Context effects on memory retrieval
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Accumulators in context: an integrated theory of context effects on memory retrieval

INTRODUCTION

Cognitive architectures (e.g., Anderson, 2007a; EPIC, Meyer & Kieras, 1997a; Soar, Newell, 1990; CLARION, Sun, 2006), have had considerable success explaining cognition in an integrative way. This means that theories developed within a cognitive architecture are supported by theories of other aspects of cognition. For instance, for an explanation of visual search tasks, in which participants are asked to search an array of stimuli for a previously presented target stimulus, it is important to include a theory of decision processes to account for a stopping rule of the visual search, and of declarative memory to explain how participants retrieve the target from memory. During the task, participants have to decide whether they have found the target stimulus, based on a memory of the previous presentation of the stimulus. Therefore, it makes sense to study different cognitive phenomena within one framework, so that one theory (for instance about visual search) remains consistent with others (for instance about decision making or declarative memory).

One of the successes of cognitive architectures (particularly from the architecture ACT-R) is the account of declarative learning. By incorporating a model that estimates the environmental demands on memory (Anderson & Milson, 1989; Anderson & Schooler, 1991), ACT-R models have been able to account for many effects of learning and memory (e.g., Anderson, Bothell, Lebiere, & Matessa, 1998; Anderson, Fincham, & Douglass, 1999; Pavlik & Anderson, 2005). In addition, this declarative memory account has been used to study the interactions between memory and other cognitive processes, such as prospective time estimation (e.g., Taatgen, Van Rijn, & Anderson, 2007; Van Rijn & Taatgen, 2008) and cognitive control (e.g., Altmann & Gray, 2008) or the role of memory in interactive behavior (e.g., Lebiere & West, 1999; West, Lebiere, & Bothell, 2006).

However, one of the drawbacks of the theory of declarative memory retrieval that has been adopted in the cognitive architecture ACT-R is that it does not provide a theory of the actual retrieval process. Rather, it provides a prediction of the retrieval time of declarative information, as well as the probability of successful retrieval, under normal conditions. However, circumstances exist where such a ballistic model (Brown & Heathcote, 2005; Van Maanen & Van Rijn, 2007b) of declarative memory retrieval does not provide accurate predictions. This is illustrated in Figure 2.1, which shows the retrieval process as captured by a ballistic theory of declarative memory retrieval. At the onset of the retrieval process the time it takes to retrieve a declarative fact from memory (referred to as chunk A in Figure 2.1) as well as the identity of that fact are already known. However, cognition and perception do not stop while retrieving information from declarative memory, and it might very well be that new, relevant information becomes available during the interval between retrieval onset and the actual retrieval that may influence the retrieval process.
Consider for example the following experiment. A participant is requested to name a picture that appears on a computer screen. The picture is accompanied by a word from the same semantic category (e.g., a picture of a cat with the word “dog”), which may appear at various time intervals just before or after the onset of the picture. When inspecting the latency data from this experiment (W. R. Glaser & Düngelhoff, 1984, see also Figure 2.8a below), it turns out that the presence of the word interferes with processing of the picture. Moreover, the time interval between the presentation of a word and the presentation of a picture mediates the response latency for the picture. The closer the word precedes the picture the slower the response. Surprisingly however, the maximum interference effect of the word on the picture is when the word trails the picture by 100ms.

What this example shows is that when studying interference effects such as these, many task aspects may play an important role. In this case, the asynchronous presentation of stimuli mediates the interference effect, and also the different qualities of words and pictures influence the latency, reflected by the fact that the maximum interference is not at an stimulus onset asynchrony (SOA) of 0ms (when word and picture are presented simultaneously), but at an SOA of 100ms. Complex interference patterns such as this cannot be fully explained by traditional architectural models that focus on a broad range of tasks. In the “Asynchronously presented stimuli” section we will further discuss how these two aspects (asynchronous presentation and stimulus quality) determine response latencies in this task.

Many specialized models exist that specifically address the interference issues in declarative memory, however. For example, a large body of work is devoted to understanding the decision dynamics in two-choice reaction time tasks (Ratcliff & Smith, 2004). In these models, the decision process is thought of as a process in which evidence for two response options is sampled, until a decision for one or the other has been reached. The decision time is determined by the length of this “deliberation process” (Busemeyer & Townsend, 1993, p. 432), and will be influenced by the accrual rate of the evidence for the response options. Thus, if all evidence points in one direction, the deliberation will be fast, and the decision time will be short.

In this chapter, we propose to integrate such a sampling process in a cognitive architecture, which we will refer to as Retrieval by Accumulating Evidence in an Architecture (RACE/A). This way, a number of new memory related phenomena can be explained by the architectural approach. Because in RACE/A it is possible to dynamically adapt the sampling process to new information, it becomes possible to model tasks in which asynchronies between stimulus presentations exist, something that is currently not possible in architectural models. For instance, in a dual-task in which the interval between the tasks governs the response
latency (as for example in Psychological Refractory Period experiments), RACE/A explains how the decision process depends on the interval change (Van Maanen, Van Rijn, & Borst, submitted, as well as Experiments 1 and 2 of the current chapter). For these situations, RACE/A can provide quantitative model fits.

Related Theories of Memory Retrieval Dynamics

Previous models of memory retrieval have focused on the functional process underlying simple decision making (e.g., Ratcliff & McKoon, 2008) or perceptual identification (e.g., Usher & McClelland, 2001). These models are often referred to as sequential sampling models (Ratcliff & Smith, 2004). In sequential sampling models, the discrimination between mental representations is thought of as a mechanism that accumulates the likelihood that a certain mental representation is the intended one. Typically, there is a boundary, either fixed or relative to another accumulator, above which the representation is discriminated and may be used in another cognitive process. Accumulation depends on the quality or the quantity of a stimulus, either absolute or relative to other stimuli. Because the latency in these kinds of paradigms depends for a large extent on when the boundary for a specific accumulator is reached and accuracy depends on which accumulator reaches the boundary first, sequential sampling models provide an elegant explanation for speed-accuracy trade-offs often observed in cognitive tasks (Ratcliff & Smith, 2004).

Retrieval from declarative memory also involves discriminating between different mental representations. Thus, memory retrieval could also be described as a process in which the likelihood is accumulated that a certain mental representation is the intended one. Sequential sampling models therefore provide an explanation of many memory related phenomena (e.g., Ratcliff, 1978).

The three most important parameters that determine behavior in sequential sampling models are (Figure 2.2, Wagenmakers, van der Maas, & Grasman, 2007):
- A starting point of accumulation (z)
- Match boundaries (a and b)
- Mean drift rate (v)

The match boundaries a and b in these kinds of models represent the two response options for a participant in the tasks that are modeled with the sequential sampling models. For instance, in lexical decision the match boundary represents the amount of accumulated evidence to give a “word” response and the non-match boundary represents the amount of evidence needed to give a “non-word” response.

The position of the starting point (z) relative to the match boundaries determines the
prior likelihood of a match and a non-match. For example, if the starting point is closer to match boundary $a$ than to match boundary $b$, the accumulation needed to cross $a$ is less than the accumulation necessary to cross $b$. In this case, in the absence of any drift towards $a$ or $b$, the likelihood of reaching $a$ is higher than reaching $b$. Manipulation of this parameter has been used to model participants’ prior expectations on the probability of stimuli, for instance the probability of non-words in a lexical decision task (Wagenmakers et al., 2008). In the model of Wagenmakers et al. a high non-word probability was modeled by setting $\tau$ to a lower value. This meant that crossing the non-word boundary was faster than the word-boundary because the accumulation process was shorter, which is visible in the data as well.

The third important parameter, mean drift rate, indicates the average speed of accumulation. A high value indicates a faster accumulation (a high drift). This parameter has for instance been manipulated to account for stimulus discriminability effects (Usher & McClelland, 2001). Thus, highly discriminable stimuli may be modeled by a high drift in either direction, and stimuli that are more difficult to discriminate may be modeled with a lower drift rate.

One of the drawbacks of the classical diffusion model is that it only accounts for two response options (a match and a non-match). Other memory retrieval models have been proposed that overcome this. For example, Usher and McClelland (2001) proposed a sequential sampling model for perceptual choice tasks in which each response option is represented by an accumulator, but in which the drift rates are dependent. Apart from accumulation caused by stimuli (the mean drift rate), the drift is also determined by lateral inhibition from other accumulators and decay. In this model, the time course of a perceptual choice is determined by the likelihood that a stimulus leads to one response, as well as the likelihoods of other responses.

Another well-known memory retrieval model is the REM model (Shiffrin & Steyvers, 1997). In this model, the retrieval process is thought of as a continuous Bayesian decision process, in which the odds that a particular decision will be made depend on the ratio of likelihoods between the response options. For instance, for lexical decision, the likelihoods for the “word” and “non-word” responses are considered to be a function of features of the stimulus. If the stimulus resembles a word, the likelihood of the “word” response is higher than if the stimulus consists of a completely randomized letter string. Certain instances of the REM model also include an aspect of sequential sampling (e.g., Norris & Kinoshita, 2008; Wagenmakers et al., 2004a). In these models, the likelihoods of the response options continuously drift and a decision is based on the current likelihood ratio in the system. In this way, the REM model accounts for pseudo-homophone effects in lexical decision under deadline or signal-to-respond conditions (Wagenmakers et al., 2004a).

These accounts have provided much insight in how retrieval from declarative memory works. However, computational models that are derived from these theoretical accounts often only model a single retrieval event. These models fail to appreciate that retrieving declarative knowledge from memory does not stand alone, but is always part of the execution of a particular task. Cognitive architectures on the other hand provide a theory of task execution (Newell, 1990). However, the explanation provided by these models is not always at the level of detail of sequential sampling models. RACE/A reconciles both approaches.

**COGNITIVE ARCHITECTURES**

From the many variants of a cognitive architecture that exist (Anderson, 2007a; e.g., ACT-R, Anderson et al., 2004; Soar, Laird, Newell, & Rosenbloom, 1987; EPIC, Meyer & Kieras, 1997a; Meyer & Kieras, 1997b; Newell, 1990; Rosenbloom, Laird, & Newell, 1993; CLARION, Sun,
ACT-R

ACT-R is a hybrid cognitive architecture in which behavior in a task can be described by a sequence of production rule executions. The rules specify which actions to execute given certain conditions. To execute a production rule, the conditions are matched against the current information state, which is represented by a set of buffers, each containing one piece of information. Which information is present at a certain point in time is determined by each of the specialized modules, that each process one kind of information. For instance, visual perception is handled by the visual module, and motor commands are executed by the motor module. The declarative module is used for storing and retrieving declarative memory information, the speech module handles the speech output, the aural module handles auditory perception, and the goal and imaginal are modules for keeping track of (sub) goals and intentions (Figure 2.3). The modules can be regarded as theories on that particular aspect of cognition, and the production rule system connects these theories to account for overall behavior.

Thus, the presence of information determines which production rule is selected and executed. Both the presence and absence of stimuli can modify the buffer content and determine the selection of production rules, and the actions that are executed as part of a previous production rule. For instance, a production rule’s actions may contain a request to retrieve certain information from memory, which will be stored in the retrieval buffer after it has been retrieved.

Declarative information in the ACT-R cognitive architecture is represented by chunks. These are simple facts about the world, such as *Amsterdam is the capital of the Netherlands*, or *The object I am looking at is a computer screen*. Both these example chunks are declarative facts, but the first example can typically be found in the retrieval buffer and thus represents a fact retrieved from declarative memory, whereas the second example represents a visually observable fact of the world and might be present in the visual buffer.

All chunks in declarative memory have an activation level that represents the likelihood that a chunk will be needed in the near future. The likelihood is partly determined by a
component describing the history of usage of a chunk called the base-level activation \(B_j\) in Equation 2.1. 

\[ B_j = \ln \left( \sum_{i=1}^{n} e^{-d} \right) \]  

(equation 2.1)

The base-level activation represents the theory that declarative memory is optimally adapted to the environment (Anderson & Schooler, 1991). That is, chunks that are most active are the ones that are most likely needed, given the demands of the environment. By incorporating both the frequency with which particular information is used and the recency of these occurrences, the base-level activation predicts learning effects as well as forgetting (e.g., the power laws of learning and forgetting, Anderson, Fincham, & Douglass, 1999). In Equation 2.1, \(t_j\) represents the time since the \(j\)th presentation of a memory chunk and \(d\) is the parameter that controls decay, which in most \text{ACT-R} models is fixed at 0.5 (Anderson et al., 2004).

In the standard conception of \text{ACT-R}, the total activation is the sum of the base-level activation, noise (\(\varepsilon\) in Equation 2.2), and another component describing the influence of the current context (spreading activation, Equation 2.2). The \text{RACE/A} theory will extend \text{ACT-R} by substituting the spreading activation component of the activation by a component describing spreading activation as part of the retrieval process. The spreading activation component is composed of the associative values of other chunks, which are referred to in the slots of a chunk (chunks \(j\) in Equation 2.2) to chunk \(i\), weighed by \(W_j\), representing the importance of associated chunks (\(j\)).

\[ A_i = B_i + \sum_j W_j S_{ji} + \varepsilon \]  

(equation 2.2)

The assumption in \text{ACT-R} is that chunks that are temporarily available to central cognition (that is, chunks that are present in the buffers) increase the probability that related chunks will be needed. The associations that exist between two chunks (\(S_{ji}\)) reflect the pattern of co-occurrences of the two events that these chunks represent (Anderson & Milson, 1989). For instance, in the presence of a green stimulus in the visual buffer, the probability of retrieval of chunks that are related to green - such as a chunk representing grass or a chunk representing the concept of Ireland - increases. This is because grass and green as well as Ireland and green often co-occur.

An important reason to compute the need probability of a chunk (captured by the activation value) in \text{ACT-R} is to predict the time it will take to retrieve chunks. If a chunk has a low activation value, indicating that it is not likely that this particular chunk will be needed right now, it is harder to remember, which will be reflected by a long retrieval time. This observation is captured by Equation 2.3, which determines the latency of retrieval, given a certain activation value, with \(F\) a scaling parameter:

\[ RT = Fe^{-A_i} \]  

(equation 2.3)

However, this approximation of the declarative retrieval process suggests that information that becomes available after the declarative retrieval is initiated, but before the predicted retrieval time, cannot influence the time course anymore (Figure 2.1). We will refer to this type of retrieval model as \textit{ballistic} (Van Maanen & Van Rijn, 2007b), to indicate that once initiated, the memory retrieval process can no longer be influenced.

**RETRIEVAL BY ACCUMULATING EVIDENCE**

In this section, we will develop the dynamics of the Retrieval by ACCumulating Evidence in an Architecture (\text{RACE/A}) memory retrieval theory. We will first present the equations that
govern the activation dynamics and show how they relate to ACT-R concepts. As RACE/A is integrated in a cognitive architecture, we will show next how RACE/A in the architecture can account for simple reaction time experiments. Third, we will present data and a model of a task that can only be explained with the integrated account.

The accumulation process can be characterized by two equations that determine the long-term dynamics and the short-term dynamics of the activation. The long-term dynamics of the activation are expressed by the default base-level activation equation from ACT-R (Equation 2.1). The short-term dynamics are mediated by spreading activation from other chunks and the presence or absence of perceptual stimuli. During a retrieval process (e.g., the interval between Onset and Retrieval in Figure 2.4), the activation of chunks that match a set of retrieval conditions (chunks A and B) gradually accumulates until a certain decision criterion (explained below) has been reached. The chunk that has been decided upon (chunk A) will be retrieved from declarative memory, and the accumulation of activation stops. Because no new activation is being accumulated, the short-term component of the activation of all chunks decays. However, given that the usage history of the retrieved chunk has been altered (because it is currently being used), the chunk’s long-term component is being increased in such a way that it greatly exceeds the current level of short-term activation. For this reason, the net activation of each chunk in the system can be described as

\[ A_i = \max(B_i, C_i) \]  

indicating that the activation of a chunk is the maximum of the need probability of a chunk (reflected by \( B_i \)) and the accumulating evidence for that chunk (reflected by \( C_i \)). Similar to most sequential sampling models, the short-term activation dynamics can be represented by a starting point, a drift, and a decision boundary, which will be discussed below.

**STARTING POINT**

The starting point of the accumulation reflects the prior probability that a chunk is needed. This is reflected by ACT-R’s base-level activation equation (Equation 2.1), which incorporates the usage history of a chunk. Chunks with a high base-level activation start the accumulation of activation at a higher starting point, and are thus more likely to be retrieved from memory.

**DRIFT**

Drift in RACE/A is the reflection of the current demands of the environment. Thus, drift is a function of stimuli, as well as the currently active declarative facts. All facts and stimuli, which will collectively referred to as sources of activation, continuously spread excitatory activation.
towards associated chunks. This means that a chunk that has more sources of activation (more evidence) or sources with more activation (“stronger” evidence) will accumulate faster than a chunk with less sources of activation or sources with less activation. In the absence of evidence for a particular chunk, the short-term activation will decay (indicated decaying chunk B in Figure 2.4). The drift in race/a is also determined by a logistically distributed noise sample, that adds stochasticity to the system.

These considerations are reflected by Equation 2.5, which may be referred to as the drift equation. The drift equation captures the dynamics of short-term activation ($C_i$) of one chunk ($i$) over time.

$$dC_i = [-\alpha C_i + \beta \sum_j S_{ji} A_j + \varepsilon] dt$$

In this equation, the decay of short-term activation is expressed by $\alpha$, which should be a value in the range $[0,1]$ to create decay. The spreading activation component is a sum of the activation of other chunks ($A_j$), weighted by the associations that exist with chunk $i$ ($S_{ji}$). The spreading activation component is scaled by a factor $\beta$ that determines the overall accumulation speed. The noise is expressed by $\varepsilon$. To summarize, the decay parameter $\alpha$ together with scaling factor $\beta$ determine the average drift of the chunks in the system. However, the chunk that receives the most spreading activation from sources of activation will (in the absence of noise) be the first to reach the decision boundary.

DECISION BOUNDARY

The decision boundary in race/a is relative to the activation of competitors in the system. This choice reflects the insight that if multiple memory representations are relevant, responding becomes more difficult (Hick, 1952; Luce, 1986). This is reflected by Equation 2.6, which expresses the conditions under which a decision will be made. If the activation of a certain chunk (chunk $i$ in Equation 2.6) exceeds the activation of all competitors ($j$, including $i$), in the system by a certain ratio $\theta$ (referred to as the decision ratio), then that chunk is retrieved from memory. The duration of the retrieval process constitutes the interval between the onset of the retrieval process (when the request for a retrieval is made) and the moment at which the decision is made.

$$\sum_j \frac{e^{\theta - \theta_j}}{e^{\theta_j}} \geq \theta$$

The relative likelihood of one chunk is the Luce ratio for that chunk (Luce, 1963).

One important special case for race/a is when there is no competition. Often, there is only a single chunk that matches a retrieval request. Consider for example an adult who wants to retrieve the answer to the problem $3 + 4 = ?$. The activation of competing answers is very low, because adults are very experienced in this task and rarely make errors. Therefore, this results in a retrieval process in which there is practically no competition.

This special case is addressed in (Anderson, 2007a, Appendix 3.1), in which act-r’s latency predictions are compared with an instance of the diffusion model. Assuming no noise (and no competitors), the retrieval time in race/a can be described as a ballistic model, in which the retrieval time is a function of the distance between the decision boundary and the Luce ratio for the chunk. Figure 2.5 presents the predicted retrieval time for various activation values. Especially for low activation values, race/a closely follows the act-r predictions of retrieval times. This ensures that a race/a model can fit experimental data set in which no competition effects are to be expected, similar to default act-r models.

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3. In the simulations reported throughout this paper, we used the discrete version of Equation 2.5:

$$dC_i = [-\alpha C_i + \beta \sum_j S_{ji} A_j + \varepsilon] dt$$
Before discussing memory retrievals using RACE/A in the broader scope of complex task execution, it is important to understand the activation dynamics of the model. In this section, we present the results of a set of simple simulations of how RACE/A behaves under varying circumstances. In these simulations, two unrelated chunks are competing for retrieval from declarative memory. In addition, no noise is added to the system. Figure 2.6a (left) presents how activation develops over time for the default case, in which both chunks have the same starting point and one stimulus is present that activates only one chunk. That chunk accumulates activation, whereas the other remains at its minimum value, which is the starting point (the base-level activation). Figure 2.6a (right) presents the relative Luce ratios for both chunks, with the dotted horizontal line indicating the decision ratio $\theta$. Because there are two equally probable chunks in this competition, the Luce ratio at the start of the process is 0.5 for both chunks, but quickly changes in favor of the accumulating chunk, until it crosses the decision ratio.

Figures 2.6b presents the activation and Luce ratios for two chunks, of which one receives activation from a stimulus, but the other has a higher starting point. This is for instance the case if one chunk has a higher base-level activation because it is more familiar, or because the chunk has been recently retrieved. Under these conditions, retrieval takes longer because the Luce ratio of the activated chunk is smaller due to the higher initial activation from the other chunk.

In Figure 2.6c, a situation is depicted in which one chunk is activated later than the other. This will be an important case in the picture-word interference model described in the next section. Even though the retrieval process of the first chunk has already initiated, activation of the second chunk at a later moment in time influences the Luce ratio and thus increases the retrieval time of the first chunk. It should be noted that in order for the first chunk to be retrieved before the second, spreading activation from the stimulus to this chunk should be at least as high as spreading activation to the other chunk. Otherwise, the secondly activated chunk will be retrieved. This is what happens if a target stimulus trails a to be ignored stimulus in time, as in the picture-word interference experiment described below.

The last simulation addresses a condition in which one of the chunks is only activated for a short duration (Figure 2.6d). This is what happens in masked priming, in which one stimulus is only available for a short duration and thus only has a short interval in which to activate related concepts, while another stimulus remains present. Initially, both chunks accumulate, because both receive activation from a stimulus. After one of the stimuli disappears, the activation of one of the chunks decays, but the other chunks accumulates further. Again, the retrieval time is increased as compared to the default situation in Figure 2.6a, because the activation of the decaying chunk still influences the Luce ratios. The simulations depicted by
Figure 2.6c and Figure 2.6d are particularly difficult to explain with a ballistic theory of memory retrieval, because they simulate conditions in which information becomes available during the retrieval process.

To summarize these simple simulations, the Luce ratio of a particular chunk is negatively accelerated by the activation of other chunks that compete with that chunk for retrieval from declarative memory. This competitive process results in an increase in retrieval time. If the chunks are associated, then the behavior is similar, but the retrieval times are increased even more (Figure 2.7, note that the x-axis differs from Figure 2.6). Under these conditions, both chunks accumulate due to spreading activation from the other chunk (compare Figure 2.6a with Figure 2.7a). This results in slower accrual of the Luce ratios and therefore a longer retrieval. This explains the semantic gradient effect found in picture-word interference studies (e.g., W. R. Glaser & Düngelhoff, 1984; Klein, 1964; Rayner & Springer, 1986; Smith & Magee, 1980). If two concepts are associated, for instance because they belong to the same semantic
category, the will excite each other, increasing decision boundary and thus the retrieval time and the response latency. A full RACE/A model of picture-word interference will be presented in the next section.

ASYNCHRONOUSLY PRESENTED STIMULI

In this section, we will discuss a picture-word interference experiment performed by Glaser and Düngelhoff (1984, Experiment 1). As this is a prime example of an experiment that is difficult to explain with a ballistic model of memory retrieval. After introducing the experiment, we will provide RACE/A model fits to this data set.

Glaser and Düngelhoff’s (1984) Experiment 1 consists of two tasks: One is naming a picture, while a word is presented (picture naming task); the other consists of reading a word while a picture is presented as distractor (word reading task). In both tasks, the distractors
are presented on different SOAs relative to the target stimulus (either the picture or the word, depending on the task). Thus, if a distractor is presented at negative SOA, it is presented before the target stimulus. At positive SOAs, the distractor is presented after the target stimulus. The first condition is one in which both distractor and target stimulus refer to the same concept (e.g., a picture of a house versus the word house). This is referred to as the congruent condition. In two other conditions, distractor and target stimulus refer to different concepts. In the related condition the concepts belong to the same semantic category (e.g., a picture of a church versus the word house), in the unrelated condition the concepts do not belong to the same semantic category (e.g., a picture of a cat versus the word house). As control condition target stimuli were presented together with meaningless letter strings (picture naming task) or rectangles (word reading task).

Glaser and Düngelhoff (1984) show that interference decreases as the semantic relation of the word to the picture decreases, which is known as the semantic gradient effect (Klein, 1964; Lupker, 1979; Rayner & Springer, 1986; Smith & Magee, 1980). They also show facilitation in the congruent condition, meaning that latency is decreased when both target and distractor stimuli refer to the same concept (Bajo, 1988; Ehri, 1976). The most interesting finding for the current discussion is that the size of the interference effect is mediated by the temporal distance between target and distractor. If the onset asynchrony of the two stimuli is small, the interference is high. However, the interference does not maximize at an SOA of 0 ms, indicating simultaneous presentation of the two stimuli, but rather at an SOA of 100ms, indicating that interference is highest if the distractor is presented slightly after the target. A final effect observed in PWI studies is a clear asymmetry between the picture-naming task and the word-reading task: The semantic gradient and facilitatory effect virtually disappear in the word-reading task, while they were visible in the picture-naming task. The data of Glaser and Düngelhoff’s Experiment 1 are provided in Figure 2.8a.

**PICTURE-WORD INTERFERENCE MODEL**

We will now turn to a RACE/A model that explains the effects found in the picture-word interference paradigm. As RACE/A is tightly integrated with the ACT-R cognitive architecture, we will present the model in ACT-R terminology. Our model of picture-word interference comprises two chunk types: lemma chunks and concept chunks. The concept chunks can be regarded as representations of semantic properties of a certain concept. Chunks of the lemma type can be regarded as sets of orthographic and syntactic properties of a word (cf., Levelt, 1989).

Two types of stimuli can be presented to the model, pictures and text. If a stimulus is presented, it spreads activation to related chunks in declarative memory (Equation 2.5). Because of the familiarity of the depicted concepts, we assume that all pictures have been attended equally often. Thus, spreading activation from the pictures is kept at a constant value, which is a parameter of the model. However, to represent more prior practice with processing words than with processing pictures (e.g., Cohen, Dunbar, & McClelland, 1990; MacLeod & Dunbar, 1988), spreading activation from the textual stimuli is higher than from pictures.

Figure 2.9 summarizes the connections that exist between chunks in this model. Text engages directly on the lemma chunks, while for pictures, conceptual information needs to be retrieved before the lemma of the picture can be retrieved. This reflects the finding that words can be processed without a conceptual level (W. R. Glaser & Glaser, 1989; La Heij, Happel, & Mulder, 1990), that is, the meaning of a word is not necessary for pronouncing the word. By contrast, an interpretation of the depicted concept is necessary for naming a picture.
When a stimulus is presented, the model accumulates activation for concept and lemma chunks. After lemma retrieval, the model can commence word-form encoding and pronunciation of the response. For explanatory purposes, we assume for this data set that these stages do not influence the latency differences. Note however that in subsequent models these stages are included, as they will play an important explanatory role.

For both the picture-naming task and the word-reading task, we presented the model with the same conditions as the participants; a neutral, congruent, related, and unrelated condition, with SOAs of -400, -300, -200, -100, 0, +100, +200, +300, and +400ms, similar to the original Glaser and Düngelhoff (1984) experiment. In the neutral condition, no distractor stimulus was presented. That is, no text chunk was in the visual buffer at any moment. Glaser and Düngelhoff presented the subjects with a non-word distractor and a non-picture distractor respectively in the picture-naming and word-reading control condition. These were chosen in such a way as to minimize the amount of picture or word processing. Assuming a successful operationalization by Glaser and Düngelhoff, we simulated this condition by not presenting a distractor in the neutral condition. In the congruent condition, the distractor and the target stimulus both refer to the same concept. In the unrelated condition, distractor and target stimulus refer to different concepts.

When the picture is presented in the neutral condition, it spreads activation to its associated concept. At the same time, all concept chunks spread their activation to the lemma chunks. Because there is no distractor present, the most likely lemma to be retrieved from memory is the one related to the depicted item. Because there is no competition from
other sources apart from the standard activation of the lemma representations, retrieval is relatively quick.

For the congruent condition, the distractor word is the name of the picture. If the distractor and target stimulus are both presented at the same time, then not only the effect from the picture contributes to the activation of the desired lemma, as in the neutral condition, but also activation spreading from the word. Therefore, retrieval will be faster than in the neutral condition. If the SOA is negative, that is, if the word is presented before the picture, the desired lemma is already active, because of spreading activation from the word to the lemma. The size of this effect correlates with the distance between the stimuli. For (positive) SOAs larger than +100 ms, the desired lemma is already retrieved before the word can contribute spreading activation. Therefore, no difference between the neutral and congruent conditions is predicted for these SOA levels.

In the unrelated condition, the word and the picture do not refer to the same concept. If both stimuli are presented simultaneously, a competing lemma is activated by the distractor word before the target lemma is activated. This will result in increased competition. At large negative SOAs, the word will be processed completely and rejected as a response option. Because of subsequent decay, there will be less interference at negative SOAs. The degree of interference is negatively correlated with the SOA, because shorter intervals will result in more active word-related lemmas when the picture is presented and thus more competition (cf., Figure 2.7b). At positive SOAs, the target lemma will become active before the distractor stimulus is presented. Thus, less time is available for the distractor to interfere (cf., Figure 2.7c). An interesting consequence of the asynchrony in the model between pictures and words in lemma activation is that interference is highest at a SOA of +100ms. Because pictures first activate conceptual representations, a slightly later presentation of a word will result in maximum competition between the lemmas. This patterns is supported by the data (Figure 2.8a).

If the target and distractor stimuli are semantically related, the distractor lemma is not only activated by the word, but also by the conceptual representation of the picture, mediated by a related conceptual representation. Thus, higher associations result in stronger competition and more interference.

The experimental setup for the word-reading task was equal to that of the picture-naming task. The only difference was that participants were instructed to read the words, while ignoring the pictures. In general, pronouncing a written word is faster than naming an item in a picture (W. R. Glaser & Düngelehoff, 1984). As said, our model explains this by a shorter processing route for word-like stimuli and faster encoding of word-like stimuli. The faster encoding is reflected by higher activation of the text chunks than the picture chunks in the visual buffer.
Figure 2.8 presents the results of our picture-word interference model. Because the model does not capture the vocalization aspects of the task, Figure 2.8 presents the latency differences between the neutral condition and the other conditions to account for differences in competition during memory retrieval. The Root Mean Square Error (RMSE) of the model fit is 28 ms (Here and throughout this article, we will only report RMSE and not the $R^2$ of the model fit, because for current purposes it is a more insightful measure of goodness-of-fit than $R^2$).

Because of the shorter processing route for words and faster encoding, there is less time for picture-induced competition to influence the word-reading process. This results in the typical Stroop asymmetry described by Glaser and Düngelhoff (1984) (Figure 2.8, RMSE=18ms). However, at negative SOAs, our model does predict a small interference effect, which is not in the data. Because of the longer processing route, it takes about 400ms for the picture-related distractor lemma to become fully activated. Therefore, at a negative SOA of 300-400 ms, the competition posed by the distractor lemma is maximal at the onset of the word.

Interestingly, in the Stroop variant of this experiment (M. O. Glaser & Glaser, 1982), a small but significant interference effect is observed at negative SOAs over 300ms, similar to our model prediction for pwi. This indicates that the Stroop effect could be explained by a longer processing account only. However, since generally pwi and Stroop are considered instances of the same process (e.g., Cohen, Dunbar, & McClelland, 1990; MacLeod, 1991; Roelofs, 2003; Van Maanen & Van Rijn, 2007b; Van Maanen, Van Rijn, & Borst, submitted), the issue of interference in word reading remains unsolved. We did not examine this issue further, because the model presented here is aimed at providing a general account of interference effects in memory retrieval.

A ballistic model of picture-word interference would not have been able to account for the SOA effects in pwi. Consider the latency equation of ACT-R (Equation 2.3): Given the ballistic nature of declarative memory retrieval, a standard ACT-R model cannot explain the interference and facilitation effects that are observed at small positive SOAs, since the latency is already determined at the onset of the target stimulus. At negative SOAs, the retrieval initiated by the distractor might not yet be finished once the retrieval initiated from the target stimulus is requested. Therefore, in a model that does not consider the retrieval process, no influence from the distractor stimulus would be predicted, resulting in identical predictions for all conditions.

MASKED STIMULI

The previous section showed that RACE/A can account for the effects of asynchronous presentation of stimuli at very short intervals. The pwi model is an example of how RACE/A processes information that becomes available after a memory retrieval process has already initiated. In this section, we will discuss a model that demonstrates how RACE/A accounts for conditions in which information is not available for the full duration of a trial. More specific, we will discuss a model of a classical masked priming experiment (Marcel, 1983, Experiment 3).

The experiment consisted of a Stroop task in which participants were asked to name the color of a slide, while a color word was flashed in front of the slide for a brief duration. Four prime type conditions were tested: Color congruent, color unrelated, neutral, and no-word. In the congruent condition, the prime was the name of the target color, whereas in the unrelated condition the prime was the name of another color. In the neutral condition, the prime was a non-color word. The no-word condition presented the mask only. Thus, no prime
was presented. Two awareness conditions were tested. One in which the prime was masked (unaware condition) and one in which the prime was presented for 400 ms (aware condition). The presentation duration of the masked prime was chosen in such a way that participants could not discriminate between the presence or absence of a prime. Prime and cue were presented simultaneously (Marcel, 1983).

Participants had to respond to the color patches by pressing a button associated to one of the colors. The aware condition replicated the typical patterns of interference and facilitation as commonly found in the Stroop paradigm. In the unaware condition, a smaller interference effect was found as compared to the aware condition (Figure 2.10a).

**Masked Priming Model**

The masked priming model is very similar to the PWI model. Concept chunks and lemma chunks contain the conceptual information on color and the syntactic information on color words, respectively. However, because the original experiment involved a response using a button press, we included extra chunks that represented information on which button was associated with which concept. These chunks will be referred to as motor-mapping chunks, because they map a conceptual representation onto a motor response (Figure 2.11).

The rest of the model was similar to the picture-word interference model. Thus, textual features of a stimulus (such as the word "red") activate lemma chunks. Color patches activate concept chunks that represent color information. Concepts and lemmas spread activation to
context effects on memory retrieval: theory and applications

We estimated the presentation duration of the prime in the unaware condition at 70 ms, which is in the range of durations used in the original experiment (30-80 ms, Marcel, 1983). With this duration, the prime’s Luce ratio did not exceed the decision boundary, indicating that the model remained unaware of the presence or absence of the prime.

model results & discussion

Figure 2.10 presents latency differences (RMSE = 2ms). The model predicts similar effects of awareness as are present in the data, as well as the normal Stroop effects. Because the prime (the color word) is only present for a short duration in the unaware condition, it spreads less activation towards the associated lemma. Therefore, the competition between color concepts is less (because the lemma is also less activated than in the aware condition), resulting in a smaller interference effect in the unaware condition than in the aware condition.

In the congruent condition, the model predicts no effect of awareness. This results from a floor effect in the retrieval time. Because the color patch already activates the concept enough for retrieval, the added value of the congruent word is diminished and therefore the presentation duration has no effect on the latency.

As in picture-word interference, an extra stimulus in masked priming influences the retrieval of a target stimulus. From a symbolic perspective, stimuli have to be active in order to engage in cognitive processing. In ACT-R, this means that a stimulus has to be present in a buffer in order to influence other cognitive processes. Stimuli that are presented for such short times as are common in masked priming paradigms will not become available in the visual buffer, because ACT-R assumes an attention shift to the stimulus which takes a certain amount of time, exceeding the presentation duration of the prime (Anderson, Matessa, & Lebiere, 1998). In addition, if a prime were present in the visual buffer it would be available to conscious processing. In that case, the model would no longer be an accurate description of the task. Thus, the ballistic nature of the declarative retrieval theory in the cognitive architecture prohibits accurate modeling of masked priming experiments.

experiment 1: repetition priming

The previous models addressed competition effects in relatively straightforward conditions. In each trial, one chunk was retrieved, and the latency was a function of the competitive effects. The experiment and model presented in this section have a more complex structure. In this experiment, a picture-word interference (PWI) task is performed as the second, main task of a psychological refractory period (PRP) design. In addition to the normal PRP setup, which will be discussed shortly, we introduced a systematic repetition of the presented items. This way, this experiment requires the interaction of RACE/A - to account for the PWI interference effects – with ACT-R’s long-term declarative memory theory to account for the repetition effects, and ACT-R’s production rule and buffer system to account for the general task setup.

In a PRP design, participants are asked to perform two tasks sequentially. The first task is often relatively simple, whereas the second task is the task of interest (the main task). The interval between the stimulus onsets of the two tasks is manipulated (SOA). A typical finding, known as the PRP effect (Telford, 1931) is a negative correlation between SOA and response latency on the main task, Responses to the first task are typically unaffected by varying the SOA. The PRP effect has been explained (McCann, 1992, but see Meyer & Kieras, 1997b; e.g.,
Pashler, 1994; Welford, 1967, 1980) by the assumption that both tasks share a cognitive resource that can only be used by one task at a time. Thus, the second task is delayed because the first task still requires a critical resource (Figure 2.12). As the interval between the tasks increases, the delay becomes smaller, resulting in a faster main task response.

Applying the PRP design to PWI, (Dell’Acqua et al., 2007) have shown that the effect size of picture-word interference diminishes with decreasing PRP-SOA. Dell’Acqua et al. argued that these results indicate that the locus of interference in PWI is located before the singular resource that both tasks share. The reasoning behind this is that a small interval between the first and the second task generates a large delay (referred to as “cognitive slack”), in which the interference can be resolved. If the interval increases, the delay of the second task decreases, and therefore the interference becomes apparent in the reaction times (for a different interpretation of this data, see Van Maanen, Van Rijn, & Borst, submitted).

The different SOAs of the PWI task show different effects because of short-term changes in priming-related activation. Another possible cause for differences in retrieval latency is the number of repetitions of a particular target: the more repetitions, the shorter the latency (repetition priming). It has been shown that repetition of items results in priming effects that span intervening trials (e.g., Becker, Moscovitch, Behrmann, & Joordens, 1997; Joordens & Besner, 1992; Scarborough, Cortese, & Scarborough, 1977), suggesting that this form of priming affects long-term memory, rather than short-lived residual activation from a previous trial. We predict that the stronger long-term representation of the stimuli decreases the interference from related and unrelated distractor words, because the starting points of the accumulation process are higher on each repetition, resulting in faster retrieval process and thus less interference.

METHODS

Participants

23 students of the University of Groningen (mean age 22.7, 14 male, 9 female) took part in this experiment for course credit. All were native speakers of Dutch and had normal hearing and normal or corrected-to-normal vision.

Stimuli

49 images were taken from the PD/DPSS image set (Dell’Acqua, Lotto, & Job, 2000). The images that were selected for inclusion in this study had a naming agreement of 95%. Of each image, two PWI stimuli were created that consisted of the image, with a word written in the center of the image. The words were selected as follows: For the related condition, category members of the image descriptors were selected. The words for the unrelated condition were then selected from the CELEX lexical database (Baayen, Piepenbrock, & Van Rijn, 1993) and...
matched to the related distractors with respect to word length (plus or minus 1 letter) and word frequency (plus or minus 10%).

The tones for the primary task consisted of a 300Hz, 600Hz, and 1200Hz tone, similar to the experiment conducted by Dell’Acqua et al. (2007).

**Design**

For each participant, an experimental list was created in which each image was combined with each relatedness condition (related and unrelated) and every PRP-SOA (100ms, 350ms, and 800ms). This resulted in 294 trials per participant, in which each picture was repeated six times. The lists were pseudo-randomized in such a way that: (1) The same condition (relatedness or PRP-SOA) did not occur more than twice in a row, and (2) the same tone did not occur more than twice in a row.

**Procedure**

Each trial started with the presentation of a fixation cross for 1500ms followed by the tone-classification tone for 150ms. After the PRP-SOA, the PWI stimulus was presented. The word and the picture that formed the PWI stimulus were presented simultaneously (that is, all trials were presented with a PWI-SOA of 0ms). The participants were instructed to always respond to the tone first and then to the PWI-stimulus. The tone had to be classified as either low, medium, or high pitch by pressing the b, n, or m keys respectively with the index, middle and ring fingers of the right hand. For the PWI task, the participants were instructed to name the picture. If participants failed to answer in the correct sequence, a screen informing them of the correct procedure was presented.

The participants were tested individually. First, each participant practiced the tone classification task in isolation. Second, a set of PWI stimuli was presented in single task setting and the participant was instructed to name the picture and ignore the word. Before each of these practice blocks, the speed of responding was stressed as the important factor. Third, the participant was presented with a practice block of the dual-task. After this practice block, the actual experiment started. The experimental block was preceded by two filler trials that were the same for all participants and that were not analyzed.

**RESULTS**

One participant was excluded from the analyses because of an excessive error pattern (52% erroneous trials). Trials on which the remaining participants responded to the picture-word stimulus before responding to the tone were excluded from further analysis (2.4% of the trials). In addition, trials in which the participant’s response on either the PWI stimulus or the tone was more than three standard deviations from the participant’s mean (per relatedness/PRP-SOA combination) were excluded (2.0% and 2.0%, respectively). Because these exclusion criteria partly overlap, this resulted in exclusion of 5.2% of the trials. Following Dell’Acqua et al. (2007), no other trials were excluded.

The overall pattern in the data is presented in Figure 2.13. A linear mixed-effects model (Bates, 2005) was fit to the data to find the relative contribution of the factors to the response latency in the PWI task. Relatedness, PRP-SOA level, and number of repetitions were included as fixed effects, together with the interactions between these factors. Participant and Picture were included as random effects, to account for inter-subject and inter-item variability. An ANOVA on the mixed-effects model (Baayen, Davidson, & Bates, 2008) showed that the
following factors contributed significantly to the participants’ reaction times: PRP-SOA $\beta = -0.401$; $F(1,6122) = 741$; $p < 0.001$, relatedness $\beta = 45.5$; $F(1,6122) = 10.3$; $p = 0.001$, repetition $\beta = -48.2$; $F(1,6122) = 246$; $p < 0.001$, and a three-way interaction between SOA, relatedness, and repetition $\beta = 0.0529$; $F(1,6122) = 4.10$; $p = 0.04$. Further analysis of the effects per SOA level revealed that this three-way interaction is caused by the decreasing interference over repetition at a PRP-SOA of 800ms (relatedness times repetition, $\beta = 21.9$; $F(1,2059) = 5.20$; $p = 0.02$). This interaction was not significant at other PRP-SOAs ($Fs < 1$). To summarize, this experiment replicates the typical PRP effect, in which response latency on the main task are negatively correlated with PRP-SOA, the typical effect of interference when the distractor word is related but not identical to the to be named picture, and, additionally, a relatively straightforward effect of repetition priming. The interaction indicates that at the 800ms PRP-SOA, the repetition effect was smaller for trials with related distractors as compared to the 100ms PRP-SOA.

![Figure 2.13. Data from Experiment 1. Each panel represents the latency on each PRP-SOA level for all repetitions of the picture.](image)

**DISCUSSION**

The difference between the related and the unrelated condition is reflected by a difference in response latency, the interference effect. Since in the related condition picture and word are semantically related (and not in the unrelated condition), the interference may be an effect of competition between semantically related concepts. In both conditions, the word and picture activate a conceptual representation, but in the related condition, it is harder to decide on the correct conceptual representation of the picture (e.g., W. R. Glaser & Düngelhoff, 1984; Van Maanen & Van Rijn, 2007b). In the model, this effect of competition is accounted for by the retrieval ratio presented in Equation 2.5.

The size of the interference effect decreased with decreasing SOA, as well as with repetition of pictures. This observation suggests that the competition between the word and the picture is resolved early in the mental processing stream. If the interference effect under single-task conditions is caused early in the process (for instance during the visual processing of the picture), then this effect will be absorbed in the cognitive slack that is created by the PRP paradigm. Therefore, the presence of cognitive slack decreases the overt interference effect (Dell'Acqua et al., 2007).

All three panels of Figure 2.13 show latency curves very similar to the power law of learning, indicating that participants become faster with more repetitions. This is in line with the idea that at each repetition, the conceptual representation of the picture is retrieved from memory, strengthening its memory trace and making it easier to retrieve the concept at the next presentation. The effect of repetition on interference can be modeled by incorporating...
the long-term declarative memory mechanisms of ACT-R. This way, the starting points of all competing memory representations will be set at a principled value, because the starting values are determined by a validated theory of long-term memory processes, as well as precise predictions of the time course of the memory retrievals, both within trial and between trials.

**MODEL OF EXPERIMENT 1**

The low-level aspects of the model of Experiment 1 are identical to the earlier discussed models: The model retrieves conceptual representations from memory if a picture-like stimulus is presented and retrieves a lemma representation from memory if a word-like stimulus is presented. Because lemmas spread activation to the conceptual representations that relate to them, the presentation of a distractor word causes interference at the conceptual level. The relative decision boundary that determines retrieval from memory becomes harder to reach for the conceptual representation of the picture, increasing the retrieval time. The different activation levels of the target chunk versus competing chunks determine the latency difference between the related and unrelated conditions. In the related condition, the concepts of the target and the distractor spread activation to each other, making it even harder to reach the relative decision boundary. This mutual excitation is not present in the unrelated condition, resulting in less competition and thus a faster retrieval. These dynamics are also apparent from the simple simulations presented in Figure 2.6a and Figure 2.7a, which reflect the competition in the unrelated and related condition, respectively.

Once a concept has been retrieved, the model initiates a response. First it retrieves a lemma representation that encodes the syntactic information associated with the desired response, than it retrieves a motor program to articulate the desired response.

In addition to mechanisms to account for the PWI-aspects of the experiment, the model also contains mechanisms to account for the tone-classification task. If a tone is presented, the model processes auditory information and retrieves a memory trace that encodes the appropriate stimulus-response mapping (that is, which button to press given the perceived tone). Because of the task instruction to withhold the vocal PWI response until the tone classification is made, the model includes a control state that ensures that the retrieval of the response lemma (as part of the PWI task) does not start until the retrieval of the response stimulus response mapping (as part of the tone classification task) has been completed. As soon as the response mapping is retrieved, the PWI mechanisms can access declarative memory again, so the PWI task can continue before the actual button-press is made.

Each time a chunk has been retrieved from memory, its base-level activation is updated because it has gained an additional reference. This means that the starting point in the accumulation process differs in the next retrieval for which that chunk is a competitor. Thus, at each repetition of a picture, the starting point for the associated conceptual representation is higher than on the previous repetition. A higher starting point results in a faster retrieval of the relevant concept and therefore a faster response. Moreover, a fast retrieval results in little time for the other, distractor-related chunks to accumulate activation, resulting in a smaller interference effect. This accounts for the repetition priming effect observed in Experiment 1.

*Model results and discussion*

Similar to Experiment 1, we excluded outliers that were more than three standard deviations of the mean of each PRP-SOA-Relatedness combination. In the model, these outliers represent cases in which the model is unable to come to a decision due to multiple
chunks accumulating at the same rate. When the model reaches a deadline, the accumulation is halted and an error is returned. Consecutively, the model tries to retrieve the desired chunk again, resulting in prolonged response latencies.

Figure 2.14 shows that the model accounts for the repetition effect (RMSE = 56 ms). As the number of repetitions increases, the responses become faster. In the model, strengthening the memory trace of conceptual information as well as information at response levels causes the repetition priming effect. Previous studies have provided evidence for the existence of this dual process. For example, bilinguals show repetition priming for concepts that are presented in one language on the first presentation and in another language on the next presentation (e.g., Francis, Augustini, & Saenz, 2003; Francis & Saenz, 2007). Thus, a repetition benefit was present in the absence of a repetition of responses. This is evidence that conceptual information is being reinforced on the first presentation, enabling a faster response on the second presentation. On the other hand, certain lexical decision studies demonstrate that non-word response latencies are also decreased by repetition, indicating that repetition priming also has a speed-up effect if no conceptual representation is present, as is generally believed to be the case for non-words (e.g., Wagenmakers, Zeelenberg, Steyvers, Shiffrin, & Raaijmakers, 2004b; Zeelenberg, Wagenmakers, & Shiffrin, 2004).

As an extra validation of the model, Figure 2.15 shows the models fit to the main PRP effects (RMSE = 20 ms); a decreased latency as a function of increased SOA (for all relatedness conditions), and a decreased interference effect with increased SOA.

**EXPERIMENT 2: TASK STRATEGY**

Experiment and Model 1 illustrate how RACE/A naturally interacts with an important intrinsic property of the cognitive architecture ACT-R. The theory of long-term learning and forgetting that was already present in the architecture was extended with a theory on short-term dynamics of memory retrieval. This way, the interaction between (long-term) repetition priming and (short-term) interference could be explained. Also, the model makes use of the timing of the different subprocesses that are controlled by the production rule system. Thus, the model makes use of the possibility to formulate a theory on task execution in terms of the cognitive architecture.

This synergistic advantage of the integration of RACE/A with a cognitive architecture will be further demonstrated in Experiment 2. Participants in Experiment 2 were asked to perform exactly the same two tasks as in Experiment 1. However, this time an extra condition is included in which the word names the picture. This condition will be referred to as the congruent condition. This relative minor manipulation has the potential to change the outcome of the
task significantly. In the context of Experiment 1 it is assumed that the participants tried to minimize the processing of the words as much as possible, since in all conditions the word hampered task execution (that is, naming the picture). However, in Experiment 2 it might be beneficial to follow a different strategy, because in one third of the trials (the congruent trials), reading the word actually facilitates the correct answer. Because of the increased benefit of word processing as opposed to Experiment 1, more interference is predicted, which should be observable in a larger latency difference between the related and the unrelated condition.

METHODS
Participants
22 students of the University of Groningen (mean age 22.2, 14 male, 8 female) took part in this experiment for course credit. All were native speakers of Dutch and had normal hearing and normal or corrected-to-normal vision. The participants that took part in Experiment 1 were excluded from participation in Experiment 2.

Stimuli
The stimuli were the same as in Experiment 1, except that for the congruent condition, a third set of PWI-stimuli was created. The distractor words for these stimuli were the Dutch image descriptors.

Design
The design was the same as in Experiment 1.

Procedure
The procedure was the same as in Experiment 1. Due to the length of the experimental block (441 trials and three filler trials), the participants were allowed three breaks, after 25%, 50%, and 75% of the trials.
RESULTS

Again, we excluded trials according to the following criteria: Responses that were more than three standard deviations from a participants’ mean were excluded (2.1% on the PWI stimulus, and 2.3% on the tone, respectively). Trials in which the responses were in the incorrect order were also excluded (5.3%). Overall, 7.7% of the trials were excluded. The data of Experiment 2 are presented in Figure 2.16b. Experiment 2 is analyzed analogous to Experiment 1. Thus, we fitted a linear mixed effects model with relatedness, PRP-SOA, and repetition as fixed effects and participant and picture as random effects. An ANOVA on the factors revealed that there were main effects of PRP-SOA level ($\beta = -0.460; F(1, 8947) = 1192; p < 0.001$), relatedness ($\beta_{\text{related}} = 408; \beta_{\text{unrelated}} = 238; F(2, 8947) = 188; p < 0.001$), and repetition ($\beta = -22.0; F(1, 8947) = 315; p < 0.001$). Repetition also interacted with the other factors (repetition times relatedness interaction: $\beta_{\text{repetition x related}} = -43.7; \beta_{\text{repetition x unrelated}} = -16.7; F(2,8947) = 9.23; p < 0.001$ and repetition times PRP-SOA interaction: $\beta_{\text{repetition x SOA}} = -0.00586; F(1,8947) = 18.7; p < 0.001$) and there was a significant three-way interaction ($\beta_{\text{repetition x SOA x related}} = 0.0639; \beta_{\text{repetition x SOA x unrelated}} = 0.0352; F(2,8947)=8.41; p<0.001$). However, the main finding in Experiment 2 is that the PRP-SOA between tone presentation and PWI presentation does not have an effect on the interference effect size (PRP-SOA times relatedness interaction: $F(2,8947) < 1$).

DISCUSSION

The typical PRP speed-up is present, suggesting a correct operationalization of the PRP design and indicating the presence of “cognitive slack”. Therefore, the observation that the mean response latencies per relatedness condition differ at the shortest SOA (100 ms), suggests that the interference between distractor word and picture was longer than could be absorbed in the cognitive slack time. If participants process the word more often or to a higher level than in Experiment 1, the competition between conceptual representations will be stronger and hence the interference of the related words will be higher. However, it cannot simply be the case that the interference in the first stage of the process becomes larger. That would mean that for the long SOA level of 800 ms, the interference effect would become even larger, because with an SOA of 800 ms there is no cognitive slack time in which part of the interference can be resolved.

Figure 2.16: Data from (a) Experiment 1 and (b) Experiment 2.
Since the data show no interaction between interference and SOA, this simplest explanation does not seem likely. An explanation for this observation might be that the interference becomes more distributed over different stages of the task. The extended processing of the word does not only cause interference during the initial conceptual processing of the picture, but also during response stages. This explanation is in line with cascading models (Levelt, Roelofs, & Meyer, 1999; McClelland, 1979) in which activation from different stages spreads to each other, affecting processing later in the task. In this experiment, cascading activation means that the increased interference may partly be due to competition in the response stages, and is therefore not affected by the cognitive slack time, because the response is always after the delay. The cognitive model discussed below will demonstrate that one way of accounting for these effects is by assuming a different strategy than the one taken in Experiment 1.

**MODEL OF EXPERIMENT 2**

The model of Experiment 2 is the same as the model of Experiment 1, with the exception of the repetition priming mechanisms to keep the model tractable. The model performs the same task as in Experiment 1, but we assumed that participants in Experiment 2 were more likely to process the word than in Experiment 1. To account for this strategy, the model retrieves the lemma activation associated with the word stimulus upon word presentation. This differs from the strategy in the model of Experiment 1 in which the word was not actively retrieved and stored in the retrieval buffer until the response selection stage.

If word and picture are congruent, this new strategy means that lemma information on the picture is already available when the model requires it. It can therefore directly continue with retrieving relevant wordform information. In this case, the model performs two steps in parallel (conceptual and lemma retrieval), which accounts for the faster responses in the congruent condition. However, if word and picture are not congruent (that is, in the related or unrelated condition), the model initially retrieves the incorrect lemma. The reason for this is that the lemma’s activation was increased by the presentation of the word, which spreads more activation than the picture. Thus, the incorrect lemma is much more activated than the correct lemma, which represents the picture. Next, the model retries to retrieve the correct lemma, this time excluding the previously retrieved lemma from the retrieval set. However, the incorrect lemma still spreads activation, mediated by the concept chunks, to other lemmas, increasing the relative decision boundary. Therefore, retrieval in the related condition is slower than in the unrelated condition. To validate that a different strategy has been adopted in Experiment 2 as compared to Experiment 1, we also ran a model without the reading strategy.

**Model results and discussion**

Figure 2.17b presents the fit of the model to Experiment 2 (RMSE = 74 ms). Similar to the empirical data, the model shows an increased interference effect at an PRP-SOA of 100ms as compared to Experiment 1. Also, the model shows the standard PRP effect.

Figure 2.17a presents the model’s fit without the reading strategy on the previous experiment (Experiment 1, RMSE = 48 ms). Here, the model shows the dependence of the interference effect (the difference between the relatedness conditions) on the PRP-SOA between the tasks. If we calculate how well the no-reading-strategy model fits with Experiment 2, we find a much worse fit (RMSE = 392ms). Likewise, if we compare latency predictions of the reading-strategy model of Experiment 2 with the data of Experiment 1, we also find...
a worse fit (RMSE = 514ms, with congruent condition excluded). Thus, the two simulations combined show that in Experiment 1 participants are more likely to ignore the word as much as possible, whereas in Experiment 2 they are more likely to read the word upon presentation. This difference in strategy accounts for the difference in response latency patterns observed between Experiments 1 and 2.

GENERAL DISCUSSION

SUMMARY

In this paper, we have provided a theory of context effects on declarative memory. The theory, called Retrieval by Accumulating Evidence in an Architecture or RACE/A makes three important assumptions. First, RACE/A assumes that memory retrieval is a dynamic process, in which the probability of retrieval of information is continuously updated. Second, RACE/A assumes that memory retrieval consists of a competitive process, in which potentially relevant pieces of information influence each other’s probability of retrieval. Third, RACE/A takes into consideration that memory retrievals are embedded in a larger cognitive system. Although architectures or models that share the first two assumptions are not uncommon, RACE/A is the first account in which the detailed accounts of memory retrieval are embedded in a larger cognitive system that enables explanations on all levels of processing. Thus, these three assumptions make it possible to account for a large range of phenomena with a single theory.

First, RACE/A explains how latencies are a function of the distributed presentation of stimuli. Because the probability of retrieval is continuously updated, the cognitive system can adapt its retrieval process to new information that becomes available during the retrieval process (as in the PWI model), or adapt the retrieval process when information is no longer available (as in the masked priming model).

Second, RACE/A provides an explanation for interference effects found in the Stroop paradigm. The interference that exist between the target stimulus and the distractor stimulus is explained as a competition between chunks, in which both chunks related to the target stimulus and chunks related to the distractor stimulus accumulate activation, which results in lower Luce ratios and slower retrieval. Two major characteristics of the Stroop effect, the semantic gradient effect and the Stroop asymmetry, naturally follow from RACE/A.
The semantic gradient effect refers to the finding that the degree with which a distractor is semantically related determines the size of the interference effect (Klein, 1964). For picture-word interference this is apparent from the latency difference that exist between the related and unrelated distractors (see also Figure 2.8a and W. R. Glaser & Düngelhoff, 1984; Lupker, 1979). In RACE/A, distractors that have a stronger relationship spread more activation towards each other, which leads to decreased Luce ratios and increased competition. In the PWI model and the repetition-priming model, this property of RACE/A explains the difference between the related and unrelated conditions.

The asymmetry between word reading responses and color naming (or picture naming) responses that is present in the Stroop paradigm is explained by the different processing routes that are often hypothesized for words and pictures and colors (e.g., W. R. Glaser & Glaser, 1989; La Heij, Happel, & Mulder, 1990; Roelofs, 1992). Whereas naming colors or words requires retrieval of conceptual information from declarative memory, pronouncing a word can be done without access to the meaning of that word. Thus, the longer route for colors or pictures creates an asynchronous start of accumulation for the potential responses. As words are also processed faster than colors or pictures, the correct lemma is retrieved before the color or picture concept increases the activation of associated lemmas, effectively precluding any interference effects for word reading in Stroop or PWI tasks.

The third class of phenomena that are accounted for by RACE/A relate to the interplay between long-term memory and short-term retrieval processes. Because in RACE/A memory retrievals are embedded in a general theory of cognition, RACE/A can explain the interference dynamics in complex experimental designs. For example, the different interference patterns that Experiment 1 and Experiment 2 provide is explained by assuming that participants use a different strategy in Experiment 2, which boosts the activation of the distractor in such a way that the interference is increased.

WHY NOT JUST RETRIEVAL MODELS?

Many tasks can be thought of a sequence of declarative memory retrievals. For instance, word production can be thought of as a process in which the speaker first need to retrieve a message from memory, then lexical information, then morpho-phonological information finishing with a phonetic code (cf., Levelt, Roelofs, & Meyer, 1999). Each of these stages comprises one or more memory retrievals, that all influence each other. Moreover, when producing multiple words, each new word is influenced by the memory processes of the previous words. This is similar to a simple experiment with a sequence of trials, all of which comprise one or more memory processes. Often this results in (undesired) between-trial effects.

A cognitive architecture provides a framework in which between-trial effects can be studied, because it provides a theory on how declarative memory processes interact – with each other as well as with other cognitive processes. In addition, the architecture provides a theory on the temporal dynamics of a task or a sequence of trials. For a theory in which memory retrieval is presented as an sequential sampling process with asynchronous retrieval onsets, such as RACE/A, this is a crucial feature, because it provides a validated basis for the starting point values of the sampling process. The benefits of an architecture become clear when examining the cognitive models developed for the experiments reported in this paper. The PWI model demonstrates that a competitive memory process as RACE/A proposes can account for the interference effects observed in typical PWI experiments. However, to account for the complex interference patterns observed in Experiments 1 and 2, it is necessary to incorporate
the repetition priming mechanism in the model. In addition, theories of cognitive control as well as visual and aural perception as well as of manual and vocal responses are necessary to provide a quantitative prediction of the response latencies in Experiments 1 and 2.

In contrast, consider a study of a lexical decision task that had been repeated over 5 days, Dutilh et al. (in press; see also Wagenmakers, in press) found the typical speed-up in performance usually observed in practiced behavior. A diffusion model analysis of this task revealed that the speed-up could be attributed in part to the non-decision part of the response times. That is, the speed-up could be explained by processes other than the actual lexical decision, but rather by the perceptual or motor response processes that are also part of the task execution. We hypothesize that a \textsc{race/a} model analysis would have provided a similar result, but with \textsc{race/a} it would have been possible to theorize on the mechanism underlying the speed-up in non-decision time. One explanation would be that proceduralization of the motor responses would account for the speed-up. In \textsc{race/a} this process may be accounted for by production compilation (Taatgen & Anderson, 2002; Taatgen & Lee, 2003), in which multiple production rules are combined in one new one. This speeds up task execution because less production rules have to be selected in order to finish a trial.

This example shows that integrating an accumulator model of memory retrieval in a cognitive architecture may enhance the explanations derived from the model. In this case, an extra explanation for why the non-decision time decreases might be provided. In the cognitive models of the experiments reported above, the architectural structure provides a theory of cognitive control (Altmann & Gray, 2008; Salvucci & Taatgen, 2008), as well as theories on perception and action. While these theories may not be extremely detailed, they provide enough detail to understand memory and decision behavior in various task contexts (Gray, 2007a).

\textbf{WHY NOT JUST ACT-R?}

There have been previous attempts to model the Stroop effect in ACT-R (e.g., Altmann & Davidson, 2001; Juvina & Taatgen, 2009; Lovett, 2002, 2005). Thus, the question arises why a more detailed retrieval theory is needed in the first place. However, these models describe retrieval in a Stroop task as a ballistic process, with a retry-mechanism that checks if a retrieved chunk matches already retrieved information; If not, the retrieval is retried. Because words are processed faster than colors, the probability of an incorrect retrieval is highest if word and color do not match. If they do match, the response to the word is also the correct response, so no retry is required. Stroop interference is in this sense a function of the mean number of retrieval attempts before the correct answer has been retrieved. Although on average this may result in correct latency predictions, the predicted latency distributions essentially consist of a set of unimodal distributions, distributed around the time required to perform one retrieval, two retrievals, and so on, plus the time required for other processing steps. This does not seem to be a correct interpretation of the Stroop effect, since generally the latency distribution is considered to be unimodally (Heathcote, Popiel, & Mewhort, 1991).

A previous more general solution to interference effects in ACT-R is competitive latency. In this account, the predicted retrieval time is scaled according to the activation of competitors. If there are multiple competitors or relatively active competitors, retrieval times are decreased (Equation 2.7).

\[
RT = F \sum_{j \neq i} e^{A_j} \quad \text{(equation 2.7)}
\]
While in some situations this equation may give an accurate prediction of response time (e.g., Van Rijn & Anderson, 2003), there are some modeling-technical difficulties. However, the competitive latency equation remains a ballistic model of response time and is therefore not able to account for the kind of interference effect that we address in this paper. Similar to the default latency prediction in ACT-R (Equation 2.3), this model cannot account for the effects of asynchronously presented stimuli or masked stimuli.

**IMPLICATIONS FOR THE STROOP EFFECT AND PICTURE-WORD INTERFERENCE**

The PRP paradigm has been used to elucidate the mechanisms underlying the Stroop effect and picture-word interference (Dell’Acqua et al., 2007; Fagot & Pashler, 1992; Van Maanen, Van Rijn, & Borst, submitted). Fagot and Pashler (1992) performed a similar experiment as the Experiment 1 reported above, but instead of a picture-word interference task they used a Stroop task. In their experiment, participants were requested to classify a tone as either high or low and subsequently name the color of a Stroop stimulus. Fagot and Pashler tested two Stroop conditions, a congruent one in which word and color refer to the same color concept, and an incongruent one in which word and color refer to different color concepts. To remain consistent with our terminology, we will refer to this second condition as the related condition. The results of this experiment show that the difference between the congruent and related condition (the Stroop interference) is not dependent on the PRP-SOA between the tone onset and the Stroop stimulus onset. Assuming a central processing bottleneck (Pashler, 1994) or a cognitive control structure (Meyer & Kieras, 1997b; Salvucci & Taatgen, 2008), this result suggests that interference in a Stroop task takes place after the bottleneck stage, because otherwise the interference would have been absorbed in the cognitive slack time at small PRP-SOAs. This result is different from Experiment 1 as well as from (Dell’Acqua et al., 2007), where interference was found to be affected by PRP-SOA, suggesting that interference in pwi is absorbed in the cognitive slack time.

Dell’Acqua et al. argue that this difference between pwi and Stroop (absorption in cognitive slack time versus no absorption in cognitive slack time) is an indication that the mechanism that causes Stroop interference differs from the mechanism that causes picture-word interference (but see Van Maanen, Van Rijn, & Borst, submitted, for another interpretation of these results). However, the pwi conditions contrasted in our Experiment 1 and in the Dell’Acqua study are the related and the unrelated conditions, whereas the Fagot and Pashler (1992) study contrasts the related and the congruent conditions. Experiment 2 provides a new perspective on this discussion, because here a congruent pwi condition is included. Given that in Experiment 2 the difference between the congruent and related condition was not mediated by PRP-SOA, we might conclude that the difference between picture-word interference and Stroop was a difference in task conditions, and not caused by a different processing stage. However, this conclusion is still speculative, since Experiment 2 included a third condition as well. As our experiments demonstrate, the latency patterns in PRP experiments depend on the participants’ expectations as much as on constraints on cognitive processing.

RACE/A shows that an accumulator model in the context of a cognitive architecture provides accurate latency predictions, that can account for the interactions that exist between competitive processes in memory retrieval, long-term learning effects, and cognitive control.
Evaluation of the RACE/A Integrated Model of Memory Retrieval

Introduction

In the previous chapter Retrieval by ACcumulating Evidence in an Architecture (RACE/A) was introduced. This theory is aimed at explaining competitive effects during memory retrieval. The competition between different memory traces is evoked by association between the competing traces. Thus, if two traces spread activation to each other and they are both possible candidates for a particular retrieval from memory, they will compete for retrieval. Competition in memory retrieval seems to be ubiquitous in behavior. For example, every decision one makes based on previous knowledge involves memory retrieval. To demonstrate that many interference phenomena are competitive effects in memory retrieval, we will discuss a series of different experiments in this chapter that show the breadth of RACE/A. The most obvious effects that RACE/A should account for are effects in lexical decision. The accumulator models on which RACE/A is inspired are often intended at lexical decision experiments (e.g., Wagenmakers et al., 2008). We will first shortly introduce the RACE/A model of lexical decision (Section 3.1), and then elaborate on two RACE/A models that account for competitive effects that are less straightforward. These are the asynchronous presentation of stimuli (Section 3.2) and the masked or subliminal priming paradigm (Section 3.3).

If the onset of stimulus presentation is asynchronous, the interference effects that stimuli have on each other is a function of the onset asynchrony. That is, the closer the stimuli are presented in time, the more effect there is. For example, in picture-word interference, in which participants are required to name a picture, while ignoring a word that is presented at an asynchronous onset (either before or after the picture), the effect size is correlated with the onset (but not monotonically, see Section 3.1 and W. R. Glaser & Düngelhoff, 1984). While this effect is something that may be studied in a regular accumulator model, the architectural foundation of RACE/A provides a theoretical framework for the onset timing of the various memory retrievals that play a role in the picture-word interference paradigm.

If the presentation of a stimulus is only present temporary, such as if the stimulus is masked (e.g., Marcel, 1983) or in a signal-to-respond paradigm (e.g., Wagenmakers et al., 2004a), than the effect size of interference effects is also affected. The model in Section 3.3 describes this situation. The model fits data from a Stroop task in which the words are presented subliminally. That is, the words are presented for such a short time that participants report not being aware of the presence or absence of the word. The color patches on which they have to respond are continuously present. Smaller Stroop effects than in the default experiment are found under these conditions (Marcel, 1983), which is explained by RACE/A by less time to accumulate activation for the word, resulting in a higher Luce ratio for the color.
A RACE/A MODEL OF LEXICAL DECISION

In lexical decision, participants are presented with a letter string and are required to indicate whether the string forms a correct word (e.g., BALK for Dutch or CREAM for English) or not (e.g., BALC and CEARM). Lexical decision is often ascribed to a sampling process in which evidence for the hypothesis that the letter string is a word is sampled, until a threshold has been reached. If the threshold is reached, the participant will provide a “word” response. If a certain fixed amount of time (a deadline) has passed, the participant will respond “non-word” (e.g., Coltheart, Rastle, Perry, Langdon, & Ziegler, 2001; Grainger & Jacobs, 1996). These models can be interpreted as a serial search of memory for a word matching the letter string.

Contrary to these deadline models, in the RACE/A model of lexical decision, the non-word responses are driven by an extra accumulator that samples the likelihood that the current letter string is not a word. This means that when time passes, the likelihood of a non-word response increases. If the Luce ratio of the non-word crosses the decision boundary (as discussed in Chapter 2), the model responds with a non-word response. If the Luce ratio of the word-response crosses the decision boundary, the model responds “word”.

Because the drift rate in the model is determined by the familiarity of the word (in case of “word” responses), words that have a high frequency of occurrence in natural language are recognized faster, resulting in faster responses. Figure 3.1 presents the fit of the lexical decision model on data from an experiment by Glanzer and Ehrenreich (1979). In the experiment, Glanzer and Ehrenreich studied the difference in response time between high frequent and low frequent words, as well as the response time associated with non-word responses. They found that on average, participants respond faster on high frequent words than on low frequent words, and slowest to non-words.

The model accounts for the basic lexical decision word frequency effect by assuming higher base-level activation values for high frequent than for low frequent words. This results in a faster decision process, and therefore shorter response times.

The model is very straightforward and in line with previous accumulator models of lexical decision (e.g., Brown & Heathcote, 2008; Ratcliff, Gomez, & McKoon, 2004; Wagenmakers et al., 2008; Wagenmakers et al., 2004a), but it accounts for an extra finding that most accumulator models of lexical decision cannot explain (but for an exception see, Wagenmakers et al., 2008).
If the stimuli are words that are very infrequent, that is, word that are extremely rare in natural language use, then participants remain able to accurately respond to these, but at a significant time cost: The average response time under these conditions exceeds the average response time for non-word responses (Wagenmakers et al., 2008). Models that incorporate a strict deadline for the accumulation process fall short here, because these would assume that the non-word responses are only given if the word search has terminated. Therefore, the mean latency of non-word responses is predicted not to exceed the mean latency of correct word responses. These model predictions are not in agreement with Wagenmakers et al.’s findings.

The RACE/A model of lexical decision does account for the effects found by Wagenmakers et al. (2008). In the RACE/A model, the probability of not retrieving a word accumulates, similar to the probabilities of finding a particular word. Because the decision on what to retrieve from memory depends on the Luce ratios of the words and the non-word representation, the response latency for very low frequent (VLF) words can be extended beyond the average non-word response time. In case of a VLF trial, the memory trace of the VLF word accumulates very slowly, but so does the non-word representation. The Luce ratio of the VLF word increments thus very slowly, increasing the decision time. In case of a non-word trial, only the non-word representation accumulates. Because no word representations (including the VLF word) interfere, the decision time may be shorter than on VLF trials (and so is the latency). By contrast, the non-word decision time is longer than the decision time for words that are more frequent. For these words, the decision time is fast because the accrual rate is much higher than the accrual rate of the non-word representation. Figure 3.2 presents the fit of the model on the data from Wagenmakers et al. (2008). Besides the median latency, the model also captures the latency distributions to some extent, as indicated by the plotted quantiles.

![Figure 3.2. Fit of the lexical decision model to a data set of Wagenmakers et al. (2008). The figure shows the 10%, 30%, 50% (black markings), 70%, and 90% quantiles of the latency distributions. HF: High frequent words; LF: Low frequent words; VLF: Very low frequent words; NW: non-word letter strings.](image)
**INTRODUCTION**

Often, symbolic models of cognition can be thought of as giving a stroboscopic account of cognition. By illuminating a process such as a movement with a stroboscope, the movement is sliced into discrete steps that together represent the original, continuous, movement. However, information about the movement is lost when the stroboscope does not flash, and an observer will not be aware of how the movement develops during these brief flash intervals. Similarly, symbolic models of cognition reflect a continuous cognitive process on a higher level of analysis, but on a lower level of analysis, analogous to a single flash of the stroboscope, these models provide a discrete account of that process. In most cases, interpreting the higher level of analysis as a continuous process is sufficient for understanding cognitive functioning, but in some tasks, the underlying discrete account might provide a misinterpretation of the process.

As a general example of such a task, consider the way retrieval of memory chunks is modeled in the ACT-R architecture of cognition (Anderson et al., 2004; Anderson & Lebiere, 1998). Retrieval latency is based on the activation of the to-be-retrieved memory chunk:

\[ RT_i = F e^{-A_i} \]  

Equation 3.1 states that the retrieval time (RT) of a chunk (i) is inversely proportional to the exponentionally scaled activation of that chunk (A_i), with F a scaling parameter. If a retrieval request is made to the declarative memory system, the activations of all chunks are compared, and the highest is selected for retrieval. The latency is calculated according to the above equation and, after the appropriate amount of time has passed, retrieval of that chunk is reported. Even if new information is presented between the retrieval request and the actual retrieval, the retrieval result and latency cannot be influenced.

However, many experiments show that information that is presented shortly before or after a target stimulus can influence both the timing and accuracy of the task at hand (e.g., MacLeod, 1991; Neely, 1991). In a picture-word interference task for example, participants respond slower in the picture-naming task when a distractor word is presented, even if that distractor word is presented shortly after the target stimulus.

Since ACT-R has been successfully applied to numerous memory related tasks (e.g., Anderson et al., 1998; Pavlik & Anderson, 2005; Taatgen & Anderson, 2002), it should also provide an explanation of picture-word interference phenomena. However, given the ballistic nature of the way memory retrieval is currently modeled in ACT-R, the question becomes how ACT-R can be extended to include interference phenomena on very short latencies. In this paper, we will present a means to extend the ACT-R architecture of cognition to incorporate these interference effects. While we extended the memory system of ACT-R, we have made sure that the main characteristics of the tested and proven declarative memory equations were not altered. This way, we made sure that our approach towards semantic interference fits in with a broader theory of cognition, while at the same time we add a new phenomenon to the subset of cognition that ACT-R can account for.

A candidate explanation for semantic interference effects comes from the field of choice behavior modeling. In sequential sampling models of simple choice behavior, the choice between candidates is modeled by competition between candidates. Sequential sampling is based on the idea that choosing one option over the other is based on sampling of inherently noisy neural representations of these choices, until one has sampled enough evidence to be chosen (Ratcliff & Smith, 2004). The RACE (Retrieval by ACcumulating Evidence) model
presented in this chapter is very similar to a specific instance of sequential sampling models: The leaky competing accumulator model as discussed by Usher and McClelland (2001). RACE is implemented using the same basic principles as the leaky competing accumulator model: (a) it consists of a set of non-linear stochastic accumulators, all of which represent one memory chunk that can be retrieved. (b) The activations of the accumulator units are increased by external input and recurrent activation, but are decreased by lateral inhibition and decay. However, the actual implementation of some aspects differs, most importantly different activation and evidence accumulator functions, both of which have been adapted to fit RACE in the ACT-R framework.

**RACE Architecture**

The name RACE (Retrieval by ACcumulating Evidence) reflects both the accumulation of evidence for memory representations and the competition between memory chunks during retrieval: The comparison with a race between chunks seems appropriate in this respect. The activation levels of memory chunks in RACE consist of two components: A long-term component that governs the global activation of chunks and a short-term component that comes into play during the retrieval process. The long-term component is represented by the ACT-R base-level activation equation (Anderson et al., 2004):

$$B_i = \ln \left( \sum_{j=1}^{n} e^{-d(t_j - d)} \right) \quad [\text{equation 3.2}]$$

where $t_j$ is the time since the $j$th presentation of a memory chunk and $d$ is the parameter that controls decay, which is fixed at 0.5, as is common practice for ACT-R models (Anderson et al., 2004). The idea is that memory decays over time unless attention is shifted to a memory chunk and its activation is strengthened.

RACE’s short-term component, called accumulated activation ($C_i$, to avoid confusion with the general symbol for activation $A_i$ used in ACT-R), is continuously computed from the moment that a request for retrieval of a chunk is made. The accumulated activation of chunks changes as a consequence of positive and negative influences from other chunks. Chunks from the same chunk type inhibit each other, thereby competing for accumulated activation increase. Chunks of different chunk types excite each other, spreading their activation in the classical sense (Collins & Loftus, 1975). Thus, by continuously updating positive and negative spreading activation, some chunks may reach a level of activation at which retrieval can take place.

The accumulated activation can be described as a system of two dependent equations (Equations 3.3 and 3.4 presented below). As stated earlier, these equations incorporate the basic assumptions of Usher and McClelland (2001), but are adapted to fit in the ACT-R framework.

$$E_i^k(t) = \sum_{j \not= k} e^{A_j(t-1)} S_{ij} - \sum_{l \not= k} e^{A_l(t-1)} S_{il} \quad [\text{equation 3.3}]$$

The system functions as follows: At every time step, positive associative values (reflected by the first term of Equation 3.3) and negative associative values (second term of Equation 3.3) towards a memory chunk are computed and the difference is calculated. This is called the net evidence $E_i^k(t)$ of chunk $i$ of chunk type $k$ at a certain time $t$. Since relative – not absolute – activation values are what count in ACT-R, an exponential scaling is applied to calculate net evidence. Also, both positive and negative associative values are weighted by the associative strengths ($S_{ij}$ and $S_{il}$) that exist between sources of activation and the chunk $i$. There are two types of sources of activation in RACE: Chunks ($l$ in Equation 3.3) of the same chunk type ($k$)
spread negative activation to each other, while chunks \( j \) of different types spread positive activation. This is analogous to neurobiological findings from which it is clear that lateral inhibition between cortical representations of visual stimuli (Kastner, De Weerd, Desimone, & Ungerleider, 1998) as well as excitatory projections to other cortical layers (Callaway, 1998) exist. Note that most ACT-R models do not place constraints on the functional role of chunk types (although it does pay a role in production compilation, Taatgen, 2005).

\[
C_i(t) = C_i(t-1) + e^{\beta E_i(t-1)} - d_{\text{acc}} \cdot \ln T.
\]  

(equation 3.4)

At each point in time, the net evidence determines the accumulated activation growth (Equation 3.4). Accumulated activation increases exponentially according to the amount of net evidence and a scaling factor \( \beta \). If net evidence is negative (that is, more inhibition than excitation), then growth is negative. At all time steps, evidence decays with (represented by the second term of Equation 3.4), in which \( T \) is the time since the start of the accumulation and \( d_{\text{acc}} \) a decay parameter. This way, accumulation decay in RACE resembles decay in the ACT-R optimized learning equation (Anderson & Lebiere, 1998).

The activation of a chunk at any time is the sum of base-level and accumulated activation, plus a small normally distributed noise sample. A chunk is retrieved if this total activation crosses the accumulation threshold. The retrieval latency is defined as the time between the retrieval request and the time that the total activation of a matching chunk reaches this accumulation threshold.

If no evidence is sampled, accumulated activation decreases because of decay. Therefore, continuous evidence-based positive reinforcement is necessary for successful retrieval, and absence of positive evidence results in prolonged retrieval latencies or retrieval failures.

**PICTURE–WORD INTERFERENCE**

One of the most well-known experimental paradigms in cognitive psychology is the Stroop-task (Dyer, 1973; Stroop, 1935), where, in the original setup, participants have to either name the color a word is written in, or read the word, which is always a color name. It turns out that naming the color is much more difficult than reading the word – especially if color and word of a single stimulus do not correspond – as is reflected in increased reaction times and decreased accuracy in the color naming condition. The Stroop-task can be regarded as an instance of a more general class of experiments that demonstrate interference effects in various naming tasks between pictorial stimuli and word-form stimuli. These experiments are generally called picture-word interference experiments (W. R. Glaser & Düngehoff, 1984; MacLeod, 1991). In the case of the Stroop-task, the pictorial stimulus is the word color.

We tested the RACE model in a picture-word interference task, using two tasks and four different conditions, similar to the experimental setup in Glaser and Düngehoff (1984, Experiment 1). One task consisted of reading a word (target stimulus) while a picture is presented as distractor; the other task consisted of naming the depicted item (target stimulus), while a word is presented (distractor). In both tasks, the distractors were presented at different SOAs (Stimulus Onset Asynchronies). If a distractor was presented at a negative SOA, it was presented before the target stimulus. At positive SOAs, the distractor was presented after the target stimulus. Figure 3.3 presents stimuli examples of the different conditions. The first condition (Figure 3.3a) was one in which both target and distractor stimulus refer to the same concept. This is referred to as the concept-congruent condition. In two other conditions, target and distractor stimulus refer to different concepts. In the category-congruent condition the concepts belong to the same semantic category (e.g., a picture of a house and the word...
church were presented, Figure 3.3b), in the incongruent condition the concepts do not belong to the same semantic category (e.g., a picture of a house versus the word cat, Figure 3.3c). In the neutral condition the target stimuli were accompanied by non-word or non-picture distractors, respectively, to minimize the amount of processing of the distractor stimulus (Figure 3.3d and 3.3e).

Glaser and Düngelhoff (1984) found that interference is highest in the category-congruent condition, which is known as the semantic gradient effect. They also showed facilitation in the concept-congruent condition, meaning that latency is decreased when both target and distractor stimuli refer to the same concept. A third effect they report is a clear asymmetry between the picture naming task and the word reading task. The semantic gradient and facilitatory effect virtually disappear in the word reading task, but they are prominent in the picture-naming task.

**PICTURE-WORD INTERFERENCE MODEL**

We will begin our discussion of the picture-word interference model with a review of the weaver++ model of speech production (Levelt, Roelofs, & Meyer, 1999). weaver++ is similar to RACE in some ways, but lacks the integration in a cognitive architecture that we provide. weaver++ has a similar memory structure as RACE, and a similar activation accumulation mechanism as RACE. In weaver++ however, it remains unclear how the model is connected with other aspects of cognition besides language production. Although weaver++ and previous versions of that theory have been demonstrated to fit an impressive number of data sets (e.g., Levelt, Roelofs, & Meyer, 1999; Roelofs, 1992, 1997, 2003), it lacks a unified account of cognition, that for instance ACT-R does provide. RACE’s integration in the ACT-R framework ensures that our account can be naturally integrated in models of other aspects of cognition. One example of this is the subliminal priming model described by Van Maanen and Van Rijn (2007a).

Word production in weaver++ goes through a sequence of stages, one of which is the retrieval of the to-be-spoken word from semantic memory. In weaver++ this response selection stage (choosing a lemma) is followed by response programming and execution stages. Since our focus has been on the retrieval process, these vocalization aspects of the task are not included in our model of picture-word interference. The RACE mechanism is similar to the mechanism proposed for the lexical selection stage in weaver++ (1992).

The lexical processing stage from weaver++ is modeled as follows: A network of conceptual nodes is connected to a network of lemma nodes. The conceptual nodes convey meanings, and are connected with labeled links. For instance, The concept DOG(X) represents...
the meaning of the noun dog, and has a labeled connection of the type IS-A to the concept node ANIMAL(X), indicating that a dog is an animal (Roelofs, 1992). The nodes in the lemma network represent the syntactical dependencies of the concept nodes. Each lemma node has a labeled SENSE link to the corresponding concept node, labeled links to syntactic properties – grammatical gender, syntactic category. The links between concept nodes and between concept and lemma nodes differ in their connection strength, indicating a difference in accessibility. Via a spreading activation mechanism, activation of one node influences activation of neighboring nodes. Activation is also mediated by decay.

If the ratio of the activation of one lemma node against the activations of the others exceeds a predefined (relative) criterion, selection of that lemma node takes place, and WEAVER++ will proceed with the retrieval of the morpho-phonological properties of that lemma.

Analogous to WEAVER++, our model of picture-word interference comprises three chunk types (Figure 3.4): Icons, lemmas, and concepts. The concept chunks can be regarded as representations of semantic properties. Chunks of the icon type represent iconographic instances of the stimuli. This might be similar to Roelofs (1992) object-form memory store. Chunks of the lemma type can be regarded as sets of both orthographic and syntactic properties of a word. Note that this is a simplification of Roelofs’ (1992) model, in which the response selection stage (choosing a lemma) is followed by response programming and execution stages. Since our focus is on the retrieval process, these vocalization aspects of the task are not included in our model of picture-word interference.

Figure 3.4. Processing route for pictures and words in the picture-word interference model. The route for words is shorter, since words do not require concept retrieval. Interference takes place between concept type chunks.

Positive activation is spread between chunks of different types. That is, icons spread to concepts and vice versa, and lemmas spread to concepts and vice versa. As in Roelofs’ (1992) model, no direct spreading activation was allowed between lemmas and icons. The concept chunks also have negative associations between them and spread negative activation to each other.

At different SOAs, distractor stimuli were presented to the model, except in the neutral condition in which only a target stimulus was presented. We tested the same four conditions as Glaser and Düngelhoff (1984) did. The only deviation from the original experiment was the neutral condition: Glaser and Düngelhoff presented the participants with a non-word distractor and a non-picture distractor respectively in the picture naming and word reading neutral condition. As said, these were chosen in such a way as to minimize the amount of picture or word
processing as possible. Assuming a successful operationalization by Glaser and Düngelhoff, we simulated this condition by not presenting a distractor in the neutral condition.

In the concept-congruent condition, the distractor consisted of a word stimulus referring to the same concept as the target, but of a different stimulus type (as in Figure 3.3a). When activation spreads through the model, both distractor and target activate the same chunks, but not in the same order. The word will activate its associated lemma directly, whereas the picture will first activate the associated icon and concept chunks. In the category-congruent condition and the incongruent condition, the distractor and the target refer to different concepts. However, in the category-congruent condition, associations between chunks representing these concepts exist, reflecting the fact that the target and distractor stimuli belong to the same semantic category.

The distractors were presented at SOA times relative to the onset of the target stimulus of -400, -300, -200, -100, 0, +100, +200, +300, and +400ms, similar to the original Glaser and Düngelhoff experiment. The stimuli presentations were modeled as a fixed increase in activation of the lemma or icon type chunks during the period that a stimulus was presented.

Since the task was a verbalization of either the picture name or the word, a trial was finished when the stimulus-designated lemma was retrieved or after two seconds, indicating a retrieval failure.

In the picture naming task, the model predicts the following behavior: In the concept-congruent condition with negative SOAs, a distractor word is presented before the target picture. The word activates a lemma chunk, which increases the activation of the associated concept chunks, but inhibits the activation increase of other lemma chunks. The higher activation of the concept chunks increases the activation of the associated icon chunks. Thus, after the distractor is presented, all chunks that are involved in naming the picture (one icon, one concept, and one lemma chunk) have an increased activation. When the target is presented, all concept-congruent chunks have a higher activation as compared to the stimulus onset in the neutral condition, and thus a shorter retrieval latency. In the concept-congruent condition with positive SOAs, the same process occurs, but to a lesser extent since the distractor lemma’s activation has less time to influence the activation of the target lemma before it is retrieved: The picture has already increased the target lemma’s activation before the word is presented.

In the incongruent and category-congruent conditions (both at negative and positive SOAs), the activation of the chunks that are activated by the distractor interferes with the activation of the chunks that are activated by the target, because the target and the distractor stimulus activate different sets of chunks.

RESULTS

Figure 3.5 summarizes the results of our simulation studies. The figure represents the latency differences in different conditions relative to the neutral condition. Since the focus of our model is on the retrieval part of the picture naming and word reading tasks, we can compare the latency differences between the different conditions from the model to the data. The observed latencies from the data set also comprise timing effects from other subtasks, such as pronunciation or perceptual encoding.

Negative values in Figure 3.5 indicate faster retrievals than in the neutral condition, and positive values indicate slower retrieval than in the neutral condition. The qualitative effects
observed in Glaser and Düngelhoff (1984 Experiment 1) can be seen in the predicted latency differences from the RACE model. The semantic gradient effect can be observed by noting the different relative latencies of the category-congruent and incongruent conditions. The higher latencies in the category-congruent condition compared to the incongruent condition indicate that higher associations between concepts result in stronger inhibition.

The facilitatory effect in the picture-naming task is also apparent, although the effect appears to be too large. Our explanation for this increased effect is that the activation of the target lemma chunk is too high if the target stimulus is presented, probably caused by too little decay after the previous retrieval initiated by the distractor stimulus. Another consideration might be that the base-level activation goes to near infinity directly following a retrieval, thus causing too much increase in activation of the target lemma chunk. This may also explain the observed effect in the simulation of the word-reading task. Thus, it seems that the base-level activation may not be a good measure of the level of activation of a chunk at these short time intervals. Because RACE is intended as an extension of the ACT-R framework, it did not seem appropriate to change the way in which the global, long-term activation is computed.

When comparing the differences between the two simulated tasks (picture naming and word reading), the asymmetry observed by Glaser and Düngelhoff is also shown by RACE. We explain this asymmetry by two effects: The shorter processing route and the faster encoding of word type stimuli. As Roelofs (W. R. Glaser & Glaser, 1989; La Heij, Happel, & Mulder, 1990; 1992) noted, pronouncing words does not require retrieving a concept from memory, therefore processing word type stimuli can be much faster than processing pictorial stimuli. In Figure 3.3 it can be seen that the route in our model from a picture to the associated lemma is much longer than from the word to the associated lemma: Two intermediate steps have to be taken (that is, processing of icon chunks and processing of concept chunks), before the lemma chunk is retrieved. Thus, potentially interfering pictures do not activate lemma chunks before the target lemma is retrieved. Only at high negative SOAs an effect can be seen (Figure 3.5), because under that condition there is enough time for the distractor stimulus to activate the inhibiting distractor lemma and interfere with retrieval of the target lemma.

A difference in encoding speed is incorporated to account for the observation that word recognition is an automated process and picture recognition is not. Without this difference, the model processes pictures nearly as fast as words, and picture naming in the incongruent condition is as fast as in the neutral condition. The faster encoding of words reinforces the
effect that the lemma associated with a word is processed before the lemma associated with the picture stimulus is retrieved.

**DISCUSSION**

We have shown that a sequential sampling model can account for the time course of memory retrieval during asynchronously presented stimuli. This is an extension of the results from Usher and McClelland (2001) in which they only investigated accumulators with equal onset times. Moreover, RACE can be regarded as an extension of the ACT-R theory of cognition. It combines the long-term base-level activation equation of ACT-R with a short-term accumulated activation used for retrieval. RACE replaces the retrieval mechanism in ACT-R represented by Equation 3.1.

The general fit of our model of picture-word interference is quite reasonable, thereby indicating that the RACE equations can provide for semantic interference effect in memory retrieval. Retrieval in the concept-congruent condition seems to be too fast, however. We hypothesize that this is a result of the way we modeled the global, long-term activation component, namely by using ACT-R’s base-level activation equation. Because in the concept-congruent condition the target and distractor stimuli both refer to the same chunks, retrieval of these chunks - caused by the distractor stimulus - increases their base-level activations. The high activation of these chunks will result in a very short latency for the retrieval caused by the target stimulus. It seems that the base-level activation equation is a better predictor of activation at slightly larger time scales, when the retrievals are more spaced. This is supported by the observation that retrievals in most ACT-R models are temporally more separated than ~100ms. Further research in the interaction between the base-level activation and accumulated activation seems necessary to correct for the fast retrievals in the concept-congruent condition.

Also, our model accounts for facilitatory effects. In line with the findings from Glaser and Düngelhoff (1984), RACE predicts that semantic facilitation occurs if target and distractor both refer to the same concept.

In the past, ACT-R models of semantic interference effects have been proposed (Altmann & Davidson, 2001; Lovett, 2002, 2005). The WACT model (Altmann & Davidson, 2001) seems similar to RACE at first sight, since it combines ACT-R with insights from the WEaver++ model. However, WACT describes retrieval in a Stroop task as ballistic, but with a retry-mechanism that checks if a retrieved lemma chunk matches already retrieved conceptual information; If not, retrieval is retried. Thus, WACT accounts for inhibitory effects by multiple retrievals caused by retrieval failures. As such, WACT is a perfect example of a stroboscopic account of cognition. Retrieval latency for one trial can be the latency associated to one retrieval attempt, or two retrieval attempts, or many, but nothing in between. Therefore, the distribution of reaction times predicted by WACT is clustered around the time it takes for one or multiple retrieval attempts. This does not correspond with the general assumption that participants’ reaction times in the Stroop-task are unimodally distributed (Heathcote, Popiel, & Mewhort, 1991).

NJAMOS (Lovett, 2002, 2005) is an ACT-R model of the Stroop task that theorizes that the Stroop effects are due to utility differences in the production rules for word and picture recognition. In the model, a general production rule is assumed that fires if a stimulus is present that has some word-like qualities, irrespective of the current task (color naming or reading). In addition, a more specific production rule is assumed that only fires if the task is
color naming. The second rule has a lower utility than the first, meaning that the system has a preference to execute the first rule over the second. Therefore, in most cases (because of noise over the utility values), the second rule will only be selected after the first production has fired. In those cases the first rule has not completed the task successfully, because the task was color naming, not word reading. The second rule thus has to fire to complete the task. This two-step procedure for color naming is intended to explain the Stroop asynchrony between reading and color naming.

If the color and the word are congruent, the chunk that encodes the word-like features of the stimulus spreads activation to the chunk that encodes the color information. The activation of that chunk will increase, resulting in the facilitatory effect at negative SOAs. In the incongruent condition, negative spreading activation is introduced to explain the interference effects.\(^7\)

At small positive SOAs (e.g., +100ms), NJAMOS also predicts a divergence between the latencies for different conditions, although smaller than that observed in the data (Lovett, 2002). Given the ballistic retrieval latency equation of ACT-R, it seems that these latencies can only be explained by averaging over several trials. That is, either one (the general rule) or two production rules (both general and specific) will fire, resulting in a bimodal distribution of the data. Again, the distribution of the Stroop-latencies does not seem bimodal (Heathcote, Popiel, & Mewhort, 1991).

We suggest that not fully processed words at small positive SOAs might explain this difference between model and data. Perhaps a combination of the utility-based explanation Lovett proposes combined with RACE will produce a better fit to the data.

The picture-word interference experiment shows that the RACE model can be a useful extension of the ACT-R architecture of cognition. However, one crucial feature of RACE is not supported by the ACT-R architecture. In RACE, all chunks in declarative memory spread activation to all other chunks. ACT-R assumes that only chunks that are presently in the buffers spread their activation (Anderson et al., 2004).\(^8\) Global spreading-activation was not included in the architecture because it appeared that no second-order priming effect exists, indicating that spreading of activation through declarative memory was not necessary (Anderson, 1990).

However, more recent evidence suggests a second-order priming effect, although very weak, that cannot be explained by assuming only first-order associations between prime and stimulus (Livesay & Burgess, 1998). Therefore, we consider this deviation of ACT-R theory reasonable.

Experiments using subliminal primes indicate that priming may also occur when a prime is not fully processed (Marcel, 1983; Mericle, Smilek, & Eastwood, 2001), which hints that priming already occurs before chunks in the buffers are fully identified. A dynamical activation mechanism such as RACE may provide accurate modeling accounts for this observation. In RACE, activation of chunks – either in the buffers or in declarative memory – always affects the activation of other chunks, even before the accumulation threshold is reached and a chunk might be retrieved. A RACE model of a subliminal priming task has been shown to account for retrieval latencies typically observed in these kinds of tasks (Van Maanen & Van Rijn, 2007a).

This section demonstrates how RACE can account for picture-word interference phenomena. We believe that RACE can account for all effects that involve semantic interference or facilitation. Using RACE, an explanation of these effects can be provided on a higher level of abstraction than connectionist modeling, because it is integrated in a full cognitive architecture. This way, RACE combines insights from multiple levels of abstraction.

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\(^7\) Note however that this is an undisputed deviation from standard ACT-R, where spreading activation is intended to be positive because it represents the increased likelihood of needing one chunk when another chunk is present.

\(^8\) In ACT-R 6.0, chunks in all buffers can spread activation, as opposed to ACT-R 5.0, in which only chunks in the goal buffer could be a source of activation.
A MODEL OF SUBLIMINAL PERCEPTION

INTRODUCTION

Successful behavior depends for a large part on having declarative knowledge available at the right time. Humans are therefore continuously retrieving declarative facts from long-term memory storage, based on their continuously updated perception of the environment. The continuous character of perception is reflected in the memory retrieval process, as can for instance be observed in the retrieval latencies of psychonomic experiments in which stimuli are asynchronously presented (e.g., picture-word interference, W.R. Glaser & Düngelhoff, 1984) or in experiments in which the presentation durations of stimuli are manipulated (e.g., subliminal priming, Marcel, 1983). A cognitive model of declarative memory retrieval should also reflect the continuous character of the input on which memory retrievals are based. However, current cognitive architectures such as ACT-R (Anderson et al., 2004) or Soar (Newell, 1990) cannot satisfactorily account for this (Van Maanen & Van Rijn, 2006; Van Maanen & Van Rijn, 2007b).

Retrieval by ACcumulating Evidence (RACE) is a model that does describe the process of retrieving one or more chunks of information from memory. In RACE, memory retrieval is not considered ballistic, but is rather thought of as a process in which the likelihood that a piece of information will be needed for successful behavior is continuously estimated. Therefore, the likelihood estimate can be continuously adapted to the changing environment.

RACE can be perceived as an interaction of ideas from cognitive architectures that rely on symbol manipulation (Anderson et al., 2004; Newell, 1990) and ideas from sequential sampling models (Ratcliff & Smith, 2004; Usher & McClelland, 2001). The architectural nature is clear from the cognitive constraints imposed on RACE. In the current implementation of the theory, we constrained RACE by adopting the rational approach that is intrinsic to the ACT-R cognitive architecture (Anderson et al., 2004). However, the subsymbolic computations that drive declarative memory retrieval are rooted in sequential sampling.

This paper will describe how RACE is implemented in the ACT-R architecture of cognition and will present a RACE model of a subliminal priming task. We will discuss which features of RACE naturally align with ACT-R, and which features of RACE seem to contrast with ACT-R. We chose to implement RACE as an extension to ACT-R because of ACT-R’s widespread use in the cognitive modeling world (see for instance the web site of the ACT-R community: http://actr.psy.cmu.edu). More importantly however, adopting an existing general approach towards cognition will reduce the proliferation of different cognitive theories (Newell, 1990), and will constrain theorizing about RACE. A third reason for choosing ACT-R as a modeling framework is that the way ACT-R defines retrieval latency has difficulties with modeling semantic interference (Van Maanen & Van Rijn, 2006; Van Maanen & Van Rijn, 2007b). Extending ACT-R with RACE might solve this issue.

ACT-R

A prominent theory that explains behavior at the symbol manipulation level is the ACT-R architecture of cognition (Anderson et al., 2004). Because RACE is implemented as an extension to ACT-R, we will give a very short overview of the architecture, concentrating on these aspects of the theory that relate to declarative memory retrieval.

ACT-R is a cognitive theory in which production rules operate on declarative memory and the environment. Production rules are conditions-actions pairs whose actions are executed if their conditions are met. To determine which production rule’s actions will be executed,
ACT-R contains a set of buffers of which the content is matched against the conditions of each production rule. If multiple production rules are applicable – meaning that, given the buffer contents, multiple sets of actions may be performed – the production rule with the highest utility will be selected, a process called conflict resolution. By default, the buffers represent the current goal of the system, the current perceptual state, and a declarative fact that is currently in the focus of attention, that is, that is recently retrieved from long-term memory. Other buffers may be defined if necessary for the task at hand (as has for instance been done for prospective time interval estimation, Taatgen, Van Rijn, & Anderson, 2007). The content of a buffer is a chunk: a symbolic unit that represents a simple fact, such as The capital of Canada is Ottawa, or The object I am attending is green and spherical. Both these example chunks are declarative facts, but the first example can typically be found in the retrieval buffer, and represents a fact that has been retrieved from long-term memory, whereas the second example represents a visually observable fact of the world, and might be present in the visual buffer. In the context of this paper, we are primarily interested in the way ACT-R incorporates retrieval of chunks from long-term memory, although we not necessarily want to constrain RACE to declarative memory retrieval.

All chunks have an activation level that represents the likelihood that a chunk will be needed in the near future. The likelihood is in part determined by a component describing the history of usage of a chunk called the base-level activation ($B_i$ in Equation 3.5).

$$B_i = \ln \left( \sum_j S_{ji} \right)$$  

(equation 3.5)

In this equation, $t_j$ represents the time since the $j$th presentation of a memory chunk and $d$ is the parameter that controls decay, which in most ACT-R models is fixed at 0.5 (Anderson et al., 2004). The idea is that the activation of a chunk decays over time unless attention is shifted to that chunk and its activation is increased. This way, the base-level activation can be used to model both forgetting and learning effects (Anderson & Schooler, 1991).

The total activation is the sum of the base-level activation and another component describing the influence of the current context (spreading activation, Equation 3.6). The spreading activation component is the sum of strengths of association from chunks $j$ to chunk $i$, weighed by $W_{kj}$, representing the importance of various buffers ($k$) and of associated chunks ($j$).

$$A_i = B_i + \sum_j W_{kj} S_{ji}$$  

(equation 3.6)

A more detailed description of the ACT-R cognitive architecture is provided in (Anderson et al., 2004; Anderson & Lebiere, 1998).

RACE MODEL OF MEMORY RETRIEVAL

RACE is a proposal for a new retrieval mechanism in ACT-R. In RACE, retrieval of a chunk is thought of as a process in which the likelihood that a chunk will be needed given the current context is continuously estimated. This is different from ACT-R, were the context can influence the retrieval of a chunk only at the onset of a particular retrieval request. Note that the continuous aspects of ACT-R’s base-level learning equation (Equation 3.5) are retained in RACE. The continuous updating of context-based activation is similar to the account presented in the leaky competitive accumulator model described by Usher and McClelland (2001).

Also similar to ACT-R, the accumulation process in RACE is influenced by various sources of evidence. Increases in activation may be caused by the current context, which may be formed by the current buffer contents, or other chunks that are currently active. Via a spreading
activation mechanism these chunks provide evidence for the likelihood that other chunks will be needed. That is, they increase the activation of these chunks.

Another source of evidence for the likelihood that a chunk will be needed is the history of usage of that chunk. Frequently or recently used chunks are more likely to be used again in the near future. In RACE, this is reflected by the starting point of the accumulation process. The level of activation at which accumulation starts is determined by the base-level activation of ACT-R, which reflects the frequency and recency of the usage of a chunk (Anderson & Schooler, 1991). To preserve the temporal nature of the evidence for a chunk, the accumulated RACE activation is subject to continuous decay. Activation of a chunk thus decreases if not enough evidence for that chunk is present. Since the context may change over time, the accumulation process is not determined when a retrieval process is initiated (the retrieval onset), but may also change. Therefore, incoming information or the removal of information from the buffers may influence which chunk will be retrieved.

Activation values represent the relative likelihood that a chunk may be needed (Anderson & Lebiere, 1998), which means that the level of activation at which a chunk has been retrieved should also be defined relative to the activation of other chunks. Therefore, RACE uses a retrieval ratio that determines how much the activation of a particular chunk must stand out against the total activation of all competing chunks. This is analogous to the relative stopping rule described by Ratcliff and Smith (2004, cf., ACT-R’s former competitive latency mechanism, discussed in Van Rijn & Anderson, 2003). If multiple chunks match the criteria of the retrieval request, the chunk that reaches the retrieval ratio first will be retrieved. In these cases, the eligible chunks compete for retrieval. If the activation levels of multiple chunks increase, the total activation of the system also increases, making it more difficult for a chunk to reach the retrieval ratio. This feature of RACE will prove to be important in explaining differences in retrieval latency, for example in the model of subliminal priming explained later in this paper.

So far, we described the general idea of the RACE model of memory retrieval. In this section, the exact implementation of RACE will be presented and how RACE relates to the ACT-R architecture.

The accumulated activation component of RACE is described by the following equation:

$\dot{C}_i(t + \Delta t) = d^{ac}C_i(t) + \beta \sum_j C_j(t)S_{ij}$  \hspace{1cm} (equation 3.7)

This equation reflects the idea that the accumulated activation of a chunk at a certain moment in time ($C_i(t+\Delta t)$) is determined by the level of accumulated activation one time step ago ($C_i(t)$), summed with spreading activation from other chunks; that is, the accumulated activation of other chunks ($C_j(t)$) weighed by strengths of association between these chunks and the chunk $i$ ($S_{ij}$). At retrieval onset, accumulation starts with the history-based evidence, which is the current base-level activation. Thus

$\dot{C}_i(\text{retrieval onset}) = B_i(\text{retrieval onset})$  \hspace{1cm} (equation 3.8)

Accumulated activation decays away, the speed of which is controlled by the parameter $d^{ac}$. A smaller value of $d^{ac}$ results in faster decay. The parameter $\beta$ in Equation 3.7 controls the amount of influence of the context. Although in ACT-R activation can have a negative value, we have chosen in our current implementation to ignore the spreading activation from very small – that is, negative – activation values for reasons of computational efficiency.

By continuously updating spreading activation towards a chunk, the chunk may reach a level of activation at which retrieval can take place. The time at which retrieval takes place is
the first moment after the start of accumulation at which the following inequality holds:
\[ \sum_j e^{A_j} \cdot i \geq \theta \]

This means that for a chunk to be retrieved (i in Inequality 3.9) the activation should be high with respect to all competing chunks (j). Because ACT-R activation values represent the relative likelihood that a chunk will be needed, an exponential scaling is applied to eliminate effects from possible negative values, as is common in ACT-R equations.

Perhaps a clarification is needed on the notions base-level activation \( B_i \) defined in Equations 3.5 and 3.8 and accumulated activation \( C_i \) in Equation 3.7. To incorporate frequency and recency effects in the retrieval process, the accumulation of activation starts at the current level of base-level activation (Equation 3.8). During a retrieval process however, activation is estimated according to Equation 3.7. At retrieval, the base-level activation of the retrieved chunk is also increased to account for the recent encounter with the retrieved chunk, because at the next retrieval attempt the base-level activation is again used as the starting value of the accumulation process.

The question arises which of the two activations \( B_i \) or \( C_i \) is a better predictor of the likelihood that a chunk will be needed. We believe that at very short time intervals – such as the SOAs from the subliminal priming experiment discussed below – accumulated activation better aligns with the empirical data. However, at longer time intervals, base-level activation has been shown to give good predictions (e.g., Anderson et al., 1998; Anderson & Schooler, 1991). Because in the subliminal priming task and model described below prime and target are retrieved in a very small time window, focusing on accumulated activation only will suffice to model the priming effects. Therefore, for this model the base-level activation values were kept constant over all chunks.

Subliminal priming

In this section, we will discuss the task we modeled using RACE: a subliminal priming study by Marcel (1983). Also, we will discuss why this particular task is interesting given the specific nature of RACE. In subliminal priming tasks, primes are presented that are not consciously perceived by the participant. Usually, primes are presented for a very short period and are followed by a visual mask, so that participants can not discriminate between the presence and absence of a prime (Marcel, 1983; Merikle, Smilek, & Eastwood, 2001). Marcel (1983) showed that under these circumstances priming effects persisted. His Experiment 3 describes a Stroop-task in which words are presented as primes, and color patches are presented as cues. Participants had to respond to the color patches by pressing a button associated to one of the colors. He found the same kind of interference and facilitation as usual in the Stroop paradigm, but a smaller effect for the subliminal primes than for the consciously perceived primes (Figure 3.8 presents the latencies that Marcel observed). Marcel concluded that subliminal primes have an effect on latency, even though participants are not aware of their presence.

Four prime conditions were tested by Marcel (1983 Experiment 3): Color congruent, color incongruent, neutral, and no-word. In the congruent condition, the prime was the name of the target color, whereas in the incongruent condition the prime was the name of another color. In the neutral condition, the prime was a non-color word that was also unrelated to colors. The no-word condition presented the mask only. Thus, no prime was presented. The condition in
which the prime was subliminal was called the unaware condition. In the aware condition, by contrast, the presentation duration was 400ms. Both prime and cue were presented at the same time.9

From a symbolic perspective, stimuli have to be considered as symbols in order to engage in cognitive processing. In ACT-R, this means that a stimulus has to be present in a buffer. However, stimuli that are presented for such short durations as common in subliminal priming paradigms do not reach the visual buffer. ACT-R assumes an attention shift to the stimulus before an object can be encoded as a symbolic chunk, which takes a certain amount of time, estimated at 185ms (Anderson, Matessa, & Lebiere, 1998). This exceeds the presentation duration of the prime in the unaware conditions (which is 80ms at maximum, Marcel, 1983). In ACT-R models, stimuli that are presented for less than the time it takes to shift attention can therefore not influence central cognition. The way ACT-R deals with stimulus durations is all or none. Either the stimulus has been presented not long enough, and the stimulus is not perceived at all, or it is fully is perceived. Consequently, symbolic theories of cognition cannot account for subliminal priming data. The next section will show how RACE deals with the short presentation durations typical in subliminal priming tasks.

**SUBLIMINAL PRIMING MODEL**

The subliminal priming model comprises three chunk types, as outlined in Figure 3.6: Lemmas, concepts, and motor mappings. The concept chunks can be regarded as representations of semantic properties. Chunks of the lemma type can be regarded as sets of orthographic and syntactic properties of a word. The motor mapping chunks represent the information which button to press for which color.

![Figure 3.6. The flow of activation in the congruent condition of the subliminal priming model.](image)

Now, for example in a no-word condition, the cue (being a color patch) spreads activation to its associated concept, which spreads activation to the associated motor mapping resulting in a button press. A similar flow of activation will occur in the other conditions, albeit that because of the presentation of a prime word, lemma chunks will also be activated. The activation of multiple motor mapping chunks causes competition in RACE, because the retrieval ratio is harder to reach with multiple accumulating chunks.
Before the experiment, Marcel determined for each participant the critical presentation duration for which participants could not discriminate between presence and absence of a prime (see Marcel, 1983 for details of the procedure). The presentation durations he found ranged from 30 to 80 ms. We used the presentation duration as an extra parameter in fitting the model to the data, with the constraints that its value should be in the range that Marcel found and that the activation of the prime chunk would not exceed the retrieval ratio (Inequality 3.9). Because the primes in the original experiment were visually masked, we assume that the presentation duration is equal to the time that the prime is available to the visual system.

Table 3.1 presents all relevant parameters for the subliminal priming model. The presentation duration of primes in the aware condition is 400 ms, as in the original experiment. The unaware presentation duration was estimated at 70 ms, serving as the model’s critical presentation duration. This duration depends on the RACE parameters presented in bold-face in Table 3.1. These parameters were not estimated for this experiment, but rather copied from a RACE model of picture-word interference (an updated version of Van Maanen & Van Rijn, 2006; Van Maanen & Van Rijn, 2007b). Hence, the only parameters presented here that were estimated for this model were the activation of the words ($A_{text}$) and of the color ($A_{color}$). The association values ($S_{ij}$) between chunks are presented in Figure 3.7.

Table 3.1: Estimated parameter values for the subliminal priming model.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_{color}$</td>
<td>1.8</td>
</tr>
<tr>
<td>$A_{text}$</td>
<td>1.5</td>
</tr>
<tr>
<td>$\beta$</td>
<td>-0.255</td>
</tr>
<tr>
<td>$d_{acc}$</td>
<td>0.72</td>
</tr>
<tr>
<td>$\Delta t$</td>
<td>5 ms</td>
</tr>
<tr>
<td>$\theta$</td>
<td>0.81</td>
</tr>
<tr>
<td>Aware presentation duration</td>
<td>400 ms</td>
</tr>
<tr>
<td>Unaware presentation duration</td>
<td>70 ms</td>
</tr>
</tbody>
</table>
RESULTS

The results of the subliminal priming model are presented in Figure 3.8. We present here differences in latency relative to the no-word condition as this model only captures the memory retrieval process, which comprises the time course from the start of retrieval of a chunk until the retrieval of the motor mapping chunk. The model captures quite nicely the effects observed in the data10 by Marcel (1983) ($r^2 = 0.987$).

In the unaware conditions, only the target chunks reached the retrieval ratio, and no other chunks. Therefore, these chunks are the only ones that are consciously perceived by the model. The model thus remained unaware of all other chunks, as is required for these conditions.

An explication of how the activation flows through the model will be insightful. We split this up in four sections, each describing one condition.

Neutral

In the neutral condition, there is no competition between motor mappings, because there is no button associated with the neutral word. The activation cascades through the network similarly to the no-word condition, because no association exists between the neutral word and the target color, both at the lemma level and at the concept level. Therefore, the activation of the motor mapping associated with the target color increases similarly to the no-word condition because the activation of all the motor mapping chunks increases as in the no-word condition.

As an example, Figure 3.9 gives the activation accumulation in the neutral unaware condition. The activation of the neutral word lemma increases, but, due to the short presentation duration, it does not reach the retrieval ratio. This indicates that the neutral word does not reach awareness.

No-word

The no-word condition is similar to the Neutral condition, because no distractor stimulus is present, resulting in the same behavior of the model as in the Neutral condition. Because in the no-word condition, there is no distractor, there is no difference between aware and unaware.

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10. As the variance in the original data cannot be deduced from the published results, a sensible formal comparison is not possible.
Congruent

Both target and distractor stimuli activate the same concept: the color chunk directly, the text chunk mediated via the lemma chunk. Spreading activation towards the associated motor mapping chunk is therefore higher than in the Neutral and No-word conditions, resulting in faster retrieval.

Incongruent

Because both target stimulus and distractor activate a motor mapping, competition for retrieval takes place at the motor-mapping level. Higher activation for competing chunks means that it is more difficult to cross the retrieval ratio, leading to longer retrieval latencies. The effect is strongest in the aware condition, representing the longer presentation duration of the prime, and thus the longer accumulation of activation of prime-related chunks.

DISCUSSION

A difficult question when modeling cognitive tasks that deal with awareness is how awareness is defined within the model. We chose to set a strict boundary for awareness, the retrieval ratio. When a chunk reaches the retrieval ratio, it becomes available inside the
buffers. We assume that people are aware of chunks that are currently in the buffers (Taatgen, in press), and not aware of chunks that have not yet reached the activation needed to enter the buffers.

RACE involves a direct connection between information in the external world (that is, the visual module) and the activation values of declarative chunks in declarative memory. In this respect, RACE deviates from ACT-R, in which all visual information must be mediated by the visual buffer. However, since the visual buffer is associated with awareness as chunks appearing in the visual buffer enter the declarative system, another pathway must be present to account for the subliminal priming data modeled in this paper. We hypothesize that the connections in RACE from the visual module to the declarative memory module may represent part of the ventral visual pathway, that is known to involve connections from striate cortex (associated with ACT-R’s visual module) to temporal brain regions (associated with the declarative memory module Anderson et al., 2004).

The model of subliminal priming discussed in this paper demonstrates that RACE can account for the retrieval latencies observed by Marcel (1983, Experiment 3). By using standard RACE parameter values, the fit of our model to the data set of Marcel was quite good. In combination with previous models of declarative memory retrieval that use RACE (Borst & Van Rijn, 2006; Van Maanen & Van Rijn, 2006; Van Maanen & Van Rijn, 2007b), this suggests that RACE might be regarded as a general model of declarative memory retrieval. The added value of the RACE model is that it gives a rational account of how the process of declarative memory retrieval develops. Even the effects on declarative memory retrievals of changes in the world that last only milliseconds can now be taken into account.
Stroop and picture-word interference are two sides of the same coin

INTRODUCTION

Over the years, the idea that the picture-word interference (PWI) effect and the Stroop effect are two manifestations of the same process has gained wide support. For instance, MacLeod's influential review on the Stroop effect (MacLeod, 1991) also discusses picture-word interference, and even lists the picture-word task in his list of “eighteen major empirical results that must be explained by any successful account of the Stroop effect” (MacLeod, 1991, Appendix B, p. 203). Recently, Dell’Acqua, Job, Peressotti, and Pascali (2007) have argued that the underlying processes of both effects are different, challenging the assumption of a single underlying process. In this paper, we will present a computational model that, on the basis of a single process, can explain both the traditional phenomena discussed by MacLeod (1991) and the data of Dell’Acqua et al. (2007).

In the Stroop paradigm, participants are presented with a word written in a specific color, and are instructed to either read the word, or name the color the word is printed in (MacLeod, 1991; Stroop, 1935). A typical Stroop experiment usually consist of three conditions: a congruent condition in which the word and the color refer to the same color concept (e.g., the word “red” written in red ink), an incongruent condition in which the word and the color refer to different color concepts (e.g., the word “red” written in green ink), and a neutral condition in which only the text or the color is displayed. This is often operationalized by presenting a set of X’s in red ink (for color naming) or the word “red” printed in black ink (for word reading).

Three experimental findings in a Stroop study are extremely robust. First, color naming in the incongruent condition is slower than color naming in the neutral condition. That is, participants who are required to name the color of the ink are slower if the word describes a different color than if they have to name a color of a row of X’s. This is often referred to as semantic interference, since many accounts of this effect assume that the relation in meaning between the color of the ink and the word itself causes the interference that results in reaction time differentiation (e.g., Cohen, Dunbar, & McClelland, 1990; W. R. Glaser & Glaser, 1989; Klein, 1964). A second finding in the Stroop literature is that naming the color of the ink of a word that describes the same color (congruent condition) is faster than the neutral condition. This will be referred to as semantic facilitation (but see MacLeod & MacDonald, 2000, for an alternative explanation of semantic facilitation that is based on accidental reading of the word). A third important observation is that both semantic interference and semantic facilitation disappear when the participants are not instructed to name the color of the stimulus, but instead are asked to pronounce the word, irrespective of the color the word is printed in. This so-called Stroop asynchrony is often explained by the difference in processing speed between colors and words (e.g., Cohen, Dunbar, & McClelland, 1990; Roelofs, 1992), or the difference in automaticity between color-naming and word-reading (e.g., Lovett, 2005).

The picture-word interference task (PWI) typically has a similar set-up to the Stroop task. Participants are presented with a picture on which a word is super-imposed, and are instructed to either name the picture, or read the word. As in the Stroop task, semantic interference,
semantic facilitation and Stroop asynchrony are usually observed in the PWI task (W. R. Glaser & Düngelhoff, 1984). Semantic interference is observed if participants are required to name a picture on which a category-member word of that picture is super-imposed (e.g., a picture of a dog with the word “cat” inscribed in it) as their responses are slower compared to the condition in which a picture without a superimposed word has to be named or to the condition in which the superimposed word is completely unrelated (e.g., a picture of a dog with the word “desk” superimposed). Semantic facilitation is observed if, by contrast, the picture and the word refer to the same concept (e.g., a picture of a cat with the word “cat” superimposed) as the participants are faster. The Stroop asynchrony can be observed in the disappearance of these effects if the task is to read the word instead of naming the picture.

At a more general level, these effects are often aggregated in terms of a single Stroop or PWI-effect. This more general effect is the difference in performance for trials in which there is an interfering stimulus present versus trials in which there is no interfering stimulus. For the Stroop task, this entails the difference between trials in which a color word is written in different colored ink and trials in which a color word is written in similar colored ink. For the PWI task, the effect is the difference between trials in which the picture is presented with a semantically related, but different word superimposed versus trials in which picture and word are completely unrelated.

Given the similarity of both tasks, it is not surprising that both tasks have often been explained in similar terms. In fact, in our previous work in which we presented a computational model of PWI, we took for granted that picture-word interference is just an instance of the Stroop effect. (Van Maanen & Van Rijn, 2007b). Other computational models also present a single mechanism that underlies both PWI and Stroop performance (e.g., Cohen, Dunbar, & McClelland, 1990; Lovett, 2005; Roelofs, 1992, 2003).

Most of the theoretical accounts of Stroop-like effects have focussed on finding the locus of the interference effect in the mental processing stream. For instance, many theorists assume that interference is caused by a competition between different response options (Cohen, Dunbar, & McClelland, 1990; e.g. Dyer, 1973; and W. R. Glaser & Glaser, 1989; Kuipers, La Heij, & Costa, 2006; Lovett, 2005; Roelofs, 1992, 2003). In this view, interference is caused by an increased difficulty of selecting the appropriate response in the incongruent condition. Often, this has been attributed to either a difference in the speed of processing between the stimulus dimensions or to a difference in automaticity between the stimulus dimensions (MacLeod, 1991).

Some theoretical accounts assume an interference effect during an early stage. In particular, Dell’Acqua et al. (2007) argue that the picture-word interference effect is caused by a competition that occurs before an appropriate response is selected. With respect to the Stroop effect, many studies now suggest that the Stroop effect may be manifested at multiple stages (e.g., De Houwer, 2003; Risko, Schmidt, & Besner, 2006; Schmidt & Cheesman, 2005; Van Veen & Carter, 2005).

Recently it has been suggested that the Stroop effect and picture-word interference are not caused by the same process (Dell’Acqua et al., 2007). In particular, it has been argued that the loci of the two interference effects in the mental processing stream differ. Many studies suggest that the locus of the Stroop effect is on the level of response selection (e.g., Fagot & Pashler, 1992; Kuipers, La Heij, & Costa, 2006; MacLeod, 1991; Roelofs, 2003). That is, Stroop interference occurs because an incorrect response possibility that is triggered by the distracting feature of the stimulus (the word), interferes with the correct response that is triggered by the target feature (the color). Dell’Acqua et al. argue that this is not the case.
for PWI. Their result suggests that picture-word interference is on the level of the perceptual encoding. Based on these results, Dell’Acqua et al. concluded that although the effects in both tasks seem similar, they are in fact caused by different mechanisms.

This paper presents a computational cognitive model of both the Stroop and the PWI effect, reconciling the recently observed differences between Stroop and PWI with the general view that PWI is an instance of the Stroop effect. In this model, both Stroop and PWI effects are accounted for by the same underlying mechanism. In other words, the model provides additional evidence for the view that the underlying mechanism that causes interference in both tasks is the same (cf. Cohen, Dunbar, & McClelland, 1990; Lovett, 2005; Roelofs, 1992, 2003), whilst still being able to explain the observation that participants respond differently to Stroop and PWI stimuli under certain circumstances (Dell’Acqua et al., 2007).

**Analyzing the Locus of Interference**

To analyze the time course of the Stroop effect, Fagot and Pashler (1992, Experiment 7) studied whether the Stroop effect would persist in a psychological refractory period (PRP) design. In a PRP design, participants are required to perform two tasks concurrently. The main manipulation in PRP designs is an asynchrony in onset between both tasks. Usually, the instruction is to first give the response associated with the stimulus that was displayed first. If the stimulus onset asynchrony (SOA) between tasks is relatively long, the processing of the first task is finished before the stimulus of the second task is presented. On the other hand, if the SOA is short, processing associated with the first stimulus might not be finished yet when the second stimulus appears. The typical observation with short SOAs is that the response to the second task is delayed (Telford, 1931). This delay is often interpreted as evidence for a bottleneck in processing. The central bottleneck theory assumes that there exists a processing stage during which only a single process can proceed concurrently (e.g., Pashler, 1994). Therefore, the secondly presented task will be delayed by processing of the first task. By testing the effect of different SOAs the time course of processing can be unraveled.

Fagot and Pashler (1992) used the PRP paradigm in the context of the Stroop task. They presented participants with a simple tone classification task as primary task, and a Stroop task as secondary task. Fagot and Pashler hypothesized that if the Stroop effect – operationalized as the latency difference between an incongruent Stroop stimulus and a congruent Stroop stimulus – would be caused by the perceptual encoding of the stimulus, the Stroop effect would disappear at short SOAs. This would be the result of the delay in execution of the second task. The delay causes a gap in processing of the second task in which the interference could be resolved. Fagot and Pashler found no effect of SOA on the magnitude of the Stroop effect, which they interpreted as evidence that the locus of the Stroop effect is located relatively late in the stream of mental processing. This finding, they argued, is in line with a response selection account for the locus of the Stroop effect, because response selection is also late in the mental processing stream.

In a similar experiment, Dell’Acqua et al. (2007) answered the same question for the PWI effect. Dell’Acqua et al. conducted an experiment very similar to the experiment ran by Fagot and Pashler (1992), but instead of a Stroop task, participants were presented with a PWI task. In this experiment, the interference was operationalized as the latency difference between a semantically related word-picture pair and an unrelated word-picture pair. Interestingly and surprisingly, SOA mediated the PWI effect: shorter SOAs were associated with smaller PWI effects. This indicates that the inference originates from the initial stages of processing, as
with short SOAs most interference is captured in the PRP-induced delay, but with long SOAs the delay does not account for all interference. This finding is in line with the view that the locus of PWI is early, possibly during perceptual encoding of the stimulus.

Based on this result, Dell'Acqua et al. (2007) argue that the difference between their findings and Fagot and Pashler's (1992) are “incompatible with the often reiterated principle that the PWI effect comes about for limitations of the cognitive system that are analogous to those causing the Stroop effect” (Dell'Acqua et al., 2007, p. 720). They conclude that their analysis “favor[s] an interpretation of the present findings that points to the functional dissociation of the sources of Stroop and PWI effects” (Dell'Acqua et al., 2007, p. 722).

Based on the PRP studies by Dell'Acqua et al. (2007) and Fagot and Pashler (1992), we may arrive at two possible explanations. The first possibility is the one advocated by Dell'Acqua et al., that Stroop and PWI are two different effects. The other possibility is that the interference in Stroop and PWI is distributed over multiple stages. However, the amount of interference per stage may differ between Stroop and PWI. This explanation is in line with findings from the Stroop literature that besides response competition, Stroop may be caused by stimulus-related competition as well (e.g., De Houwer, 2003; Risko, Schmidt, & Besner, 2006; Schmidt & Cheesman, 2005).

We will support this second possible explanation by presenting a cognitive model that can account for reaction time data of both PWI and Stroop experiments. The cognitive model utilizes a single mechanism to account for both data sets; the sole difference is a different speed of processing for the perceptual input (that is, pictures vs. colors). Next, we will demonstrate that the model accounts for the response time patterns of Stroop and PWI tasks under PRP conditions. As these fits are obtained with a single-mechanism model, this argues against the claim that the differential findings for Stroop and PWI favor a dissociation of the sources of Stroop and PWI effects.

The cognitive model that we will describe here is an integrated cognitive model (Gray, 2007b) of the task, implemented in a previously validated cognitive architecture (Taatgen & Anderson, 2008). We will simulate the complete process that is involved in the task, from the presentation of the stimulus up to the participant’s response, resulting in quantitative predictions of reaction time data.

The model is implemented in the cognitive architecture ACT-R (Anderson, 2007a). ACT-R assumes that specialized modules process different kinds of information. For instance, a visual module handles visual perception, and a motor module executes motor commands. Other modules that will play a role in the model described below are the declarative module, used for storing and accessing information in declarative memory, the speech module for speech output, the aural module for auditory perception, and a goal module for keeping track of goals and intentions (see Anderson, 2007a; Taatgen, Van Rijn, & Anderson, 2007 for extensive descriptions of the identified modules). A central production rule system integrates the information that is made available by the different modules, and issues new instructions to those modules. The production rule system communicates with the different modules through a set of interfaces called buffers. Behavior in ACT-R emerges from the selection and subsequent execution of production rules that consist of simple conditions-actions pairs. If the information that is present in the buffers matches the conditions of a production rule, that rule may be selected to execute its actions. Production rule actions consist of operations on the buffer contents, such as a request for new information from declarative memory, or a request for pressing a button on a keyboard.
Declarative information in ACT-R is represented in symbolic entities called chunks. Chunks represent simple facts, such as *The capital of The Netherlands is Amsterdam*, or *The object I am attending is green*. Note that where the first example is a typical semantic memory fact, the second example represents a visually observable feature of the world as might be present in the visual buffer. All chunks in an ACT-R model have an activation level that reflects the likelihood that they will be needed in the near future. The activation of a chunk depends on two components: the chunk’s history of usage (Anderson & Schooler, 1991) and the current context (Anderson & Milson, 1989). The activation of a chunk is the main determiner of the time it takes to retrieve that chunk from memory. All other things being equal, the higher the activation of a chunk, the faster it will be retrieved.

Because Stroop tasks and pwI tasks usually involve well-known colors and words, and pictures of well-known objects, we will assume that the history component of the activation is approximately equal for all chunks as well as stable over the time span of a single experiment. For the context component of the activation we will adopt a more fine-grained model that will be discussed later. This context component will be the main determiner for the reaction time differences that our models will display.

The model’s behavior is determined by the interaction between specified production rules, chunk retrievals and the task setup. In terms of response latency (the usual dependent measure in Stroop and pwI tasks), the model’s behavior is the result of an aggregation of the timing of the sub processes, such as the execution time of the production rules and the time associated with module-specific operations, such as declarative retrievals, or button presses (cf., Donders, 1868/1969; Sternberg, 1969). However, although internally most module actions are executed sequentially, the modules themselves operate in parallel. For example, while the visual system is busy with the perceptual processes involved in perceiving a new stimulus, production rules might initiate a request for the retrieval of a fact from declarative memory without disturbing the perceptual process. Critically however, the modules cannot execute multiple operations in parallel. Thus, if two tasks require retrieval from declarative memory, one of the tasks has to wait until the declarative module is finished with the request of the other task. This seriality will be critical in the explanation of pwI and Stroop performance. Although this seriality has not been specifically designed to account for performance in tasks in which scarce resources determine behavior, it has been successfully applied in many different experimental domains (Language Development, Hendriks, Van Rijn, & Valkenier, 2007; e.g., Attentional Blink, Taatgen, Juvinia, Schipper, Borst, & Martens, in press; Van Rij, Van Rijn, & Hendriks, submitted; Temporal Cognition, Van Rijn & Taatgen, 2008).

**MODEL OVERVIEW**

The model presented here, in line with the proposal of Dell’Acqua et al. (2007), assumes that both the Stroop task and pwI consist of three main stages, the perceptual encoding stage, the response selection stage, and the response execution stage. During the perceptual encoding stage, the stimulus features are transferred to the visual buffer. During the response selection stage, a chunk that reflects the syntactic properties of the response (that is, a lemma, Levelt, Roelofs, & Meyer, 1999) is retrieved from declarative memory. In the response execution stage, the model retrieves a motor program associated with the retrieved response, and this motor program is executed.

During each stage, one or more memory retrievals take place. The duration of these retrievals are the main determiners of the response latency. Given that we assumed that all
chunks are equally active, all differences in activation are driven by the context activation. If the current state of the system is favorable for a chunk that is requested from memory, the chunk will be retrieved faster than in a situation when the context is less favorable. This context phenomenon determines whether semantic interference or semantic facilitation is observed.

A MORE FINE-GRAINDED ACCOUNT OF CONTEXT EFFECTS

The current declarative retrieval module in ACT-R can account for many memory-related phenomena (e.g., Anderson et al., 1998; Taatgen & Anderson, 2002; Van Rijn & Anderson, 2003). While the module accurately predicts the duration of memory retrievals, ACT-R does not provide an account for what happens during memory retrievals. This is especially problematic in tasks with multiple stimuli presented at short SOAs, since the first, not-yet-completed retrieval is influenced by a second process. This dependency cannot be explained by default ACT-R (Van Maanen & Van Rijn, 2007b). Another issue is that context effects on retrieval latencies are solely driven by chunks that are available in the buffer of one of the modules. This results in a threshold function: no context effects can be observed of retrieval or perception processes until a chunk is placed in a buffer, at which point it starts spreading activation to contextually related chunks.

To overcome these issues, we proposed an adaptation of the declarative retrieval mechanism in the cognitive architecture ACT-R to account for the time-course of memory retrieval on short time scales (Van Maanen & Van Rijn, 2007b). This retrieval account (RACE/A, for Retrieval by ACcumulating Evidence in an Architecture) predicts what happens during the actual retrieval process. RACE/A is driven by two key assumptions: (1) The activation of one chunk is determined (in part) by the activation of other chunks. (2) The activation of one chunk relative to the activation of other chunks determines the likelihood that it will be retrieved.

The first assumption represents the notion that the relevance of information is context-dependent, even when this context is not yet available at a symbolic level (that is, accessible to the production system). This is for instance reflected in subliminal priming studies in which a related prime decreases the response latency on a target stimulus, even when participants were not consciously aware of the prime (Marcel, 1983). We operationalized this by adopting a spreading activation strategy (Collins & Loftus, 1975) in which increased activation of one chunk increases the activation of related chunks.

\[
C_i(t) = \alpha C_i(t-1) + \beta \sum_j C_j(t-1) S_{ji}
\]

Equation 4.1 implements this assumption. The equation reflects how the activation of a chunk \((C_i(t))\) accumulates during retrieval. The activation at time \(t\) depends on the previous activation of that chunk \((C_i(t-1))\), as well as additional spreading activation \((C_j(t-1)S_{ji})\) from other chunks \((k)\). This includes the chunks that are available through perceptual processing. The spreading activation is mediated by the associative strength between two chunks \((S_{ji})\), such that chunks that are strongly associated exchange more activation than chunks that are loosely associated. \(\alpha\) and \(\beta\) are scaling parameters that determine the relative contributions of both components. Because \(\alpha\) is set to a value in the range \((0,1)\), it can be interpreted as temporal decay of activation. The accumulated activation thus decays after a retrieval has been attempted.

The second assumption states that the relative activation of a chunk determines the likelihood that that chunk will be retrieved. This assumption reflects the insight that if multiple
memory representations are relevant, responding becomes more difficult (Luce, 1986). Following ACT-R, the activation of a chunk determines the likelihood that it will be needed in the near future. However, RACE/A extends the default ACT-R equations to take the activation of competing chunks into account. The activation of competing chunks are accounted for by taking the ratio of activation of the to be retrieved chunk (chunk \( i \) in Equation 4.2) to the sum of activations of other relevant chunks (chunks \( j \) in Equation 2, cf., Luce, 1986; Roelofs, 1992).

In the current model, the relevant chunks are all other chunks that match the criteria specified by a retrieval request.

If the ratio specified in Equation 4.2 crosses a threshold (\( \theta \), the retrieval ratio), the relative activation of the chunk in the denominator (chunk \( i \)) warrants the retrieval of that chunk. As soon as a chunk passes this threshold, RACE/A returns that chunk as the result of the retrieval process.

\[
e^\frac{e_i}{\sum_j e_j} \geq \theta
\]

Based on Equations 1 and 2, we have provided quantitative predictions for variants of both picture-word interference (Van Maanen & Van Rijn, 2007b) and the Stroop task (Van Maanen & Van Rijn, 2007a). The PWI model focused on the effect of SOA differences; the Stroop model fitted a data set in which the distractors were presented subliminally.

Besides a theory of memory retrieval (RACE/A), which is the core of our modeling efforts in this paper, also a theory of perceptual encoding is needed to study the Stroop and PWI effects. Similar to RACE/A, we deviate here from the theory currently implemented in ACT-R, because it is too crude for our purposes here.

**PERCEPTUAL ENCODING**

Before the processing of task-relevant information can commence, visual or auditory information has to be made available to central cognition. In both PWI and Stroop tasks, all information is presented visually. In ACT-R, the perceptual encoding process results in a chunk entering the visual buffer, and thus becoming available for further processing. By default, it is assumed that this process takes a fixed 85 ms (Anderson, 2007a). Although this is a sensible number when the details of the perceptual processing are less relevant for the task under study, the emphasis on perceptual encoding in Stroop and PWI tasks requires a more detailed account. However, it should be noted that our implementation of a perceptual encoding process should not be considered a complete theoretical account of perceptual processes. Rather, our implementation should be considered a functional description, aimed at differentiating between the effects on the encoding time caused by different stimulus features (cf., Gray, 2007a).

We assume that features of the stimulus become available during the first stages of perceptual encoding (cf., feature integration theory, Treisman & Gelade, 1980). Based on these features, chunks in declarative memory compete for retrieval. This process is implemented using the RACE/A mechanism: The visual features spread activation to chunks that represents concepts that are likely to be needed in the context of those features. Thus, concepts that relate to the visual features of the current stimulus receive activation, while concepts that do not relate do not receive activation. When a concept’s activation results in a retrieval ratio larger than the threshold (see Equation 4.2), that concept is made available for non-visual cognition as the result of visual processing. So, instead of a fixed duration for perceptual encoding, we have implemented perceptual encoding as a combination of a feature integration and selection process with a variable duration that depends on the characteristics of the input.
The variation in encoding time between different stimuli originates from two sources. First, as the relative activation of a chunk determines whether it will be encoded, the activation of other chunks in declarative memory partly determines the encoding time. Second, the speed by which activation spreads from features to chunks will be different for different types of stimuli (e.g., a color patch is easier to recognize than a complex line drawing). Therefore, a parameter is introduced that reflects the speed and strength of spreading activation from features to chunks, to account for the different encoding times associated with different types of stimuli (Dell’Acqua, Lotto, & Job, 2000; Rossion & Pourtois, 2004). Although our encoding account is much simpler than existing models of perceptual encoding (e.g., Itti & Koch, 2001; Treisman & Gelade, 1980; Wolfe, 1994) it provides the necessary detail to account for the perceptual processing in the PWI and Stroop tasks.

In the Stroop task, the color feature of the stimulus spreads activation to a concept representing that color, and the text feature of the stimulus spreads activation to the lemma associated with that word. For the PWI task, the features representing the line drawing spread activation to the concept chunk representing the content of the picture, while the word spreads activation to a lemma. As word reading is faster than color naming (M. O. Glaser & Glaser, 1982), more activation spreads from the text feature to the lemma representing the associated word, than from the color feature to the associated color lemma.

In addition, we assume that line drawings are encoded slower than color patches. This assumption is supported by studies that show faster naming for sequences of color patches as opposed to sequences of images (e.g., Denckla & Rudel, 1976; Vukovic, Wilson, & Nash, 2004).

In the model these differences are operationalized by different settings for the parameter that reflects the speed of perceptual processing. In the remainder of this paper, we will demonstrate that the interference dynamics observed in Stroop and PWI PRP tasks might be caused by differences in this perceptual processing speed.

**SIMULATION 1: A SINGLE MODEL FOR PWI AND STROOP**

Before discussing our model of the Stroop and PWI effects under PRP conditions we will first discuss the model’s performance in non-PRP Stroop or PWI trials. Note that although this section focuses on a Stroop trial, exchanging references to color dimensions with references to pictures results in a description of how the model would perform a PWI trial.

As soon as visual features become available to the model activation is spread to the chunks associated with that visual information. The color features spread activation to a conceptual chunk representing that color, whereas the textual features spread activation to a lemma.

When a chunk representing either the lemma or the concept crosses the retrieval ratio threshold, a second stage is initiated. As availability of a lemma is a prerequisite for starting the response execution stage, the model directly enters this stage when the lemma crosses the threshold. In this stage, the model retrieves a word-form and the response is uttered. If the color has to be named, the model waits until a concept is selected on the basis of the visual input, after which a retrieval is initiated to retrieve the lemma that is associated with the concept. However, because word reading is a highly trained and automated process, the word activates its associated lemma even if the model expects a color concept. Because of this activation, and the earlier discussed retrieval ratio, color naming will show interference from the presented word, whereas word reading will show less interference. Note that the model described so far is very similar to models of the Stroop and PWI tasks presented by Roelofs (1992, 2003). In some cases, the visual word representation might have spread so
much activation, that the word-based lemma chunk exceeds the color-based lemma chunk in activation. In these situations, an incorrect lemma will be retrieved. To account for this, the model checks if the meaning of the lemma is consistent with the stimulus color (other models of the Stroop task that incorporate a similar strategy include Altmann & Davidson, 2001; Juvina & Taatgen, 2009; cf., Van Rijn & Anderson, 2004). If the correct lemma has been retrieved, the model continues with the response execution. If not, the model tries to retrieve another lemma. The response selection stage is the same for the word reading task: the model retrieves a word-form and utters a response.

**SIMULATION RESULTS & DISCUSSION**

Figure 4.1A presents the fit of the Stroop model for both the color naming task and the word reading task ($RMSE=33ms$, $R^2=0.93$) on the data from Glaser and Glaser (1982, Experiment 1 for SOA=0). The model captures both Stroop interference in the incongruent color naming condition, and facilitation in the congruent color naming condition. In addition, the Stroop asynchrony between color naming and word reading can be observed. Given our hypothesis that the Stroop effect and picture-word interference are manifestations of the same process, the challenge is to demonstrate that both effects can be fitted with the same model. Figure 4.1B presents the model fit on picture-word interference response time data (W. R. Glaser & Düngelhoff, 1984, Experiment 1 for SOA=0). Similar to the fit of the Stroop task, all the behavioral patterns (interference, facilitation, and asynchrony) are captured by the model ($RMSE=60ms$, $R^2=0.85$). The only difference between the two simulations underlying Figure 4.1 is a single parameter that controls the speed of processing of the stimulus that is adjusted to reflect the differences in stimuli between the two tasks: The processing speed was set lower for the picture-word stimulus than for the color-word stimulus, to reflect that visual processing of pictures is slower than visual processing of colors.

![Figure 4.1](image)

Following our assumption that semantic interference is an effect of competition during the retrieval of declarative facts, we analyzed the amount of interference by comparing the duration of declarative memory retrievals between conditions. Thus, in our model, interference constitutes the difference in retrieval times. Figure 4.2 presents the difference in memory retrieval time between the model’s incongruent and congruent conditions, for both the Stroop task and the pwi task. Following others (e.g., Fagot & Pashler, 1992; Ferreira & Pashler, 2002; Jolicoeur & Dell’Acqua, 1998; McCann & Johnston, 1992; Pashler, 1994; VanSelst & Jolicoeur, 1997) we assume that the bottleneck that Fagot and Pashler (1992) and Dell’Acqua et al. (2007) hypothesize is located after the perceptual encoding stage. Figure 4.2 shows the
proportion of interference that is located before and after the hypothesized bottleneck. In the model of the Stroop task, 9% of the interference is located before the bottleneck, and 91% is located after the bottleneck. For PWI, these percentages are different. 18% of the retrieval-induced interference is located before the bottleneck, which is twice as much as the early interference in the Stroop task. This is in line with Dell’Acqua et al.’s conclusions, because more interference in the picture-word interference simulation is indeed located early in the processing stream.

Simulation 1 shows how a single cognitive model can account for PWI and the Stroop effect. Although this result has been obtained before (e.g., Cohen, Dunbar, & McClelland, 1990; Roelofs, 2003), the model presented here provides insights in the temporal distribution of the interference patterns. The model assumes that interference is a consequence of competition during memory retrieval, and shows that different processing speeds for different stimulus types (pictures vs. colors) mediates the competition in subsequent stages of the task.

The ability to model both a Stroop task and a PWI task with a single model, supports the view that both tasks are manifestations of the same interference process (e.g., MacLeod, 1991). By studying the memory retrieval times in different processing stages, we showed that different stimulus features may lead to a different temporal distribution of the interference patterns. This result leaves the puzzling observation by Dell’Acqua et al. (2007) that Stroop and PWI behave differently under PRP conditions. In the next section, our model will be extended to account for the PRP experiments by Fagot and Pashler (1992) and Dell’Acqua et al. (2007). We will demonstrate that a difference in stimulus features between colors and pictures may lead to different behavior in the Stroop and PWI tasks under PRP conditions.

**SIMULATION 2: A COGNITIVE MODEL OF INTERFERENCE DURING PRP**

The cognitive model presented above can account for prototypical Stroop and PWI data sets (M. O. Glaser & Glaser, 1982, Experiment 1 for SOA=0; W. R. Glaser & Dünkelhoff, 1984, Experiment 1 for SOA=0). Moreover, analysis of the locus of interference in the model suggested that the magnitude of the interference effects differed between stages of the model, as well as between tasks. To demonstrate that the different loci of interference may appear as different response latencies under PRP conditions, we added PRP conditions to the model. With this extension, we can assess whether the results of Fagot and Pashler (1992) and Dell’Acqua et al. (2007) can indeed be explained with a single mechanism.
MODEL OF FAGOT AND PASHLER (1992, EXPERIMENT 7)

Following the experimental setup by Fagot and Pashler (1992), each trial started with a tone classification task. In this task, the participants were instructed to classify presented tones as either having a low or a high pitch by pressing one of two buttons. This additional task was added to the model using ACT-R’s standard auditory perception module. As soon as the auditory system perceived a tone, a retrieval was initiated for a tone-to-button mapping. Finally, the model made a motor response to press the correct button. The model’s processing of the Stroop stimulus only commenced after the response to the tone was selected, as was required according to the instructions provided to the participants. Note that this does not mean that the button press has to be finished, but that the information that has to be sent to the motor system has become available. As in the Fagot and Pashler experiment, the delays between tone onset and Stroop stimulus were -50ms, 50ms, 150ms, and 450 ms. All other aspects of the model were kept constant, apart from the estimation of a fixed intercept for voice-key responses. To account for differences in naming speed between this experiment and the previously modeled datasets, we estimated the voice-key response parameter at 167 ms (see also Meyer & Kieras, 1997a; Salvucci & Taatgen, 2008).

Simulation Results & Discussion

The model fits of the PRP Stroop experiment (Fagot & Pashler, 1992, Experiment 7) are presented in Figure 4.3. The model shows the same latency effects as Fagot and Pashler observed (RMSE=16ms, R²=1.00). First, latency in the tone classification task is not affected by the interval between tone and the combined picture-word stimulus. In discussion of their paper, Fagot and Pashler attribute this to the instruction that was given to the participants to always respond to the tone first and to the Stroop stimulus second. We simulated this in the model by requiring a response to be selected for the tone before the model could commence with the response selection for the Stroop task.

Second, the model shows a decrease in reaction time as a function of an increasing SOA, similar to the typical PRP effect found in the data. The model achieves this because as the interval between the two tasks increases, the probability that both tasks need one of the ACT-R modules at the same time decreases. As only one task can use a module at a certain
time, one of the tasks has to wait when two parallel requests are made to a module. Also, as the interval between the tasks increases, the delay due to the task instruction regarding the response order is less. That is, if the Stroop stimulus is presented later (that is, when the SOA is longer), the delay for the response is shorter. This is illustrated in Figure 4.4, which presents Gant diagrams of the module-specific processing for both tasks. The dark grey bars represent the tone classification task, and the light grey bars represent the Stroop task. In the upper panel of Figure 4.4, the SOA between the tasks is long, which is reflected by the late activity in the visual module of the model. In the lower panel, the SOA is short. Initially, the Stroop stimulus is perceived, as indicated by the activity in the visual module. However, the model withholds further Stroop processing until the response in the tone classification task has been initiated. Thus, parallel to activity in the manual module, representing the button press in response to the tone classification, the model initiates response selection in the Stroop task.

Finally, the model shows no effect of SOA on the size of the Stroop effect, which has been interpreted as evidence for a late locus of the Stroop effect (Dell’Acqua et al., 2007; Fagot & Pashler, 1992). This is because the interference in the Stroop task is mainly located in the response selection stage (see Figure 4.2), which does not overlap with the tone classification task.

**MODEL OF DELL’ACQUA ET AL. (2007)**

The model of the Dell’Acqua et al. experiment is a direct combination of the PWI model described under Simulation 1 and the PRP aspects described above. To match Dell’Acqua et al.’s experiment, we changed the SOAs to 100ms, 350ms, and 1000 ms and we extended the tone classification task to three options to mirror the exact experimental setup of Dell’Acqua et al. The single free parameter, the voice-key intercept, was estimated at 212ms.

**Simulation Results & Discussion**

The model again found no effect of SOA on tone classification latency and the PRP effect (manifested as decreased response times on the PWI stimulus as SOA increases). In addition, this time the models also shows an increase in interference with increased SOA (Figure 4.5, RMSE=61ms, \(R^2=1.00\)), which is in line with the result from Dell’Acqua et al. (2007). Because the interference is primarily expressed during the perceptual encoding stage, postponement of the response on the PWI stimulus (which happens for short SOAs) results in a decrease (or disappearance) of the interference effect. This is depicted in the Gant diagram in Figure 4.6. The upper panel shows the presentation of a neutral word-picture pair, resulting in fast...
perceptual encoding. However, although all information is available for further processing, production rules associated with the PWI task will not be selected because of the instruction to first finish the tone classification task. In the lower panel of Figure 4.6, an incongruent word-picture pair is presented, which results in a longer perceptual encoding stage. However, as the PWI production rules have to wait for the tone task, this increased processing time does not affect the response latency. Of course, if the SOA is long, the interference effect is still apparent in the PWI response latency because the increased latency in the perceptual system is not absorbed in the delayed response (Figure 4.4).

**DISCUSSION**

In this study, we reconciled the empirical findings of Dell’Acqua et al. (2007) with the vast body of evidence towards a one-mechanism theory (as reviewed by MacLeod, 1991). Using computational cognitive modeling, we demonstrated that it is possible to account for both Stroop and picture-word interference effects in a single mechanism model. Besides this point, the model contributes to other discussions as well.

The first discussion our modeling results contribute to relates to theoretical accounts of
the PRP effect. The model implemented the PRP effects by assuming an adaptive executive control structure (Meyer & Kieras, 1997b) that controls the order in which the two responses are made. After the perceptual encoding stage of the second task (in this case, encoding of the Stroop or the pwi stimulus), the control structure locks out execution of the second task until the response of the first task has been initiated. This assumption reflects the typical task instructions given in PRP tasks, in which participants are either instructed to respond to the first task before the second task or the importance of the first task is stressed. In the PRP-Stroop and PRP-pwi experiments conducted by Fagot and Pashler (1992) and Dell'Acqua et al. (2007) the correct response order was stressed as well.

Although the model diverges in this respect from the standard central bottleneck model of three stages (input, bottleneck, output, e.g., Ferreira & Pashler, 2002; McCann & Johnston, 1992; Pashler, 1994; Welford, 1967, 1980), it does not refute the logic of the experimental PRP design. The executive control structure creates a cognitive slack time as well in which the initial interference can be absorbed, similar to the central bottleneck theory. However, the models presented here do support the view that such a bottleneck is not a necessary assumption for the PRP effect (Meyer & Kieras, 1997b).

Because the model implements the executive control theory of the PRP effect, we are in a unique position to predict behavior in a PRP tasks in which response order is not stressed. If the model's executive control structure is relaxed, that is, if the model is not constraint in the response order, the model's behavior does not show a PRP effect. Indeed, dual-task experiments have been conducted in which response order was not a factor, and these do not display the PRP effect (e.g., Greenwald & Shulman, 1973; Hazeltine, Teague, & Ivry, 2002; Schumacher, Lauber, Glass, Zurbriggen, Gmeindl, Kieras, & Meyer, 1999; Schumacher, Seymour, Glass, Fencsik, Lauber, Kieras, & Meyer, 2001; but see Levy & Pashler, 2001; Ruthruff, Pashler, & Klaassen, 2001 for opposing evidence). One caveat that should be made however is that the participants in these studies were trained to perform the task concurrently. Therefore, it might also be that practice, not response order was the main cause of the decrease of the PRP effect. This explanation would also be in line with experimental and model findings that show that the PRP effect also decreases with practice in a pwi variant of the task (Van Maanen, Van Rijn, & Taatgen, submitted).

Another discussion related to the picture-word interference effect is concerned with the locus of the interference. The early locus that was reported by Dell'Acqua et al. (2007), might suggest that theories that interpret pwi as a lexical selection effect (e.g., Levelt, Roelofs, & Meyer, 1999; Roelofs, 1992) are wrong. This view is supported by evidence that lexical selection is subject to central processing and therefore does not take place before the central bottleneck in the mental processing stream (Ferreira & Pashler, 2002). By contrast, our model assumes that interference is distributed over many stages, and that depending on the task and on task instructions lexical selection is either a key process, or appears as one of the many sub processes. This is in line with the observation that the Stroop asynchrony is specific to the verbal response modality. If manual responses are required, less emphasis is placed on the lexical selection, and Stroop asynchrony is often absent (MacLeod, 1991).

A third discussion our modeling efforts contribute to is the discussion between single-stage and multiple-stage accounts of semantic interference. The hypothesis that semantic interference might be distributed over different processing stages is not new (e.g., McClelland, 1979). Multiple studies (e.g., De Houwer, 2003; N. Janssen, Schirm, Mahon, & Caramazza, 2008; Risko, Schmidt, & Besner, 2006; Schmidt & Cheesman, 2005; Van Veen & Carter, 2005) - Stroop and picture-word interference are two sides of the same coin -
show that the locus of interference is not fixed for a particular phenomenon. Following the assumptions underlying our model, we postulate that semantic interference is associated with a particular sub process: the retrieval of declarative knowledge from memory instead of with the outcome of that process during a specific stage of the task. This assumption is in line with studies that suggest a dissociation between stimulus-related interference and response-related interference in the Stroop task (e.g., De Houwer, 2003; Risko, Schmidt, & Besner, 2006; Schmidt & Cheesman, 2005).

CONCLUSION

The most important point that our computational modeling efforts make, is that the observed difference between the Stroop effect and PWI effect under PRP conditions should not necessarily be interpreted as different cognitive mechanisms. Instead, interference may be driven by one single mechanism, if we assume that different types of stimuli are encoded at different speeds. With this assumption, a single computational model could account for the data that Dell’Acqua et al. (2007) and Fagot and Pashler (1992) observed, while doing justice to the many theoretical accounts that assume that PWI and Stroop are two manifestations of the same mechanism.