologically distinct

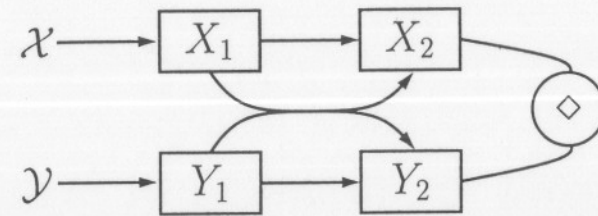


FIGURE 1. Flow chart sketch of general activation state model

stages of processing. The first stage refers to the state of activation at an early, peripheral stage of processing where no interaction among channels can occur. The second stage refers to a later, central state of activation where interaction among different channels is possible. For the  $X$ -channel, let  $X_1(t)$  and  $X_2(t)$  denote the activation state for the first and second stage, respectively. For the  $Y$ -channel,  $Y_1(t)$  and  $Y_2(t)$  are defined analogously. It should be stressed here that these two stages are not limited to be discrete, serial subprocesses in the sense of Donders (1868). Rather, at any point in time  $t$  the peripheral activation state may continuously “feed” into the second, more central stage. Moreover,  $X_2(t)$  may also get “cross-talk” from  $Y_1(t)$  and, simultaneously,  $Y_2(t)$  from  $X_1(t)$ . However, the two processes do not interact directly. Formally, this can be captured by introducing two functionals  $G_x$  and  $G_y$  as follows:

$$\begin{aligned} X_2(t) &= G_x[(X_1(t'), Y_1(t')) : t' \in [0, t]] \\ Y_2(t) &= G_y[(Y_1(t'), X_1(t')) : t' \in [0, t]]. \end{aligned} \quad (6)$$

Thus, the level of activation at time  $t$  in the second stage in the  $X$ -channel,  $X_2(t)$ , ( $Y_2(t)$  in the  $Y$ -channel, respectively) is a function of the entire “history” of the activation in the first stage up to  $t$  both of the  $X$ - and the  $Y$ -channel (see Townsend & Fikes, 1995, for a detailed treatment of the “functional” concept in sequential but continuous flow types of models). Adding a first passage time assumption then leads to the following general representation:

$$RT_{XY} = \inf\{t : X_2(t) \diamond Y_2(t) > C\} \quad (7)$$

where  $\diamond$  refers to some binary operation on the pairs  $(X_2(t), Y_2(t))$  and  $C$  is a constant criterion level of activation.

It turns out that Equation 7 encompasses the classes of models considered above. Assuming  $\diamond$  to be the *max* operation defines the class of *separate activation* or *race models* with possibly interactive channels; replacing  $\diamond$  by the *min* operation yields a class of *parallel exhaustive models* where activation in both channels must meet a criterion value to trigger the response (see, for example, Colonius & Vorberg, 1994; Townsend & Colonius, in press). Finally, the class of *coactivation models* can be defined by considering  $\diamond$  to be a *generalized addition operation*  $\oplus$ , say, an operation possessing all principal properties of addition<sup>2</sup>. The rationale for choosing

<sup>2</sup>The operation is defined as follows: Let  $g$  be an arbitrary real-valued, strictly monotonic (increasing or decreasing) and continuous function with some open interval of the reals as its domain.

an addition-like operation, rather than simple addition, for the combination of channel activations in the definition of coactivation models is that the inequality in (7) for " $\oplus$ " can always be reduced to an equivalent inequality for "+" by a monotonic transformation of the channel activations and the criterion  $C$  without changing the response time predictions.

While Equation 7 is a compact description of an activation state model of a rather general kind, there are at least two further possible directions in which to extend this representation. The first concerns the criterion. Rather than assuming a constant criterion level of activation, the criterion may be time-dependent as suggested by refractory phenomena (cf., Tuckwell, 1989). Moreover, the criterion itself may vary randomly over time, possibly as a function of the activations states in the two channels  $X_2(t)$  and  $Y_2(t)$  (e.g., Pike, 1973). Depending on how this functional dependence of  $C$  occurs, it is possible to rewrite the inequality in (7) in terms of a constant criterion.

The second extension of representation (7) is more fundamental. It is conceivable that in some cases, information concerning the activation in the separate channels is retained until a very late stage of processing. Thus, final detection in this *hybrid model* may depend on both the combined activation  $X_2(t) \diamond Y_2(t)$  as well as the separate channel activations  $X_2(t)$  and  $Y_2(t)$ . Obviously, there are different ways how these three activations could combine to determine the final output. The hybrid model will be considered in Section 4.

Finally, it should be mentioned that representation (7) does not include the *serial exhaustive model* for the RSE recently discussed in Townsend and Nozawa (1995).

#### 4. SOME SPECIAL CASES

The simplicity of Equation 7 is deceptive since the occurrence of the functionals  $G_x$  and  $G_y$  permits very complex relations between the  $X_1$  and  $Y_1$  trajectories and  $X_2$  (or  $Y_2$ , respectively). In the following, a few special cases illustrate some of the possibilities. While some of these model classes have been pursued in the literature, others, to our knowledge, have not yet been developed in any detail, let alone tested empirically.

**Markovian Models.** A considerable simplification of the two-process activation model (Equation 7) is obtained if the Markov property is introduced. For simplicity, and to avoid writing differential equations, only the discrete time case is considered here:

$$\begin{aligned} X_2(t+1) &= G_x[X_1(t), Y_1(t), X_1(t-1), Y_1(t-1), \dots, X_1(0), Y_1(0)] \\ Y_2(t+1) &= G_y[Y_1(t), X_1(t), Y_1(t-1), X_1(t-1), \dots, Y_1(0), X_1(0)]. \end{aligned}$$

In a *Markovian activation state model*, the level of activation in the second stage at time  $t+1$  only depends on the most recent history of the activations in the first

When  $a \oplus b = g^{-1}[g(a) + g(b)]$  defines a new binary operation that is associative, commutative, increasing in both arguments, and continuous in both arguments (cf., Aczél, 1966; Dzhafarov & Schweickert, 1995).

stage and on its own state at time  $t$ . Specifically,

$$\begin{aligned} X_2(t+1) &= g_x(X_1(t), Y_1(t), X_2(t)) \\ Y_2(t+1) &= g_y(Y_1(t), X_1(t), Y_2(t)). \end{aligned} \quad (8)$$

The specific form of  $g_x, g_y$  determines whether the system is linear or nonlinear.

**Activation Without Channel Interaction.** Assuming that no channel interaction occurs up until the activation process crosses a critical criterion level  $C$  makes the two-process formulation introduced in Section 3 dispensable. In fact, consider the representation in (6) without the "cross-talk" terms:

$$\begin{aligned} X_2(t) &= G_x[X_1(t') : t' \in [0, t]] \\ Y_2(t) &= G_y[Y_1(t') : t' \in [0, t]]. \end{aligned} \quad (9)$$

Since there is no restriction on the definition of  $X_2$  we may, without loss of generality, set  $X_2(t)$  equal to  $X_1(t)$  for any  $t$ . Then, Equation 9 simply states that  $X_1(t)$  is a function of  $t$  that depends on all its values  $t' < t$ . The same argument holds for channel  $Y$ . Nonetheless, it may still be plausible to distinguish between a peripheral and a more central stage of processing. However, any exploitation of this calls for additional assumptions and/or experimental manipulations, for example applying some kind of systems factorial technology (Sternberg, 1969; Townsend & Nozawa, 1995). Without channel interaction, the general representation (7) thus reduces to

$$RT_{XY} = \inf\{t : X_1(t) \diamond Y_1(t) > C\}. \quad (10)$$

Choosing an appropriate interpretation of  $\diamond$ , this representation encompasses all separate activation and coactivation models mentioned in Section 2.

**Hybrid Models.** One way to conceive of the hybrid model type is to postulate the existence of an additional channel  $Z$ , say, integrating convergent input from the other channels. For example, the Markov version from Section 4 would be

$$\begin{aligned} X_2(t+1) &= g_x(X_1(t), Y_1(t), X_2(t)) \\ Y_2(t+1) &= g_y(Y_1(t), X_1(t), Y_2(t)) \\ Z(t+1) &= g_z(X_2(t), Y_2(t), Z(t)). \end{aligned} \quad (11)$$

Final detection, i.e., the first-passage time determining the response time, could then be some function of the activation in both the  $Z$ -channel and the  $X, Y$ -channels. This hypothesis ties in with a recent observation by Miller (1991). In a bimodal experiment with auditory signals varying in pitch and visual signals varying in location ("high" vs. "low"), he found responses to redundant targets were faster when both were high or low than when they were incongruent. Preserving the activation information from both the  $X$ - and the  $Y$ -channel up to the final stage, in parallel with the integrating channel  $Z$ , could then account for these congruence effects. Obviously, alternative hypotheses locating the congruence effects at an earlier stage are conceivable. In our view, further empirical work is needed to decide this issue.

### 5. DISCUSSION: PROSPECTS FOR TESTABILITY

The distinction between separate activation and coactivation has been the starting point of our investigation. As pointed out in Section 2, violation of Inequality (3) allows rejection of all separate activation (race) models as long as context independence is assumed. On the other hand, non-violation of the inequality presents only weak support for the race model since other models may also be consistent with the inequality. Moreover, context independence is the key assumption for the inequality to be of any diagnostic value (cf., Ashby & Townsend, 1986; Colonus, 1986). As noted by Luce (1986b), one possibility for a race model to violate the inequality would be the following form of context dependence: The presence of a (nontarget) signal speeds up the detection of the other (target) signal. Interestingly, this is exactly an example of one type of *interchannel cross talk* effect that Mordkoff and Yantis (1991) hypothesized from their empirical studies and that led them to propose their "interactive race model" (mentioned in Section 3). Although this model has not been presented in a formal way, it seems obvious that it can be subsumed under the general class of (two-process) separate activation models with possibly interactive channels defined from Equation 7 in Section 3 by:

$$RT_{XY} = \inf\{t : \max\{X_2(t), Y_2(t)\} > C\}. \quad (12)$$

The upshot of this is that the general class of separate activation models defined by Equations 6 and 12 is not constrained by Inequality 3 because context independence may no longer hold.

Next, one may ask whether this model class can be tested against the general class of coactivation models defined in Section 3 by Equation 6 and by

$$RT_{XY} = \inf\{t : X_2(t) \oplus Y_2(t) > C\}. \quad (13)$$

Not surprisingly, the answer to this is in the negative since these two general classes are not disjoint. This is illustrated by the following example, where a separate activation model with channel interaction degenerates into a coactivation model.

**Example.** Consider a separate activation model of a simplified Markov type (12) with the following representation:

$$\begin{aligned} X_2(t+1) &= g_x(X_1(t), Y_1(t)) \\ Y_2(t+1) &= g_y(Y_1(t), X_1(t)). \end{aligned} \quad (14)$$

Assume that, due to some inhibitory effect, activation in the  $\mathcal{Y}$ -channel converges to an upper bound lying below the criterion  $C$ . A plausible example for this situation is the *focused-attention task*, where subjects are instructed to make a speeded response as soon as they detect a visual signal or a visual signal accompanied by an accessory auditory signal, and to withhold their response if the auditory signal occurs alone. Although the auditory signal is irrelevant for performing this task, shorter RTs result under bisensory stimulation than if the visual signal is presented alone (e.g., Bernstein, Clark, & Edelman, 1969). Thus, while the auditory signal adds to the sensory activity generated by the visual signal, the activity level in the auditory channel by itself is not sufficient to cross the criterion and to trigger the response

(see also Giray & Ulrich, 1993). Then Equation 12 reduces to

$$RT_{XY} = \inf\{t : X_2(t) > C\}. \quad (15)$$

This, however, is the first-passage time of a coactivation model as long as

$$g_x(X_1(t), Y_1(t)) = X_1(t) \oplus Y_1(t),$$

where  $\oplus$  is an addition-like operation.

Note that examples like this one do not preclude the possibility of testing specific separate activation models against specific coactivation models, even under context dependence. However, such a test will always be a test of the model and, simultaneously, some auxiliary conditions added to the model (see also Dzhabarov, 1993). This will be illustrated here by the following result. The class of coactivation models includes the general idea of superposition (as exemplified by the Poisson superposition model). While the falsifiability of the general superposition idea is still an open question, Townsend and Nozawa (1995) present some first results under auxiliary conditions. The following is a slightly stronger version of their result (Townsend & Nozawa, 1995, Theorem 7):

**Proposition 1.** *Let  $X_t$  and  $Y_t$  denote the number of counts (not necessarily Poisson distributed) that occur by time  $t$  in the  $\mathcal{X}$ - and in the  $\mathcal{Y}$ -channel, respectively. Assuming the (constant) criterion  $c$  for the first-passage times to be identical in both the superposition and in the race model,*

$$F_{\text{superposition}}(t) = P[RT_{XY} \leq t] = P[X_t + Y_t > c],$$

$$F_{\text{race}}(t) = P[RT_{XY} \leq t] = P[\max\{X_t, Y_t\} > c],$$

implies

$$F_{\text{race}}(t) \leq F_{\text{superposition}}(t)$$

for all  $t$ .

*Proof.* For a proof, consider the following subsets of the sample space:  $S(t) = \{\omega | X_t(\omega) + Y_t(\omega) > c\}$  and  $R(t) = \{\omega | \max\{X_t(\omega), Y_t(\omega)\} > c\}$ . Obviously, because  $X_t$  and  $Y_t$  are nonnegative,  $R(t) \subseteq S(t)$  for all  $t$ , implying the distribution ordering. Note that  $X_t, Y_t$  are not assumed to be independent.  $\square$

### 6. LOCALIZING THE REDUNDANT SIGNALS EFFECT

As the previous section indicates, there appear to be some severe limits on the testability of the most general models for the RSE, within single experimental conditions of an RT experiment. However, the development of meta-modeling strategies that help to test and discriminate large classes of architectures and process issues suggests that careful development of model-oriented methodology offers hope for the future (see, in this regard, Dzhabarov & Schweickert, 1995; Townsend & Nozawa, 1995). Nonetheless, it is natural to ask whether there are other dependent variables, behavioral or physiological, that could yield useful information on the nature of the RSE. Given the significant difference in the level of functional descriptions between neurophysiology and psychology, it would be presumptuous to expect physiological data to delineate psychological models for the RSE in any detail. On the other hand, there is a multitude of data on the RSE collected to date,

both neurophysiological and other non-RT data like response force, in particular in the area of multisensory integration (e.g., visual-auditory-somatosensory), and the neurophysiological-behavioral parallels prove to be striking (cf. Stein & Meredith, 1993). No attempt is made here to review these findings. Rather, the aim of this section is to see whether some broad aspects of the activation state approach are supported by evidence from data beyond measures of response speed.

Early on, a speed-up of response time for redundant signals beyond that predicted by probability summation was taken as evidence for the existence of "neural summation" performed by some specific neural correlate. For example, from their comparison of monocular and binocular response times, Blake, Martens, Garrett, and Westendorf (1980) hypothesized the existence of binocular neurons activated only by binocular stimulation. Notably, a multitude of electrophysiological studies have shown that there exist multimodal cells in the deep layers of the superior colliculus (DLSC) (of anaesthetized cats) that respond with a firing rate more than 10 times the optimal unimodal stimulus response (see Stein & Meredith, 1993, for a review). Moreover, spatial and temporal disparities of the visual-auditory stimulation caused a gradual decrease of these bimodal interactions similar to those found in the latencies of human saccadic eye movements (Frens, van Opstal, & van der Willigen, 1995; Hughes, Reuter-Lorenz, Nozawa, & Fendrich, 1994). Most interestingly, more recent electrophysiological studies suggest the existence of multisensory cortical neurons that do not project to the superior colliculus and that may be involved in higher order cognitive functions (Wallace, Meredith, & Stein, 1993).

In our view, the existence of multiple sites of multisensory integration renders models of separate activation without any channel interactions quite implausible. While, as hypothesized in Hughes et al. (1994), these different sites may be involved depending on the pathways used by a particular task (directed gaze vs. simple manual responses), the existence of at least two stages of signal processing as postulated in our general representation (6) and (7) appears tenable.

Finally, there is some evidence on the issue of separate activation models (with channel interaction) vs. coactivation models from a study of *response force* by Giray and Ulrich (1993). Besides producing the usual RSE in their response times, subjects also gave more forceful responses under bimodal than under unimodal stimulation. As noted by these authors, this evidence for a (at least) partial localization of the effect at a motoric level is not easy to reconcile with a separate activation model, even under channel interaction. The reason is that while race models assume separate response activations ("trigger times"), response execution should not depend on whether the signal was unimodal or bimodal. A coactivation model where activation is summed over possibly different sites of neural convergence, may be more appropriate for this situation.

# Choice, Decision, and Measurement: Essays in Honor of R. Duncan Luce

Copyright © 1997 by Lawrence Erlbaum Associates, Inc.  
All rights reserved. No part of this book may be reproduced  
in any form, by photostat, microform, retrieval system, or any  
other means, without the prior written permission of  
the publisher.

Lawrence Erlbaum Associates, Inc., Publishers  
10 Industrial Avenue  
Mahwah, New Jersey 07430

Edited by  
A. A. J. Marley

## Library of Congress Cataloging-in-Publication Data

Choice, decision, and measurement : essays in honor of R. Duncan Luce  
/ edited by A.A.J. Marley.

p. cm.

Papers originally presented at a conference held at the University  
of California, Irvine, Aug. 2-3, 1995.

Includes bibliographical references and indexes.

ISBN 0-8058-2234-8 (alk. paper)

1. Psychometrics--Congresses. 2. Choice (Psychology)--Congresses.  
3. Decision-making--Congresses. I. Luce, R. Duncan (Robert Duncan)  
II. Marley, A. A. J.

BF39.C49 1966

153.8'3--dc20

96-41621  
CIP

Books published by Lawrence Erlbaum Associates are printed  
on acid-free paper, and their bindings are chosen  
for strength and durability.

Printed in the United States of America

10 9 8 7 6 5 4 3 2 1



LAWRENCE ERLBAUM ASSOCIATES, PUBLISHERS  
1997 Mahwah, New Jersey London