On the Development of Conscious and Unconscious Memory

C. J. Brainerd, L. M. Stein, and V. F. Reyna
University of Arizona

The distinction between conscious and unconscious memory, which is central to modern theories of cognition, has received only limited scrutiny in developmental research. One reason is a need for developmental methodologies that allow age variability in conscious and unconscious memory to be quantified. A simple paradigm (called conjoint recognition) and model are presented that quantify conscious and unconscious memory for learned materials and for the types of unlearned materials that have been found to induce false memories in children. A validation study showed that the model gave excellent accounts of the performance of 7- and 10-year-olds and that conscious and unconscious memory parameters reacted in appropriate ways to 3 manipulations (age, meaningfulness of distractors and targets, and priming).

Much research in the adult memory literature has been devoted to the question of how two processes affect performance. One has been termed conscious (controlled or explicit) memory, and the other has been termed unconscious (automatic or implicit) memory. Conscious memory is said to involve vivid recollections of the occurrence of specific items as part of previously presented material. Phenomenologically, items’ prior occurrences are “seen” in the mind’s eye or “heard” in the mind’s ear. Unconscious memory is said to involve definite feelings that items resemble presented material, but those feelings are not anchored in specific recollection of prior occurrences. Research on these two processes has produced a number of important results—for instance, that retrieval of verbatim traces of items’ surface forms is involved in conscious memory and that retrieval of gist traces of their patterns and meanings is involved in unconscious memory (Brainerd, Reyna, & Brandse, 1995; Payne, Elie, Blackwell, & Neuschatz, 1996; Reyna & Brainerd, 1995a).

Research on conscious versus unconscious memory is quite thin in the developmental literature, with only a few studies having been reported (e.g., Bullock Drummey & Newcombe, 1995; Newcombe & Fox, 1994; Newcombe & Lie, 1995; Russo, Nichelli, Gibertoni, & Cornia, 1995). Those studies have been concerned with questions such as whether above-chance performance on unconscious memory tests can be demonstrated in young children after long delays (Bullock Drummey & Newcombe, 1995; Newcombe & Fox, 1994), whether performance on unconscious memory tests exhibits age variability (Russo et al., 1995), and whether children’s performance on unconscious memory tests is dissociated from their performance on conscious memory tests (Newcombe & Lie, 1995). The present article builds on these pioneering studies, focusing on the question of how to factor the contributions of conscious and unconscious memory to children’s performance and to age changes in performance. Our guiding principle is that the developmental analysis of conscious and unconscious memory would be greatly simplified if a theoretically based methodology were available that delivers numerical estimates of these two processes. We present such a methodology and apply it to the data of an illustrative developmental study.

The article proceeds in three steps. First, we review methods of separating the contributions of conscious and unconscious memory to performance. Both task-based and model-based separation are discussed, with the exegesis of model-based separation focusing on a technique (the process-dissociation model) that has been used in several adult studies. Second, we present a simple procedure, the conjoint-recognition model, that removes some limitations of the process-dissociation model. Third, we report a developmental study in which the conjoint-recognition model was used to measure conscious and unconscious memory at different age levels under various conditions. The major purpose of this study was to validate the use of the conjoint-recognition methodology in developmental research.

Factoring Conscious and Unconscious Memory

That memory performance can be predicated on either conscious or unconscious memory creates a measurement problem: How shall we factor the respective influences of those processes? There are two approaches to this problem (cf. Howe, Rabinowitz, & Grant, 1993)—namely, task-based separation and model-based separation. We consider each in turn. We show that although model-based separation is clearly preferable, the model that has been used in prior research with adults, Jacoby’s (1991) process-dissociation model, has some limitations.

Task-Based Separation

The assumption here is that conscious memory is responsible for correct performance on certain tasks (called direct tests), whereas unconscious memory is responsible for correct performance on other tasks (called indirect tests). For instance, cued and free recall are classified as direct tests, and fragment and
purity, judgments for accepted out that direct and indirect tests are not pure measures of the of conscious and unconscious recognition, respectively. The re-

recollect its presentation as part of the studied material or as the time of study or something about its appearance or position (e.g., what came before or after that word).

Two methods of task-based separation are commonly used. In one, direct and indirect tests for the same material are admin-

istered. For example, participants may study a list of words or pictures and then receive free or cued recall tests plus fragment or stem completion. Cued or free recall performance is the measure of conscious memory, and fragment or stem completion performance is the measure of unconscious memory. This first method has been used in developmental studies. For instance, the direct and indirect tests were picture recognition and blurred picture identification in Bullock Drummey and Newcombe (1995), picture recognition and skin conductance responses to pictures in Newcombe and Fox (1994), overt recognition and covert recognition in Newcombe and Lie (1995), and picture recall and picture completion in Russo et al. (1995).

The other major task-based method is Tulving’s (1985) remember–know procedure, which is based on the notion that recognition is a mixed-process test. Participants respond to a standard recognition test in which studied items (targets) are to be accepted, and unstudied items (distractors) are to be rejected. Participants make an additional judgment about each accepted test probe: They classify it as “remember” if they consciously recollect its presentation as part of the studied material or as “know” if they recognize it but cannot specifically recollect its presentation. The proportions of “remember” and “know” judgments for accepted target probes then provide the estimates of conscious and unconscious recognition, respectively. The remember–know instructions that participants read are detailed and explicit. Examples from an article by Rajaram (1996) are provided in Table 1.

Although task-based separation is uncomplicated, it is not satisfactory. There are two major objections. The first, task impurity, was the focus of an article by Jacoby (1991). He pointed out that direct and indirect tests are not pure measures of the respective memory processes. Jacoby reviewed evidence showing, instead, that direct tests are contaminated by unconscious memory and that indirect tests are contaminated by conscious memory. Other investigators (e.g., Strack & Forster, 1995) have provided analogous evidence that remember judgments are impure measures of conscious memory, and know judgments are impure measures of unconscious memory.

The second objection to task-based separation, response scal-
ing, was explored by Howe et al. (1993). Even if it could be assumed that direct tests (or remember judgments) are pure measures of conscious memory and that indirect tests (or know judgments) are pure measures of unconscious memory, the output transformations that map true levels of conscious and unconscious memory on observed levels of performance are unknown. Therefore, the general procedure of measuring levels of performance on different tasks does not actually tell researchers anything about the corresponding levels of conscious and unconscious memory. Unless the output transformations for the tasks are known, one cannot say that the level of one memory process is higher than that of the other merely because performance on one task is higher than performance on the other task (Howe et al., 1993).

There is a further objection to task-based separation that is of special significance in developmental research—namely, age appropriateness. In both of the standard methods of task-based separation, elements of the procedures are too difficult to be successfully implemented with children in the early elementary grades or with preschoolers. For instance, the most extensively used unconscious tests are fragment and stem completion. These tests are inappropriate for children who are too young to be highly skilled in spelling and reading. Similarly, remember–know tests (Table 1) require high school levels of reading comprehension. Therefore, other tests that are more age appropriate must be substituted. Although such tests are available (e.g., Newcombe & Fox, 1994; Newcombe & Lie, 1995), their use is not without cost: The results of developmental and adult studies cannot be directly compared because the dependent variables are different.

Model-Based Separation

Jacoby (1991) and Howe et al. (1993) noted that the task-impurity and response-scaling objections can be addressed by
prior presentation is not consciously recollected but unconscious memory makes it seem familiar, with probability \( U(1 - C) \). In place of multiple tests, the model is defined over a single test. It simply expresses the probability of observed responses on that test as algebraic functions of parameters that measure the probabilities of conscious and unconscious remembrance.

Model-based separation reduces concerns about task impurity because it does not treat any test as a pure measure of any memory process. On the contrary, it is a formal implementation of the notion that memory tests normally involve mixtures of processes. Model-based separation also eliminates the response-scaling objection because it does not leave output transformations as open questions. A model specifies the quantitative relations between true levels of conscious and unconscious memory and performance on memory tests.

Jacoby’s (1991) process-dissociation model was the first attempt to achieve model-based separation of conscious and unconscious memory. The model was originally defined over a recognition paradigm, though it is easily extended to tasks such as fragment and stem completion (e.g., Jacoby, Toth, & Yonelinas, 1993) and cued recall (e.g., Jacoby, 1996). Participants make two types of recognition decisions about test probes. To begin with, all participants study two lists that differ in some property that can be used to discriminate them (e.g., they read List 1 targets but listen to List 2 targets). Half of the participants then respond to an exclusion test, and half respond to an inclusion test. On both tests, some of the probes are List 1 targets, some are List 2 targets, and some are unpresented distractors. Participants who respond to the exclusion test are instructed to accept List 2 targets and to reject both List 1 targets and distractors. Participants who respond to the inclusion test are instructed to accept both List 1 and List 2 targets and to reject distractors.

The performance data are the probabilities of accepting List 1 targets (i.e., the to-be-excluded targets) on exclusion and inclusion tests. These probabilities are expressed as

\[ p_E = U(1 - C) \]  

and

\[ p_I = C + U(1 - C), \]  

where \( C \) and \( U \) are the probabilities of conscious and unconscious memory, respectively. Conceptually, the model specifies two routes to (correct) acceptance of List 1 probes on inclusion tests, but only one route to (incorrect) acceptance on exclusion tests. Under inclusion instructions, participants may consciously recollect a probe’s prior presentation, with probability \( C \), or they may not be able to consciously recollect it, but they may nevertheless accept it because unconscious memory makes it seem familiar, with probability \( U(1 - C) \). Under exclusion instructions, however, a List 1 probe will only be accepted if its prior presentation is not consciously recollected but unconscious memory makes it seem familiar, with probability \( U(1 - C) \). Because Equations 1 and 2 are a system of two expressions in two known quantities and two unknown quantities, the latter can be estimated from the solutions

\[ C = p_I - p_E \]  

and

\[ U = p_E/(1 - C). \]  

Applications of this model in adult memory research have yielded several instructive findings, the most important of which are demonstrations of the apparent independence of conscious and unconscious memory. If conscious and unconscious memory are truly distinct processes rather than aspects of a single process, such as an overall strength factor of the sort postulated in global memory models (see Clark & Gronlund, 1996), they should be dissociated under certain experimental manipulations. Dissociations in estimates of \( C \) and \( U \) have been identified in several studies. In Jacoby’s (1991, Experiment 3) original study, participants studied targets in either a cognitively engaging manner (anagram solution) or in a more passive manner (reading). As would be expected if \( C \) measures conscious memory and \( U \) measures unconscious memory, estimates of \( C \) were higher when the study method was engaging. A similar result was reported by Yonelinas (1994). Yonelinas conducted two experiments in which more attention could be devoted to the study of individual targets in one condition than in another condition. As would be expected, estimates of \( C \) were higher when more attention was devoted to individual targets, but estimates of \( U \) were unaffected.

Limitations of the Process-Dissociation Model

The process-dissociation model has fomented much research on conscious and unconscious memory and has advanced our understanding of these processes. However, some limitations of the model have been identified in a series of recent articles (e.g., Buchner, Erdfelder, & Vaterrodt-Plunecke, 1995; Cowan & Stadler, 1996; Curran & Hintzman, 1995; Graf & Komatsu, 1994; Ratcliff, Van Zandt, & McKoon, 1995; Roediger & McDermott, 1994). Those limitations are of two sorts—namely, some untested assumptions that are made to estimate parameters and some theoretically important capabilities that the model lacks. We discuss these classes of limitations separately and then summarize some recent work that addresses two of them.

Untested Assumptions

Three assumptions have to be made for Equations 3 and 4 to deliver unique parameter estimates: \( C \) and \( U \) values must be invariant across the inclusion and exclusion conditions (Graf & Komatsu, 1994), response bias must be invariant across these conditions (Buchner et al., 1995), and \( C \) and \( U \) values must be stochastically independent (Curran & Hintzman, 1995). When any of these assumptions is violated, the model’s parameter space will be supersaturated, and unique estimates of \( C \) and \( U \) cannot be obtained. That the model’s parameter space will be supersaturated is obvious from the fact that Equations 1 and 2 become \( p_I = C + U(1 - C) \) and \( p_E = U(1 - C) \) when the
first assumption is violated, \( p_t = C + U(1 - C) + b_t(1 - C)(1 - U) \) and \( p_e = U(1 - C) + b_e(1 - C)(1 - U) \) when the second assumption is violated (where \( b_t \) and \( b_e \) are response-bias parameters), and \( p_t = C + f_R(1 - C) \) and \( p_e = f_R(1 - C) \) when the third assumption is violated (where \( f_R \) is an unknown function representing the relation between \( C \) and \( U \)).

Estimates of \( C \) and \( U \) will be biased in various ways by violations of these assumptions. For example, \( U \) will be underestimated if \( R_E > R_t \) and overestimated if \( R_E < R_t \) (Brainerd, Reyna, & Mojardin, 1997); \( C \) will be overestimated and \( U \) will be underestimated if \( b_t > b_e \) and the opposite will be true if \( b_t < b_e \) (Buchner et al., 1995); and \( U \) will be underestimated when \( C \) and \( U \) are positively correlated and overestimated when they are negatively correlated (Curran & Hintzman, 1995). Because estimation is biased when assumptions are violated, conclusions about the relative impact of the two processes on performance are hazardous (see also Roediger & McDermott, 1994).

It has also been suggested that violations of assumptions favor spurious dissociations between \( C \) and \( U \). For instance, Curran and Hintzman (1995) argued that this is the case with the stochastic independence assumption. If \( C \) and \( U \) are positively correlated, \( U \) will be underestimated because the only items that figure in its estimation are ones for which conscious memory fails (cf. Equation 1). Now, consider some treatment that increases both \( C \) and \( U \). Although estimates of \( U \) will have a downward bias in both treatment and control conditions, the bias will be stronger in the treatment condition because conscious memory fails for fewer items, and those items have \( U \) values that are farther below average than those for which conscious memory fails in the control condition. The treatment’s effects on \( U \) will therefore tend to be masked. Brainerd et al. (1997) showed that violations of the other two assumptions (constancy of memory parameters and response bias) can also favor spurious dissociations between \( C \) and \( U \) by biasing the estimate of one parameter more than the other.

It is important, therefore, to determine whether these assumptions are violated in experimental applications. The original version of the process-dissociation model does not provide procedures for testing the assumptions.

**Missing Capabilities**

The process-dissociation model supplies neither goodness-of-fit tests nor parameters that measure conscious and unconscious memory for unpresented distractors. Concerning goodness of fit, the core hypothesis of any mathematical model is that experimental data from the paradigm over which the model is defined are generated in accordance with the restrictions specified in its equations. This core hypothesis should be evaluated before a model is used to investigate theoretical proposals about memory (Theios, Leonard, & Brelsford, 1977), which is done with goodness-of-fit tests. Such tests require that the number of parameters in a model shall be less than the number of empirical quantities in its outcome space, with the difference between the two numbers being the degrees of freedom for the tests (e.g., Riefer & Batchelder, 1988).

In the process-dissociation model, there are no residual degrees of freedom because there are two empirical quantities, \( p_t \) and \( p_e \), and two theoretical quantities, \( C \) and \( U \), to be estimated. This has consequences for the model’s claim that there are separate conscious and unconscious memory processes: One cannot tell whether experimental data are more likely to have been generated by the process-dissociation model than by some other model that does not posit separate recollection and familiarity processes (Ratcliff et al., 1995).

Concerning the second missing capability, the process-dissociation model only measures the contributions of conscious and unconscious memory to target hit rates. However, one of the most productive theoretical extensions of these concepts has been to the analysis of false alarms in the rapidly expanding literature on false memory (e.g., Brainerd & Reyna, 1995, in press; Payne et al., 1996; Reyna & Brainerd, 1995a; Schacter, Verfaellie, & Pradere, 1996). These analyses have been based on the idea that conscious and unconscious memory operate in tandem to produce hits (as in Equation 2) but that they operate in opposition with distractors, with unconscious memory supporting false alarms and conscious memory supporting correct rejections (Brainerd & Reyna, in press; Brainerd, Reyna, & Knerr, 1995; Clark & Gronlund, 1996; Hintzman, Curran, & Oppy, 1992). For example, suppose that the target collie is replaced by the distractor poodle on a test list. If poodle produces retrieval of unconscious memories of collie’s presentation, this will provoke feelings of unanchored familiarity that lead to false alarms. But if poodle produces retrieval of conscious memories of the collie’s presentation, this will provoke feelings of contrast that lead to correct rejections.

Given the prevalence of this view of false alarms, it is important that a model be able to measure conscious and unconscious memory for distractors as well as for targets. This is particularly true in developmental research, in which false alarms have been used to gain leverage on important practical questions about age variation in rates of memory falsification (Brainerd & Mojardin, in press; Brainerd, Reyna, & Brandse, 1995; Reyna, 1995).

**Modifications of the Model**

Recently, certain modifications have been made to deal with two of the preceding limitations. Procedures for testing the response-bias assumption have been developed by Buchner et al. (1995) and Vinelinas, Regehr, and Jacoby (1995). Procedures for testing the stochastic-independence assumption have been developed by Curran and Hintzman (1995) and Jacoby (1996).

Two methods have been proposed to test the response-bias assumption. Buchner et al. (1995) used false-alarm rates for distractors to estimate response bias in the inclusion and exclusion conditions through the expressions:

\[
\begin{align*}
\rho_{AI} &= C + C(1 - U) + b_t(1 - C)(1 - U), \\
\rho_{AE} &= U(1 - C) + b_e(1 - C)(1 - U),
\end{align*}
\]

and

\[
\rho_{AI} = b_t, \quad \rho_{AE} = b_e,
\]

where \( b_t \) and \( b_e \) are response-bias probabilities for the inclusion and exclusion conditions, respectively, and the subscripts \( t \) and \( e \) represent the inclusion and exclusion conditions, respectively.
d denote target and distractor probes, respectively. C and U are estimated from the solutions \( C = (p_{t,1} - p_{d,1})/(1 - p_{d,1}) \) and \( U = (p_{t,1} - (1 - C)p_{d,1})/(1 - C) \). Yonelinas et al. (1995) also relied on distractor false-alarm rates to estimate response bias in the two conditions, but they used different equations that were derived from signal-detection theory. With their respective procedures, both Buchner et al. and Yonelinas et al. found that rates of response bias were not equal across inclusion and exclusion conditions.

Concerning the stochastic independence assumption, Curran and Hintzman (1995) and Jacoby (1996) computed correlations between C and U through a procedure in which individual participants performed both inclusion and exclusion tasks. For fragment completion, Curran and Hintzman reported positive interitem correlations (range = .26 to .70, \( M = .52 \)) and negative interparticipant correlations (range = -.18 to -.43, \( M = -.30 \)). For associative recognition, Jacoby (1996) also reported positive interitem correlations (range = .24 to .26, \( M = .25 \)) and negative interparticipant correlations (range = -.34 to -.46, \( M = -.40 \)).

Although the independence assumption was violated in these studies, Jacoby, Begg, and Toth (1997) subsequently demonstrated that such violations can probably be ignored in research. The reason is that the bias in U estimates that results from \( C - U \) correlations is slight and is too small to produce the parameter dissociations that have been observed in prior studies. It is important to note that this is true even when the \( C - U \) correlation is perfect. To illustrate this point, Figure 1 contains simulated data on the independence assumptions that were generated by C. J. Brainerd, L. Stein, and V. F. Reyna. In our simulations, the correlation between C and U was fixed at 1, true (population) values of C varied in the .4 to .8 range, and true values of U varied in the .2 to .6 range. (Values of the response-bias parameters in the range that has typically been observed in process-dissociation studies were used.) The upper line in Figure 1 is the plot of true values of U as a function of true values of C, whereas the lower line is the plot of (under)estimated values of U as a function of true values of C. It is important to note that the difference between the two lines is minuscule. Overall, the average difference between true values of U and corresponding estimates of U, when the \( C - U \) correlation is perfect, is only .018.

### The Conjoint-Recognition Model

We have seen that the process-dissociation model was developed to factor the contributions of conscious and unconscious memory to performance but that it has some limitations. Although two of them have been dealt with in recent work, the remaining three limitations (the untested assumption of between-condition invariance of memory parameters, lack of goodness-of-fit tests, and lack of parameters that measure conscious and unconscious memory for distractors) have not been addressed. To deal with these remaining limitations, we present an alternative model called conjoint recognition.

The conjoint-recognition model is defined over a paradigm that preserves the basic logic of the process-dissociation procedure but modifies it to include new instructional conditions and two distinct classes of distractors (related and unrelated). First, we describe the experimental paradigm and the empirical probabilities that constitute the model's outcome space; then, we present the model itself; last, we summarize statistical procedures for parameter estimation, goodness of fit, and hypothesis testing.

### Paradigm and Outcome Space

The outcome space is a set of six empirical probabilities provided by a paradigm called conjoint recognition, wherein three types of recognition probes are factorially combined with two types of recognition instructions. (Because the conjoint-recognition model also contains six theoretical parameters to be estimated from data, further empirical probabilities are added later on to obtain goodness-of-fit tests.) In both instructional conditions, children (or adults) study a common list of targets before they make yes–no (accept–reject) decisions about individual probes on a common test list. The test list consists of studied targets (T probes), distractors that are physically or semantically related to targets (R probes), and distractors that are physically and semantically unrelated to targets (U probes). The properties that T probes share with targets are obvious ones that can easily be described and exemplified to children as part of recognition-test instructions. Examples of such probes include rhymes, synonyms, and category names.

The instructions for the recognition test contain full information about the three types of probes to be presented, and examples are provided as part of the instructions. Children make recognition decisions under either T instructions (accept targets and reject both related and unrelated distractors) or R instructions (accept related distractors and reject both targets and unrelated distractors). These conditions allow conscious and unconscious memories to be separated because conscious memories should be under instructional control, whereas unconscious
memories should not be. More explicitly, responses (accept–reject) can be reversed when decisions are based on conscious memories but cannot be reversed when they are based on unconscious memories (see below). Because three types of probes are crossed with two types of recognition decisions, there are six empirical probabilities in the outcome space: $p_{t,t}$, $p_{r,r}$, $p_{t,r}$, $p_{r,t}$, and $p_{a,r}$, where the first subscript denotes probe type and the second denotes instructional condition.

The Model

The conjoint-recognition model is a multinomial model that expresses these six empirical probabilities as functions of two memory processes, conscious and unconscious memory, and of response bias. The model estimates the two memory processes separately for presented targets and unpresented distractors, the two memory processes independently of response bias, and the rates of response bias for each instructional condition. This model also tests for goodness of fit and violations of the assumption that rates of conscious and unconscious memory are invariant across the two instructional conditions. First, we present the model’s expressions for targets, then, its expressions for related distractors, and finally, its expressions for unrelated distractors.

Targets. A tree diagram showing the relationship between memory processes and response outcomes for targets in the T condition appears in Figure 2 (top). Consider $p_{t,t}$, the probability of (correctly) accepting a target under T instructions (accept targets and reject both related and unrelated distractors). Under such instructions, a target can be accepted in three ways: (a) Its presentation is consciously remembered, with probability $C_t$, (b) its presentation is not consciously remembered, with probability $1-C_t$, but it is unconsciously remembered, with probability $U_t$, (c) its presentation is neither consciously nor unconsciously remembered, with probability $(1-C_t)(1-U_t)$, but response bias produces acceptance, with probability $b_T$. The only way that a target can be rejected is if its presentation is neither consciously nor unconsciously remembered and response bias does not produce acceptance, with probability $(1-C_t)(1-U_t)(1-b_T)$.

A tree diagram showing the relationship between memory processes and response outcomes for targets in the R condition appears in Figure 2 (bottom). Consider $p_{r,r}$, the probability of (incorrectly) accepting a target under R instructions (accept related distractors and reject both targets and unrelated distractors). Acceptance can occur in two ways: (a) The target's presentation is not consciously remembered, with probability $1-C_t$, but it is unconsciously remembered, with probability $U_t$, and (b) the target's presentation is neither consciously nor unconsciously remembered, with probability $(1-C_t)(1-U_t)$, but response bias produces acceptance, with probability $b_R$. Rejection can occur in two ways: (a) The target's presentation is consciously remembered, with probability $C_t$, or (b) the target's presentation is neither consciously nor unconsciously remembered and response bias does not produce acceptance, with probability $(1-C_t)(1-U_t)(1-b_R)$. (Regarding $a$, if a target’s presentation can be consciously remembered, it will be rejected because R instructions tell children to reject targets.)

The reader should note that, as mentioned earlier, the operational difference between conscious and unconscious memory in this paradigm is that accept–reject decisions can be reversed by instructions if they are based on conscious memory, but not if they are based on unconscious memory. Specifically, because retrieval of a conscious memory produces explicit recollection of a target's presentation during the study phase, that memory can be attributed to the study phase and to a specific target. Consequently, it leads to acceptance of that target under T instructions and rejection of it under R instructions. When an unconscious memory can be retrieved, it can also be attributed to the study phase but not to a specific target. Thus, the retrieved memory, though attributable to the study phase, does not discriminate targets from related distractors, and some other basis for accept–reject decisions must used. The model assumes that participants use the only other available information, the instructions, as the basis for treating probes that produce retrieval of unconscious memories as examples of whatever type of item is specified for acceptance (targets in T instructions and related distractors in R instructions). Summing up, the target-acceptance expressions for the two instructional conditions are

$$p_{t,t} = C_t + (1-C_t)U_t + (1-C_t)(1-U_t)b_T$$

and

$$p_{r,r} = (1-C_t)U_t + (1-C_t)(1-U_t)b_R.$$
The parameters $C_t$ and $U_t$ are the probabilities of conscious and unconscious memory, respectively, for targets, and the parameters $b_T$ and $b_R$ are the probabilities of acceptances based on response bias under T instructions and R instructions, respectively.

**Related distractors.** A tree diagram showing the relationship between memory processes and response outcomes for related distractors in the T condition appears in Figure 3 (top). Consider $p_{AT}$, the probability of (incorrectly) accepting a related distractor under T instructions. Such acceptances can occur in two ways: (a) The presentation of a distractor’s instantiating target (e.g., the presentation of cattle, if battle is the distractor) is not consciously remembered, with probability $1 - C_r$, but it is unconsciously remembered, with probability $U_r$, or (b) the presentation of a distractor’s instantiating target is neither consciously nor unconsciously remembered, with probability $(1 - C_r)(1 - U_r)$, but response bias produces acceptance, with probability $b_T$. Related distractors can be rejected in two ways under T instructions: (a) The presentation of a distractor’s instantiating target is consciously remembered, with probability $C_r$, or (b) the presentation of a distractor’s instantiating target is neither consciously nor unconsciously remembered and response bias does not produce acceptance, with probability $(1 - C_r)(1 - U_r)(1 - b_T)$.

![Figure 3](image)

**Figure 3.** Relations between parameters of the conjoint-recognition model and response outcomes for related distractors. The top part of the figure presents relations for the T condition, and the bottom part presents relations for the R condition.

A tree diagram showing the relationship between memory processes and response outcomes for related distractors in the R condition appears in Figure 3 (bottom). Consider $p_{AR}$, the probability of (correctly) accepting a related distractor under R instructions. Such acceptances can occur in three ways: (a) The presentation of a distractor’s instantiating target is consciously remembered, with probability $C_r$, (b) the presentation of a distractor’s instantiating target is not consciously remembered, with probability $1 - C_r$, but it is unconsciously remembered, with probability $U_r$, or (c) the presentation of a distractor’s instantiating target is neither consciously nor unconsciously remembered, with probability $(1 - C_r)(1 - U_r)$, but response bias produces acceptance, with probability $b_R$. Related distractors can be rejected in only one way: The presentation of a distractor’s instantiating target is neither consciously nor unconsciously remembered and response bias does not produce acceptance, with probability $(1 - C_r)(1 - U_r)(1 - b_R)$.

As before, the operational difference between conscious and unconscious memory is that decisions based on conscious memory are under instructional control, but decisions based on unconscious memory are not: Retrieval of a conscious memory leads to rejection under T instructions and acceptance under R instructions (because the memory can be attributed to the study phase and to a particular target), but retrieval of an unconscious memory leads to acceptance under both T and R instructions (because the memory can be attributed to the study phase but not to a particular target). Thus, the model’s expressions for acceptance of related distractors are

$$p_{AT} = (1 - C_r)U_r + (1 - C_r)(1 - U_r)b_T$$

and

$$p_{AR} = C_r + (1 - C_r)U_r + (1 - C_r)(1 - U_r)b_R.$$  

The parameters $C_r$ and $U_r$ are the probabilities of conscious and unconscious memory, respectively, for related-distractor probes.

**Unrelated distractors.** Following Buchner et al. (1995), the conjoint-recognition model uses false-alarm rates for unrelated distractors to measure response bias in the two instructional conditions. The relevant expressions are

$$p_{uT} = b_T$$

and

$$p_{uR} = b_R.$$  

Although these parameters appear as conditional probabilities in Equations 9 through 12, they can be estimated as unconditional probabilities with Equations 13 and 14.

**Statistical Procedures**

**Parameter Identification**

Equations 9 through 14 contain six theoretical parameters—two for conscious memory ($C_t$ for targets and $C_r$ for distractors), two for unconscious memory ($U_t$ for targets and $U_r$ for distractors), and two for response bias ($b_T$ for T instructions
and \( b_R \) for R instructions). An important question about this or any model is whether it is identifiable—that is, whether unique and independent estimates of each parameter can be obtained in the outcome space. The standard procedure for proving parameter identifiability is to show that each theoretical parameter can be defined as a unique function of the empirical probabilities in the outcome space (e.g., Brainerd, Howe, & Kingma, 1982; Cooney & Troyer, 1994). The relevant proof for Equations 9 through 14 is exhibited in the Appendix.

**Parameter Estimation**

Because the model is identifiable, a likelihood function can be written from which unique maximum likelihood estimates of its six parameters can be obtained from sample data (general procedures for deriving such functions are presented in Riefer & Batchelder, 1988). The relevant function, \( L_6 \), appears in the Appendix (Equation A8). To estimate the model’s six parameters from sample data, this function is maximized with iterative search methods. A program, CONJOINT, has been written that estimates the six parameters from sample data. This program implements Hu’s (1995) general processing tree software. Readers may obtain a disk containing software for CONJOINT that will run on desktop PCs from C. J. Brainerd.

**Goodness of Fit**

Because six theoretical parameters are estimated, and Equations 9 through 14 contain exactly six empirical probabilities, additional empirical probabilities must be incorporated to test goodness of fit. This is easily done by redefining the expressions for targets and related distractors (Equations 9–12) as probabilities of joint target-distractor responses for pairs of instantiating targets (e.g., cattle) and related distractors (e.g., battle). This cannot be done with the usual process-dissociation procedure because test lists do not include pairs of targets and related distractors.) When combined with expressions for unrelated distractors (Equations 13 and 14), the available empirical probabilities increases from six to eight. The revised expressions for targets and related distractors are

\[
p_{T,T} \sim p_{T,T} = [(1 - C_t)(1 - U_t)(1 - b_T)], \quad (15)
\]

\[
p_{T,R} \sim p_{T,R} = [C_t + (1 - C_t)(1 - U_t)(1 - b_T)], \quad (16)
\]

\[
p_{R,T} \sim p_{R,T} = [C_r + (1 - C_r)(1 - U_r)(1 - b_T)], \quad (17)
\]

\[
p_{R,R} \sim p_{R,R} = [(1 - C_r)(1 - U_r)(1 - b_T)], \quad (18)
\]

where \( r_i \) is the probability of rejecting a Type \( i \) item (\( i = t \) or \( r \)) in condition \( j (j = T \) or \( R \)). The expressions for unrelated distractors are the same as before.

A Fisher-type observable-states likelihood function can be written that has 8 \( df \). That function appears as Equation A7 in the Appendix. Equations A7 and A8 are used to compute omnibus goodness-of-fit tests. First, Equation A7 is maximized for sample data to find their likelihood when all eight empirical parameters are free to vary (\( L_8 \)). Second, Equation A8 is maximized for the same data to find their likelihood when only the six parameters of the conjoint-recognition model are free to vary (\( L_6 \)). The null hypothesis that the sample data could have been generated by processes that obey the constraints of the model is then evaluated with the test statistic

\[
\chi^2(2) = -2\ln(L_6/L_8), \quad (21)
\]

which has a critical value (.05 level) of 5.99.

**Between-Condition Invariance of Memory Parameters**

It is apparent from Equations 9 through 12 that the model assumes that conscious- and unconscious-memory parameters are invariant across the T and R conditions. This assumption could be incorrect. For instance, it might be argued that instructions to accept only related distractors in the R condition could suppress target probes’ tendency to retrieve conscious memories (\( C_t \)) but increase distractor probes’ tendency to retrieve conscious memories (\( C_r \)), relative to the T condition. Or, it might be argued that children’s normal tendency to accept targets and reject distractors would interfere with their ability to follow instructions in the R condition, thereby suppressing both conscious and unconscious memory parameters for distractors in that condition. Further, it might be argued that the unconscious memories that lead to acceptance of targets in the T condition might often lead to rejection in the R condition (because children are told to reject items that they might have studied), thereby suppressing \( U_t \).

Thus, it is important to evaluate the model’s assumption that conscious- and unconscious-memory parameters are invariant across the T and R conditions. The goodness-of-fit test in Equation 21 also evaluates this assumption because fit will be poor when the assumption is violated. If instructions affect conscious memory, for either targets or related distractors, the actual number of conscious-memory parameters that is necessary to describe the data will be more than the two (\( C_t \) and \( C_r \)) posited in the model, and fit will fail. Likewise, if instructions affect unconscious memory, the actual number of unconscious-memory parameters that is necessary to describe the data will be more than the two (\( U_t \) and \( U_r \)) posited in the model, and fit will again fail.

**Hypothesis Testing**

If fit is established, within-condition and between-condition null hypotheses about estimated values of the model’s parameter...
ters can be tested. A within-condition null hypothesis stipulates either (a) that a certain parameter has a specific value (e.g., $C_t$ = 0) or (b) that two parameters have equal values (e.g., $U_t$ = $U_r$). To test either type of hypothesis, the likelihood function that was maximized to estimate the six parameters (Equation A8) is remaximized under the constraint specified in the hypothesis. Then, the likelihood ratio statistic

$$\chi^2(1) = -2\ln(L_{ij}/L_{0j})$$

is calculated, where the numerator is the value of the function when all six parameters are free to vary and the denominator is the value of the function when the constraint has been imposed.

A between-condition null hypothesis states that a certain parameter has the same value in different conditions (e.g., at different age levels). To test such hypotheses for a pair of conditions, a joint likelihood function based on Equation A8 (e.g., $L_{ij} \times L_{0j}$) is used, where $L_{0j}$ is the likelihood function for Condition $i$ and $L_{ij}$ is the likelihood function for Condition $j$. First, this likelihood function is maximized for the data of the two conditions, with all parameters free to vary. Second, the function is remaximized for the same conditions under the constraint that all six parameters have the same value in the two conditions. Third, the likelihood ratio statistic

$$\chi^2(6) = -2\ln(L_{ij}/L_{1j})$$

is calculated, where $L_{1j}$ is the likelihood from the first maximization and $L_{ij}$ is the likelihood from the second maximization. If this conditionwise test produces a null hypothesis rejection, the alternative hypothesis is that some of the parameters have different values in the two conditions. Null hypotheses about between-condition differences in specific parameters can then be tested by remaximizing the data under the constraint that a specific parameter (e.g., $C_t$) has the same value for the two conditions and by calculating the likelihood ratio statistic

$$\chi^2(1) = -2\ln(L_{1j}/L_{12})$$

where $L_{1j}$ is the new likelihood that results from the remaximization of the conditionwise test.

A Developmental Study

We now report a study whose aim was to provide preliminary validation of the model in developmental research on conscious and unconscious memory. Generally speaking, a model-validation study seeks to answer two questions (cf. Brainerd, 1985): Can fit be established for participant samples from the target population? If so, do the model’s parameters behave in ways that are consistent with extant theory and data? Obviously, the first question involves conducting tests of goodness of fit and of memory-parameter invariance (Equation 21) with developmental data sets.

The second question involves (a) investigating predictions about relations between estimated values of conscious and unconscious memory parameters and (b) investigating predictions about how those parameters react to selected experimental manipulations. Concerning (a), certain relations can be predicted on the basis of prior research. For instance, studies conducted within the framework of fuzzy-trace theory have consistently found that on immediate recognition tests with both children and adults, target probes are more likely to provoke conscious memory experiences than unconscious memory experiences (Ackerman, 1994; Brainerd & Reyna, 1995, in press; Reyna & Kiernan, 1994, 1995). Thus, $C_t > U_t$ is a predicted relation. Other studies conducted within the same framework have found that related-distractor probes (e.g., battle) are less likely to provoke conscious memories of their instantiating targets (e.g., cattle) than the targets themselves (Brainerd & Moajardin, in press; Brainerd & Reyna, 1996b; Brainerd, Reyna, & Kneer, 1995). Hence, $C_t > C_r$ is another predicted relation.

Concerning (b), prior research provides a basis for predicting that conscious and unconscious memory parameters will react in specific ways to certain experimental manipulations. Three illustrative manipulations were included in this study. First, testing an instantiating target (e.g., cattle) just before its related distractor (e.g., battle) will prime target memories, naturally, and will increase the distractor’s tendency to access those memories. However, because target probes are especially good retrieval cues for conscious memories (Reyna & Kiernan, 1994, 1995), this manipulation increases a distractor’s tendency to cue the retrieval of conscious memories more than its tendency to cue the retrieval of unconscious memories (Brainerd, Reyna, & Kneer, 1995; Reyna & Brainerd, 1995a). Consequently, target priming should increase $C_t$, and any increase in $U_t$ should be smaller than the increase in $C_t$.

Second, another finding from prior studies is that conscious memory tends to be based on retrieval of the exact surface form of target presentations, whereas unconscious memory tends to be based on retrieval of semantic gist (Conway, Collins, Gathercole, & Anderson, 1996; Pritchley & Pipe, 1997; Rajaram, 1996; Reyna & Brainerd, 1995b). Because surface information about targets fades rapidly but semantic gist does not (Reyna & Kiernan, 1994, 1995), study-phase manipulations that increase children’s ability to preserve such information should increase levels of conscious memory. Test-phase manipulations that increase children’s tendencies to retrieve surface information about targets by decreasing the availability of semantic information should also increase levels of conscious memory. In the present study, we included a content manipulation (meaningful words vs. nonsense words) for both targets and related distractors for which these principles generated clear predictions about the conscious and unconscious memory parameters. Concerning targets, a number of prior studies (e.g., Brainerd & Moajardin, in press; Murphy & Shapiro, 1994) have suggested that the retention of both surface and semantic information about targets increases as targets become more meaningful, which leads to the prediction that $C_t$ and $U_t$ both will be larger for meaningful words than for nonsense words. A different and more counterintuitive pattern is predicted for related distractors: The content manipulation should doubly dissociate conscious and unconscious memory parameters for distractors. On the one hand, nonsense rhymes (e.g., battle when cattle was a target) should increase children’s tendency to retrieve the surface information that supports conscious memory, relative to meaningful rhymes (e.g., battle), because less semantic information is available in the retrieval cue. On the other hand, for the same reason, nonsense rhymes should suppress children’s tendency to retrieve
the semantic information that supports unconscious memory. Thus, the prediction is that \( C_t \) will be larger but \( U_t \) will be smaller for nonsense materials.

Third, age is also an instructive manipulation. Prior studies (Bullock Drummey & Newcombe, 1995; Newcombe & Fox, 1994; Newcombe & Lie, 1995; Russo et al., 1995) have consistently found that performance on tests of conscious memory improves with age. Therefore, if parameters \( C_t \) and \( C_r \) actually measure conscious memory, both should increase with age.

Turning to the design of the study, two basic paradigms are used in recognition—study test and continuous. In the former, targets are presented first, followed by a buffer activity and instructions for the recognition test, followed by the test. In continuous recognition (Shepard & Teghtsoonian, 1961), there is no distinction between study and test phases. Children are instructed that a series of items will be presented and that they must make accept—reject decisions about each item as it is presented. At first, all items are new, of course, and rejection is always the correct decision. As presentation continues, however, some earlier items are repeated so that each subsequent item may be either old (accept) or new (reject).

In prior developmental studies, both the study-test procedure (e.g., Brainerd, Reyna, & Kner, 1995) and the continuous procedure (e.g., Felzen & Anisfeld, 1971) have been used. Although the conjoint-recognition methodology can be applied to either, we chose continuous recognition because it avoids the high rates of forgetting of surface information about targets that occur between targets' initial presentations and their subsequent appearance as test probes (cf. Reyna & Kiernan, 1994, 1995). This makes it easier to test some of the above predictions. Another advantage of continuous recognition is that because it maximizes reliance on conscious memory, two further parameter relations can be predicted: \( C_t > U_t \) and \( C_r > U_t \).

Method

Participants

The participants were 100 elementary-school children (50 boys and 50 girls). There were 50 second-grade children (\( M = 7 \) years 8 months; range = 7 years 4 months to 8 years 4 months) and 50 fifth-grade children (\( M = 10 \) years 10 months; range = 10 years 5 months to 11 years 6 months). All children were pupils of public elementary schools that served suburban areas of a city in the western United States. Children's participation was secured by parents' letters of permission.

Materials and Procedure

Twenty-five children from each age level were randomly assigned to conditions T (accept only targets) and R (accept only related distractors). Children were tested individually in a small, quiet room within their schools. At the start of the procedure, children listened to a tape recording of the instructions for their condition. All children were told that they would be listening to a list of vocabulary words. They were informed that there would be two types of words: concrete nouns that they hear everyday (e.g., friend, library, picture) and nonsense words that would be unfamiliar to them (e.g., nepper, wax, zaffe). The children were further informed that after the first few words, some of the words that they would hear would continue to be entirely new, but others would be like words that they had already heard. They were told that these latter words would be of two sorts: words that were exactly the same as previously presented words (i.e., target repetitions) and words that sounded like previously presented words but were not exactly the same (i.e., rhymes of targets). To ensure the children's understanding, examples of both target repetitions and rhyming distractors were provided, and children were asked to respond to these examples. Both T and R instructions were easy to understand because all children performed perfectly on these examples. Hence, there was no attrition.

Following instructions, children made recognition decisions about a list of 200 probes. They listened to audio recordings in which the words were read at a 6-s rate. The list consisted of 120 familiar concrete nouns (e.g., apple, hammer, sparrow) and 80 nonsense words (e.g., hamp, tijly, yoddle). A total of 20 of the nouns and 20 of the nonsense words were repetitions of previously presented items. These were the probes that children in the T condition were instructed to accept. A total of 20 of the nouns and 20 of the nonsense words were rhymes of previously presented items. (The following are some examples: flood, where blood had been presented earlier, girl, where durl had been presented earlier, kif, where gift had been presented earlier, and join, where mock had been presented earlier.) These were the probes that children in the R condition were instructed to accept.

The 200 probes were read in random order except for two constraints. First, a total of 10 to 15 items always intervened between repetitions of previously presented items or between presentations of rhymes and presentations of their instantiating targets. This was done to control for short-term memory effects. (In continuous recognition, performance is superior when repetitions occur within 4–5 positions of the original presentation, but not thereafter; cf. Greeno, 1967.) Second, half of the rhymes (10 of the nouns and 10 of the nonsense words) were immediately preceded by their instantiating targets. (The following are some examples: block was preceded by clock, where clock had been presented earlier; friend was preceded by drend, where drend had been presented earlier; mean was preceded by down, where down had been presented earlier; and done was preceded by yome, where yome had been presented earlier.)

To summarize, 7- and 10-year-olds made recognition decisions about 200 probes under either T instructions or R instructions. Related distractors were rhymes of previously presented items. In addition to the age manipulation, there were content and priming manipulations. Concerning content, the accessibility of semantic gist was varied independently for targets (they could be either meaningful words or nonsense words) and related distractors (rhymes could be either meaningful words or nonsense words). Concerning priming, half the rhyming distractors were immediately preceded by their instantiating targets, and half were not preceded by these targets.

Results

Goodness of Fit and Between-Condition Invariance of Memory Parameters

In Table 2, mean acceptance proportions for probes are reported by instructional condition (T or R), age level (7 or 10 years), type of item (targets, rhymes, unrelated distractors), type of content (meaningful or nonsense), and type of distractor priming (primed or unprimed). The first step in the analysis was to conduct goodness-of-fit tests. This was done with the performance data for the target-distractor pairs in the four target-priming conditions (word—word, word—nonsense, nonsense—word, and nonsense—nonsense). Recall that the test list contained five replications per child of each of these four conditions.

---

1 Complete sets of instructions and examples are available from C. J. Brainerd on request.
### Table 2
**Proportions of Acceptances for Different Types of Probes**

<table>
<thead>
<tr>
<th>Probe type</th>
<th>Instructional condition</th>
<th>7 years</th>
<th>10 years</th>
<th>7 years</th>
<th>10 years</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>M</td>
<td>SD</td>
<td>M</td>
<td>SD</td>
</tr>
<tr>
<td>Word targets</td>
<td>T</td>
<td>.90</td>
<td>.11</td>
<td>.94</td>
<td>.06</td>
</tr>
<tr>
<td>Nonsense targets</td>
<td>R</td>
<td>.60</td>
<td>.19</td>
<td>.67</td>
<td>.17</td>
</tr>
<tr>
<td>Distractors for word targets</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Word rhymes (unprimed)</td>
<td>T</td>
<td>.04</td>
<td>.10</td>
<td>.01</td>
<td>.04</td>
</tr>
<tr>
<td>Word rhymes (primed)</td>
<td>R</td>
<td>.03</td>
<td>.11</td>
<td>.02</td>
<td>.07</td>
</tr>
<tr>
<td>Nonsense rhymes (unprimed)</td>
<td></td>
<td>.07</td>
<td>.10</td>
<td>.03</td>
<td>.09</td>
</tr>
<tr>
<td>Nonsense rhymes (primed)</td>
<td></td>
<td>.02</td>
<td>.07</td>
<td>.02</td>
<td>.07</td>
</tr>
<tr>
<td>Distractors for nonsense targets</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Word rhymes (unprimed)</td>
<td>T</td>
<td>.06</td>
<td>.15</td>
<td>.05</td>
<td>.13</td>
</tr>
<tr>
<td>Word rhymes (primed)</td>
<td>R</td>
<td>.20</td>
<td>.18</td>
<td>.13</td>
<td>.14</td>
</tr>
<tr>
<td>Nonsense rhymes (unprimed)</td>
<td></td>
<td>.14</td>
<td>.17</td>
<td>.18</td>
<td>.23</td>
</tr>
<tr>
<td>Nonsense rhymes (primed)</td>
<td></td>
<td>.08</td>
<td>.13</td>
<td>.06</td>
<td>.13</td>
</tr>
<tr>
<td>Unrelated words</td>
<td></td>
<td>.04</td>
<td>.06</td>
<td>.01</td>
<td>.03</td>
</tr>
<tr>
<td>Unrelated nonsense</td>
<td></td>
<td>.08</td>
<td>.08</td>
<td>.08</td>
<td>.08</td>
</tr>
</tbody>
</table>

**Note.** T = accept only targets; R = accept only related distractors.

The joint-event probabilities in Equations 15 through 20 can be defined for each of these conditions, which allows the goodness-of-fit test in Equation 21 to be computed for each condition. A total of eight such tests were possible in this study (2 age levels × 4 target-priming conditions). We computed all eight tests, and none produced a rejection of the null hypothesis that the sample data could have been generated by processes that obey the constraints of the conjoint-recognition model. Whereas a critical value of 5.99 is required to reject this null hypothesis, the mean of the statistic for the eight tests (2.36) was less than half this value. (An appendix containing the complete matrix of predicted and observed joint-probability distributions can be obtained from C. J. Brainerd, L. Stein, and V. E. Reyna).

As noted earlier, satisfactory fits also confer support on the model’s hypothesis that the conscious and unconscious memory parameters are invariant across the two instructional conditions: If one or more of these parameters has different values for the two conditions, fit will fail because more memory parameters will be needed to describe the data than those that are posited in the model.

### Effects of Manipulations on Memory Parameters

Because fits were satisfactory at both age levels, the model’s theoretical parameters can be estimated. Within- and between-conditions predictions about the behavior of the conscious and unconscious memory parameters can then be tested.

**Developmental effects.** Mean estimates of the conjoint-recognition model’s parameters appear by age level in Table 3. To determine whether the values of these parameters changed with age, we computed the conditionwise test in Equation 23, followed by pairwise tests (Equation 24) for individual parameters. The conditionwise null hypothesis that all six parameters had equal values for the two age levels was rejected, \( \chi^2(6) = 186.06, p < .0001 \). The follow-up tests for individual parameters showed that (a) conscious memories provoked by targets (Parameter \( C_t \)) increased with age, \( \chi^2(1) = 10.69, p < .0005 \), (b) unconscious memories provoked by targets (Parameter \( U_t \)) increased with age, \( \chi^2(1) = 19.47, p < .0001 \), (c) conscious memories provoked by related distractors (Parameter \( C_r \)) but not unconscious memories (Parameter \( U_r \)), increased with age, \( \chi^2(1) = 26.09, p < .0001 \), and (d) response bias in the T condition (Parameter \( b_T \)) but not in the R condition (Parameter \( b_R \)), decreased with age, \( \chi^2(1) = 21.64, p < .0001 \). Recall that (a) and (b) were both relations that had been predicted on the basis of prior research.

As noted earlier, it would be expected (e.g., Reyna & Kiernan, 1994, 1995) that targets are better retrieval cues for conscious memories than distractors. Consistent with this prediction, we found (with Equation 22) that \( C_t > C_r \) for both 7-year-olds, \( \chi^2(1) = 312.33, p < .0001 \), and for 10-year-olds, \( \chi^2(1) = 267.51, p < .0001 \). Because continuous recognition maximizes reliance on conscious memory by minimizing the forgetting of surface information about targets, it would also be predicted that conscious memory should predominate over unconscious memory for both targets and related distractors. Consistent with this prediction, we found that \( C_t > U_t \) for 7-year-olds, \( \chi^2(1) = 937.99, p < .0001 \), and for 10-year-olds, \( \chi^2(1) = 837.61, p < .0001 \), and we found that \( C_r > U_r \) for 7-year-olds, \( \chi^2(1) = 278.12, p < .0001 \), and for 10-year-olds, \( \chi^2(1) = 449.45, p < .0001 \).

**Memory content and priming effects.** We now consider how the conscious and unconscious memory parameters reacted to the content manipulation (meaningful words vs. nonsense words) and the distractor-priming manipulation (target priming vs. no priming). Estimates of the six parameters are reported separately for the various combinations of these factors in Table...
Table 3
Mean Probabilities of Conscious Memory, Unconscious Memory, and Response Bias by Age Level

<table>
<thead>
<tr>
<th>Parameter</th>
<th>C_t</th>
<th>U_t</th>
<th>C_r</th>
<th>U_r</th>
<th>b_T</th>
<th>b_R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age level</td>
<td>7-year-olds</td>
<td>10-year-olds</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>M</td>
<td>CI</td>
<td>M</td>
<td>CI</td>
<td>M</td>
<td>CI</td>
</tr>
<tr>
<td>7-year-olds</td>
<td>.71</td>
<td>.68-.73</td>
<td>.39</td>
<td>.36-.42</td>
<td>.10</td>
<td>.08-.12</td>
</tr>
<tr>
<td>10-year-olds</td>
<td>.76</td>
<td>.73-.78</td>
<td>.19</td>
<td>.15-.23</td>
<td>.47</td>
<td>.44-.50</td>
</tr>
</tbody>
</table>

Note. CI = confidence interval.

4. Because content and priming effects were the same for 7-year-olds as for 10-year-olds, these estimates are for the pooled data of the two age levels.

Content effects. The content manipulation was included in this study because, theoretically, nonsense targets decrease retention of both surface and semantic information, and nonsense distractors increase retrieval of surface information while suppressing the retrieval of semantic information. This led to different predictions about targets and distractors. With targets, levels of conscious and unconscious memory both should be higher for meaningful words. For distractors, however, a double dissociation is expected: For nonsense words, levels of conscious memory should be higher but levels of unconscious memory should be lower.

The predictions for both targets and distractors were confirmed. Concerning targets, it can be seen in Table 4 that the estimated values of C_t were larger for meaningful words than for nonsense words (.90 vs .57) and that the same was true

Table 4
Mean Probabilities of Conscious Memory, Unconscious Memory, and Response Bias for Different Target/Rhyme Distractor Combinations

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Probe type</th>
<th>C_t</th>
<th>U_t</th>
<th>C_r</th>
<th>U_r</th>
<th>b_T</th>
<th>b_R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Word targets</td>
<td>Word rhymes (unprimed)</td>
<td>M</td>
<td>.89</td>
<td>.24</td>
<td>.11</td>
<td>.02</td>
<td>.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CI</td>
<td>.87-.91</td>
<td>.16-.33</td>
<td>.06-.15</td>
<td>.00-.05</td>
<td>.02-.03</td>
</tr>
<tr>
<td></td>
<td>Word rhymes (primed)</td>
<td>M</td>
<td>.89</td>
<td>.24</td>
<td>.77</td>
<td>.43</td>
<td>.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CI</td>
<td>.87-.91</td>
<td>.16-.33</td>
<td>.72-.82</td>
<td>.32-.54</td>
<td>.02-.03</td>
</tr>
<tr>
<td>Nonsense rhymes (unprimed)</td>
<td>M</td>
<td>.89</td>
<td>.24</td>
<td>.19</td>
<td>.00</td>
<td>.08</td>
<td>.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CI</td>
<td>.86-.91</td>
<td>.14-.32</td>
<td>.13-.26</td>
<td>.00</td>
<td>.07-.09</td>
</tr>
<tr>
<td>Nonsense rhymes (primed)</td>
<td>M</td>
<td>.89</td>
<td>.24</td>
<td>.89</td>
<td>.16</td>
<td>.08</td>
<td>.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CI</td>
<td>.86-.91</td>
<td>.14-.32</td>
<td>.85-.94</td>
<td>-.04-.37</td>
<td>.07-.09</td>
</tr>
<tr>
<td>Nonsense targets</td>
<td>Word rhymes (unprimed)</td>
<td>M</td>
<td>.57</td>
<td>.12</td>
<td>.05</td>
<td>.03</td>
<td>.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CI</td>
<td>.53-.61</td>
<td>.09-.16</td>
<td>.00-.11</td>
<td>.00-.07</td>
<td>.02-.03</td>
</tr>
<tr>
<td></td>
<td>Word rhymes (primed)</td>
<td>M</td>
<td>.57</td>
<td>.12</td>
<td>.65</td>
<td>.46</td>
<td>.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CI</td>
<td>.53-.61</td>
<td>.09-.16</td>
<td>.57-.73</td>
<td>.34-.57</td>
<td>.02-.03</td>
</tr>
<tr>
<td>Nonsense rhymes (unprimed)</td>
<td>M</td>
<td>.57</td>
<td>.12</td>
<td>.00</td>
<td>.02</td>
<td>.08</td>
<td>.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CI</td>
<td>.53-.60</td>
<td>.07-.15</td>
<td>.00</td>
<td>.02-.12</td>
<td>.07-.09</td>
</tr>
<tr>
<td>Nonsense rhymes (primed)</td>
<td>M</td>
<td>.57</td>
<td>.12</td>
<td>.82</td>
<td>.29</td>
<td>.08</td>
<td>.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CI</td>
<td>.53-.60</td>
<td>.07-.15</td>
<td>.76-.87</td>
<td>.17-.52</td>
<td>.07-.09</td>
</tr>
</tbody>
</table>

Note. The four values of C_t and U_t for word targets are the same because in each of the parameter estimation runs, the same target data were input, though the related-distractor data changed. This is also the reason why the four values for C_r and U_r for nonsense targets are the same. CI = confidence interval.
for estimated values of $U_i$ (.24 vs .12). Likelihood-ratio tests (Equation 22) showed that the difference for $C_i$ was reliable, $\chi^2(1) = 446.58, p < .0001$, and so was the difference for $U_i$, $\chi^2(1) = 11.92, p < .001$. Concerning distractors, as expected, the average value of $C_i$ was larger for nonsense words than for meaningful words (.48 vs .39), but the reverse was true for $U_i$ (.14 vs .24). Because the values of these parameters varied considerably as a function of priming condition (cf. Table 4), likelihood-ratio tests were computed separately for these conditions. With word targets, $C_i$ was significantly greater for nonsense rhymes when rhymes were either primed or unprimed. With nonsense targets, $C_i$ was significantly greater for nonsense rhymes when they were primed, but not when they were unprimed. With both word and nonsense targets, $U_i$ was significantly smaller for nonsense rhymes when they were either primed or unprimed.

Target-priming effects. Prior research on the target-priming manipulation (Brainerd, Reyna, & Kneer, 1995; Reyna & Brainerd, 1995a) suggests that testing distractors' instantiating targets just before distractors themselves are tested increases distractors' tendency to retrieve conscious memories more than their tendency to retrieve unconscious memories. Therefore, the prediction is that $C_i$ is larger for target-primed distractors for all four combinations of targets and related distractors (word-word, word-nonsense, nonsense-word, nonsense-nonsense) and that any increases in $U_i$ that are produced by target priming will be smaller than are the corresponding increases in $C_i$. It can be seen in Table 4 that these predictions were confirmed. Concerning $C_i$, the average value across the four target–distractor combinations was .78 for primed distractors and .09 for unprimed distractors. Likelihood-ratio tests showed that the difference was significant in each instance. Concerning $U_i$, the average value across the four target–distractor combinations was .34 for primed distractors and .02 for unprimed distractors. Likelihood-ratio tests showed that the difference was significant in each instance.2 Also, the effect of target priming was twice as great for $C_i$ as for $U_i$.

Summary and Conclusions

The aim of this article has been to provide developmental investigators with new tools to study age variability in conscious and unconscious memory. Those tools consist, first, of a simple paradigm (conjoint recognition) in which children make recognition decisions under different instructions and, second, of a multinominal model that uses the resulting data to find estimates of levels of conscious and unconscious memory. Those estimates allow researchers to track age changes in these processes (a) independently of each other, (b) independently of response bias, and (c) separately for presented material (targets) and unpresented material (distractors). Those estimates can also be used to determine how conscious and unconscious memory react to manipulations that embody theoretical assumptions about these processes. At the beginning of this article, we described two approaches to disentangling the respective contributions of conscious and unconscious memory to children’s performance, task-based separations and model-based separation. In task-based separation, two measurements are taken, one that assesses conscious memory and one that assesses unconscious memory. This technique is unsatisfactory because standard tests of conscious memory are contaminated by unconscious memory, and standard tests of unconscious memory are contaminated by conscious memory (Jacoby, 1991). Moreover, even pure measures of a process cannot yield accurate quantitative estimates unless the output transformations that map levels of the process onto levels of performance are well-specified (Howe et al., 1993). That requires a model in which conscious and unconscious memories figure as distinct parameters.

Although model-based separation is therefore preferable, the most commonly used technique, Jacoby’s (1991) process-dissociation model, has some characteristics that limit its usefulness. Recent work in the process-dissociation framework has removed some of these limitations. The conjoint-recognition model removes the remaining ones. It is defined over a paradigm in which children make decisions about three types of probes (targets, related distractors, unrelated distractors) under two types of instructions (accept only targets, accept only related distractors). The model delivers (a) separate estimates of levels of conscious memory for targets and related distractors, (b) separate estimates of levels of unconscious memory for targets and related distractors, and (c) separate estimates of levels of response bias for the two instructional conditions. Consequently, it is possible to chart the developmental course of each of these variables independently of the others.

We provided preliminary validation of the model as a developmental research instrument by applying it to the data of a developmental conjoint-recognition study. Two types of validation results were obtained: findings concerned with goodness of fit and findings concerned with the behavior of the conscious and unconscious memory parameters. Regarding fit, we conducted a series of omnibus goodness-of-fit tests, half for 7-year-olds and half for 10-year-olds. The null hypothesis that the data could have been generated by processes that obey the constraints of the conjoint-recognition model could not be rejected in any instance.

2 The effect for $U_i$ is also important because it rules out a possible alternative interpretation of the target-priming manipulation. It might be thought that the effects of target priming could be explained on the grounds that children in the $R$ condition are confused by the instructions and tend to adopt a yeasaying rule whenever a word rhymes with the one just before it. This response-rule interpretation is made doubtful by three considerations. First, it can be seen from the model’s equations that such an effect would show up in Parameter $C_i$, but not in Parameter $U_i$. Second, such a response rule should produce stochastic dependencies between acceptance rates for target primes and the rhyme that follows them: The yeasaying tendency should be greater if the preceding target prime has been rejected than if it has been accepted because only one of them can be the target. Consistent with data reported for $R$ conditions by Brainerd, Reyna, and Kneer (1995), acceptance rates for rhymes were stochastically independent of acceptance rates for target primes in the present $R$ condition. Third, as a further test of the response-rule interpretation, we modified the model by adding another bias parameter, $b_r$, to Figure 3 (bottom). In the modified model, when a primed rhyme produces retrieval of a conscious memory of its instantiating target, the child remembers the instructions and accepts the rhyme, with probability $1 - b_{r,y}$, or forgets the instructions and rejects the rhyme, with probability $b_{r,y}$. When the data were reanalyzed, the modified seven-parameter model did not produce significantly better fits than did the six-parameter model, and all estimates of $b_{r,y}$ were close to zero.
of these. These tests also provided collateral support for a core assumption of the model—namely, that levels of conscious and unconscious memory are not affected by instructions (T vs. R). If this assumption had been violated, more parameters would have been required to describe the data than are posited in the model.

Regarding parameter behavior, prior research allows one to predict that if \( C_t \) and \( C_r \) are measures of conscious memory and \( U_t \) and \( U_r \) are measures of unconscious memory, these parameters should behave in specific ways. Two types of predictions were tested and confirmed: within condition and between condition. Concerning within-condition predictions, prior research suggests that targets are better retrieval cues for conscious memories than related distractors are, which implies \( C_t > C_r \), and that the conscious memory should predominate over unconscious memory on continuous-recognition tasks, which implies \( C_t > U_t \) and \( C_r > U_r \). All of these predictions were confirmed at both age levels.

Concerning between-condition predictions, we studied three manipulations that, on the basis of prior research, should have specific effects on conscious and unconscious memory parameters: target priming, meaningfulness of targets and distractors, and age. Priming a distractor with its instantiating target should increase \( C_t \), and any increases in \( U_t \) should be smaller than corresponding increases in \( C_t \). Meaningful targets should produce higher values of \( C_t \) and \( U_t \), than do nonsense targets, but meaningful distractors should produce higher values of \( C_r \), coupled with lower values of \( U_r \). Both conscious-memory parameters should increase with age (cf. Bullock Drummey & Newcombe, 1995; Newcombe & Fox, 1994; Newcombe & Lie, 1995; Russo et al., 1995). All of these predictions were confirmed.

Looking down the road toward future research, a key feature of the conjoint-recognition methodology is its applicability to many paradigms that have been used in developmental research on learning, memory, and reasoning. This methodology is by no means limited to the continuous-recognition paradigm that was used in our study. Obviously, it can also be implemented in recognition experiments in which the study–test method is used. But, it can be extrapolated well beyond recognition memory to paradigms in which children make binary decisions about test items on the basis of previously experienced material. There are only two methodological requirements. First, the test probes must include previously experienced material, unexperienced material that is related to the experienced material in some specific way, and unexperienced material that is unrelated to the experienced material. Second, some children must respond by selecting for previously experienced material and against both types of unexperienced material, whereas other children must respond by selecting for unexperienced material that is related to experienced material and against both experienced material and unrelated unexperienced material.

To make the conjoint-recognition methodology's generality more concrete, consider three paradigms that have often been used in research with very young children: discrimination transfer (e.g., Esposito, 1974; Levine, 1975), misinformation (e.g., Poole & Lindsay, 1995; Reyna & Titcomb, 1996), and object sorting (e.g., Blewitt & Krackow, 1992). As these are very familiar paradigms, we shall not describe them here. In each instance, children respond by assigning the probes in a test sequence (multidimensional stimuli in discrimination transfer, statements about autobiographical experiences in misinformation, and everyday objects in object sorting) to binary categories (winner vs. loser, autobiographical vs. fictional, feature present vs. feature absent). Hence, the conjoint-recognition model allows investigators to estimate the contributions of conscious and unconscious memory to children's responses in each of these situations. To obtain such estimates, it is only necessary to include the three types of probes in the test sequence and to have children respond under both types of instructions.

In these brief examples, we have referred to paradigms that are commonly used with very young children. This choice was deliberate because we wish to emphasize the ability of the conjoint-recognition methodology to capture information about conscious and unconscious memory during early development. This is an important advantage of the model because of the strong empirical motivation to study the early origins of these processes and to determine, for instance, whether there is an age below which they are undifferentiated. Because the conjoint-recognition methodology instructs children to select for targets or to select for related distractors, it might be thought that it would not be applicable prior to the advent of language. There is no reason to suppose, however, that these two response orientations could not be taught to preverbal infants with techniques such as Rovee-Collier's (e.g., Rovee-Collier & Bollier, 1995; Rovee-Collier & Gekokski, 1979) conjugate-reinforcement procedure. In principle, then, conscious and unconscious memory could be measured in preverbal infants as well as in very young children.

References


Appendix

Statistical Appendix

Parameter Identification

We prove the identifiability of the six theoretical parameters of the conjoint-recognition model by showing that its equations (Equations 9–14) can be solved so as to express each parameter as a unique function of empirical probabilities. The solutions for the three response bias parameters are

\[ b_t = p_{at} \] (A1)

and

\[ b_r = p_{ar}. \] (A2)

Next, solutions are obtained for the conscious and unconscious memory parameters for targets with Equations 9 and 10. Those solutions are

\[ C_t = 1 - p_{rt} - ((1 - p_{rt})(1 - p_{ar}))/((1 - p_{at})) \] (A3)

and

\[ U_t = 1 - (1 - p_{rt}))/((1 - J)(1 - p_{at})) \] (A4)

where \( J \) denotes the right side of Equation A3.

Finally, solutions are obtained for the conscious and unconscious memory parameters for target-related distractors using Equations 11 and 12. Those solutions are

\[ C_r = 1 - p_{rt} - (p_{ar}(1 - p_{at}))/((1 - p_{at})) \] (A5)

and

\[ U_r = 1 - p_{at}/((1 - K)(1 - p_{ar})). \] (A6)

where \( K \) denotes the right side of Equation A5.

Parameter Estimation, Goodness of Fit, and Hypothesis Testing

All of the analyses described in this section can be conducted with the program CONJOINT, which is available from C. J. Brainerd on request. To estimate the six parameters of the conjoint-recognition model, CONJOINT maximizes the theoretical counterpart of the Fisher-type observable-states function

\[ L_{6} = [p_{1}]^{N[A(t,T)A(r,R)]} \times [p_{2}]^{N[A(t,T)B(r,R)]} \times [p_{3}]^{N[A(t,T)K(r,R)]} \times [p_{4}]^{N[A(t,R)A(r,T)]} \times [p_{5}]^{N[A(t,R)K(r,T)]} \times [p_{6}]^{N[K(t,T)K(r,R)]} \times [1 - P_{4} - P_{5} - P_{6}]^{N[K(t,R)K(r,T)]} \times [1 - P_{1} - P_{2} - P_{3}]^{N[K(t,T)K(r,R)]} \times N[A(t,T)] \times N[K(t,R)] \times N[A(r,T)] \times N[K(r,T)], \] (A7)

where the \( N[A(i, j)] \) and \( N[K(i, j)] \) are the numbers of acceptance (A) and rejection (K) responses of the indicated type that are observed in the sample data. The theoretical counterpart of this likelihood function is

\[ L_{6} = [p_{1}]^{N[A(t,T)A(r,R)]} \times [p_{2}]^{N[A(t,T)B(r,R)]} \times [p_{3}]^{N[A(t,T)K(r,R)]} \times [p_{4}]^{N[A(t,R)A(r,T)]} \times [p_{5}]^{N[K(t,T)K(r,r)]} \times [p_{6}]^{N[K(t,R)K(r,T)]} \times [1 - P_{1} - P_{2} - P_{3}]^{N[K(t,T)K(r,R)]} \times [1 - P_{4} - P_{5} - P_{6}]^{N[K(t,R)K(r,T)]} \times N[A(t,T)] \times N[K(t,R)] \times N[A(r,T)] \times N[K(r,T)], \] (A8)

where the numerals in parentheses refer to the right sides of Equations 13 through 20. When Equation A8 is maximized for sample data, maximum likelihood estimates of the conjoint-recognition model’s parameters are obtained.

Once parameter estimates have been obtained for sample data, within-condition null hypotheses about the values of the parameters can be tested with the statistic

\[ \chi^2 = -2\ln(L_{0}/L_{6}), \] (A9)

where \( L_{0} \) is the likelihood of the data when all six parameters are free to vary, and \( L_{6} \), is the likelihood of the same data when \( r \) restrictions implied by a null hypothesis have been imposed on Equation A8. Also, between-condition null hypotheses about the values of the parameters can be tested with the procedures in Equations 22 and 23.

Received August 20, 1996
Revision received August 20, 1997
Accepted August 20, 1997

Í