

Research Article

MODELING THE EFFECTS OF EXPECTATIONS ON
RECOGNITION MEMORY

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Abstract—*Expectations have consistent effects on recognition memory, but prior research has not explained these results. Three theories of how expectations affect recognition were compared. According to integration theory, the probability of recognizing a test item increases with its similarity to memory traces both for expected items and for studied items. In weighting theory and in distortion theory, recognition judgments are determined by similarity to memory traces solely for studied items. Weighting theory additionally assumes that expectation-congruent items and expectation-incongruent items have differently weighted influences. Distortion theory additionally assumes that memory traces for studied items are distorted to be more like what is expected. Predictions for the three theories were obtained by implementing them within a mathematical model of memory. These predictions were compared with the results obtained in a meta-analysis of stereotype effects on recognition (Stangor & McMillan, 1992). The conclusion was that only integration theory predicted these results.*

The memory for a particular object, event, or person does not depend only on what was observed. Rather, this memory is also affected by other knowledge in memory, including what had been expected. A complete theory of memory must be able to explain how new memories make contact with old memories, for example, how background knowledge and expectations influence what is remembered. This article is intended to answer a single question: Which theoretical ideas can explain how expectations affect recognition memory? The recognition paradigm was chosen because expectation effects on recognition have been studied extensively, and a consistent pattern of results has emerged. This pattern of results allows sharp theoretical distinctions to be made.

EXPECTATION EFFECTS ON
RECOGNITION MEMORY

Imagine that in an experiment, you are presented with descriptions of two librarians, George and Bill. George enjoys classical music but does not enjoy motorcycle racing, while Bill does not enjoy classical music but does enjoy rodeos. Later, which description would you recognize better, the description that is congruent with your expectations about librarians or the one that is incongruent? In terms of hit rate, the probability of correctly recognizing a description, performance is greater for congruent items. People are reluctant to say that they have seen something that does not match expectations. However, this reluctance leads to better performance for incongruent items in

terms of a lower false alarm rate, the probability of incorrectly recognizing a previously unseen description. Indeed, the false alarm rate for congruent items may be nearly as high as the hit rate, so that discriminability between old and new items, or d' , is much lower for congruent items than for incongruent items.

This pattern of results has been widely observed. Stangor and McMillan (1992) performed a meta-analysis of more than two dozen experiments on effects of social stereotypes on recognition. In each experiment, subjects were first induced to expect certain stereotypical traits or behaviors. Then the subjects tried to memorize person descriptions, including expectation-congruent and expectation-incongruent information. Finally, recognition memory was tested. Stangor and McMillan found that the probability of saying "old" (i.e., the average of hit rate and false alarm rate) was higher for congruent items than for incongruent items. Furthermore, Stangor and McMillan found that discriminability, d' , was higher for incongruent items than for congruent items.¹ These results for recognition memory are referred to together simply as *expectation effects*.

In addition, several experimental manipulations consistently increase the magnitude of expectation effects (Stangor & McMillan, 1992). Introducing a delay between study and test increases the advantage of congruent over incongruent items in terms of probability of saying "old," but increases the advantage of incongruent items over congruent items in terms of d' . Other factors that increase expectation effects include reducing exposure time to stimuli, increasing the overall memory load, and using younger rather than older children as subjects. These results all may be interpreted in terms of increased reliance on expectations rather than on memories for the particular stimuli presented. Indeed, Stangor and McMillan also found that studies that induced stronger stereotypes had greater expectation effects than studies that induced weaker stereotypes. Furthermore, no factors acted inconsistently with expectation effects (e.g., increasing both probability of saying "old" and d' for congruent items).

THEORIES OF EXPECTATION EFFECTS

Expectations might influence recognition judgments in at least three distinct ways. First, to make a judgment, memories for what was expected might be integrated with intact, unbiased memories of the studied stimuli. Second, the memories of what was studied might be weighted according to whether they were congruent or incongruent with expectations. Third, inference processes might cause the memory traces for what was studied to be distorted to be more like what was expected. These three

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¹ Similar results have been found outside the domain of person memory (e.g., Brewer & Treyens, 1981; D. A. Smith & Graesser, 1981).

ideas have been present in psychological research on schema theory, but there has been no consensus formed as to which explanation is best, or even which results each separate process can predict

According to *integration theory*, the expectations are themselves simply memory traces. Unweighted, undistorted memory traces for the items studied in an experiment and memory traces for expected items both contribute to a recognition judgment. Part of this proposal is derived from prior work in exemplar theory of memory and categorization (Estes, in press, Heit, 1992, Hintzman, 1986, Medin & Schaffer, 1978, Nosofsky, 1988, E. R. Smith & Zaraté, 1992). According to exemplar theory, the acquisition of a category consists of accumulating individual memory traces that together serve as an expectation. However, exemplar theory has not addressed how prior expectations and new items would be combined. The other part of this proposal comes from information integration theory (Anderson, 1991), according to which judgments are formed by integrating various biases or expectations with more or less veridical memories of new experiences. This integration would take place by a simple process, such as adding what is expected to what is observed. For the librarian experiment, integration theory asserts that your recognition judgments would use congruent and incongruent memories of the librarians you studied in the experiment, as well as your memories for prior or expected librarians (such as librarians you had met recently).

According to *weighting theory*, each stimulus has a corresponding weight that determines how much it influences a memory judgment. This selective weighting could take place at encoding or retrieval. For example, it has been proposed (Alba & Hasher, 1983) that schemas serve as filters, causing expectation-incongruent information to be underweighted or ignored, while facilitating memory for information that fits the schema. Further, the weighting might be a side effect of another mechanism, such as deeper processing or better organization for certain kinds of information. Weighting theory uses the expectations to determine whether a stimulus is congruent or incongruent, and to assign a weight to the stimulus. No further role for expectations is asserted, that is, the expectations themselves are not integrated with the encoded memory traces to make a judgment. In the librarian experiment, according to weighting theory, your recognition judgments would use both the congruent and the incongruent librarian descriptions that you studied, but the congruent descriptions would hold greater sway.

The crucial difference between *distortion theory* and the other two theories is that only distortion theory allows the memory traces for studied items to change. In particular, distortion theory assumes that memories of studied items become more like what is expected. The rationale for this proposal is found in the idea that schemas serve as a source of inferences. When a certain feature of an item is unknown, the memory for this feature may be filled in with its expected value (Taylor & Crocker, 1978). In addition, expectations may distort a memory trace that is incompletely encoded or retrieved. When some features of the item are forgotten, inferences may be used to fill in the missing information. According to distortion theory, your recognition judgments in the librarian experiment would be based on memory traces of what you studied, but some of the

unexpected information in the memories would be changed to what is expected, such as changing "enjoys rodeos" to "does not enjoy rodeos."

Prior work by Graesser (1981) has shown that these three processes together can account for expectation effects. Graesser's *schema pointer plus tag* mathematical model includes components of weighting, distortion, and integration, with additional assumptions about forgetting functions and guessing strategies. This model was fitted precisely to the results of several studies of expectation effects on memory. However, this complex modeling did not include separate evaluation of the components, so it was not clear why the model was successful. For example, congruent and incongruent memory traces had different weights, which varied over time. These memory traces were also distorted over time by copying information from the schema. This research did not make clear which of these mechanisms led to the correct results. Another problem of this model is that it includes 11 free parameters, so it is not clear what the model must predict as opposed to what the model simply can fit. The model seems flexible enough to fit results that people would never produce. Still, the substantial success of this model lends encouragement to the present investigation.

To evaluate integration, weighting, and distortion separately, a simple mathematical model of recognition memory is introduced. Then each of these theories is implemented as an additional assumption of the model. The predictions of each theory are compared with the expectation effects that serve as a standard of human performance.

A MODEL OF RECOGNITION MEMORY

Recognition may be considered in terms of categorization. A subject classifies a stimulus x as either belonging to the category "old" or to the category "new." This categorization depends on the relative familiarity of x with respect to the two categories, as expressed in Equation 1.

$$P(\text{say } x \text{ is "old"}) = \frac{\text{fam}_{\text{old}}(x)}{\text{fam}_{\text{old}}(x) + \text{fam}_{\text{new}}(x)} \quad (1)$$

Here, $\text{fam}_{\text{old}}(x)$ represents the familiarity of x with respect to the "old" category, or the total similarity of x to old items in memory. This function's value will be higher as x is more similar to what is in memory. Likewise, $\text{fam}_{\text{new}}(x)$ refers to the familiarity of x with respect to the "new" category. In the simplest case, the subject does not know what is in the distribution of new items, so $\text{fam}_{\text{new}}(x)$ simply will be assigned a nonnegative constant value. The probability of saying "old" to x will increase with the familiarity of x with respect to the "old" category, and this probability may range from 0 to 1.

This model of recognition memory (which is similar to that of Estes, in press) has in common with other models of recognition (Gillund & Shiffrin, 1984, Hintzman, 1988, Metcalfe, Eich, 1985, Murdock, 1982, Nosofsky, 1988, see also Jones & Heit, in press) the claim that the probability of recognizing x increases monotonically with its similarity to other memorized stimuli. The present model makes an additional assumption, using the ratio rule in Equation 1 to specify a particular mapping of familiarity to probability of recognition. However, integration,

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weighting, and distortion theories could be implemented and compared within any of the recognition models listed above ²

SIMULATIONS OF THEORIES

This model of recognition was used with different versions of the $fam_{old}(x)$ function to instantiate the different theories of expectation effects, and predictions were generated by computer simulations. Each simulation evaluated a group of simulated "subjects," who acted according to a particular theory. The operating assumptions of the simulations were kept minimal, to highlight differences between the theories.

Each stimulus or memory trace was described by a vector of 10 binary features, with each feature taking on a value of + or -. The stereotype, or expectation, was represented as a vector of 10 +'s. Congruent stimuli were similar to the expectation, with 8 +'s and 2 -'s, in randomly determined positions. Incongruent stimuli were dissimilar to the expectation, with 8 -'s and 2 +'s, in positions determined randomly. (The specific numbers of features are not critical to the results.) To relate this simulation to a particular psychological experiment, the stereotype may refer to what is expected about the central tendency for a social group, with each + referring to a certain expected trait or behavior. For example, a + in the first position might signify "enjoys classical music," while a - in this position would mean "does not enjoy classical music." Particular congruent and incongruent stimuli would refer to persons who generally match or mismatch the group stereotype. At a more general level, the stereotype describes what is expected about a person, group, object, event, or location, in terms of featural information.

Each simulated subject was exposed to 15 distinct congruent items and 15 distinct incongruent items. Then the subject was tested on four kinds of stimuli: 15 old congruent items, 15 old incongruent items, 15 new congruent items, and 15 new incongruent items. Equation 1 was used to predict a subject's probability of saying "old" for each test stimulus. These probabilities were averaged for the four kinds of test items, to find the subject's hit rates and false alarm rates for congruent and incongruent stimuli. To facilitate evaluation in terms of expectation effects, results are shown in the figures in terms of two measures: $P(old)$, the average of hit rate and false alarm rate, and d' , also computed from hit rate and false alarm rate. (The results are presented in alternative form, in terms of hit rates and false alarm rates, in Appendix Tables A-1 through A-5.) Because of the random processes involved, each simulation included the evaluation of 100 simulated subjects.

The similarity between two stimuli was determined by the number of matching features. For example, the stimuli (+ + + + + + - -) and (- - + + + + + +) match on six features and mismatch on four. Equation 2 is the multiplicative similarity rule of Medin and Schaffer (1978)

$$sim(x,y) = s^{mis(x,y)} \tag{2}$$

2 Preliminary work comparing the three theories of expectation effects when implemented within other recognition models has led to the same conclusions as reported for the recognition model described in this article.

Here, $mis(x,y)$ refers to the number of mismatches between x and y . For values of the parameter s , such that $0 \leq s < 1$, $sim(x,y)$ will decrease as the number of feature mismatches between x and y increases.

For all of the following simulations, two parameter values were chosen arbitrarily: $fam_{new} = .005$ and $s = 2$. These constants serve as scaling parameters, simulations with other allowable values did not change the conclusions reported here.

Integration Theory

In the simulation of integration theory, the fam_{old} function embodied the idea that the familiarity of a stimulus was influenced by its similarity to memories for what was studied in the experiment as well as by its similarity to memories for what had been expected. This simulation represented expectations in terms of prior memories that were congruent with the stereotype. Each subject's memory was first preloaded with the expectations, 15 distinct congruent items, each consisting of 8 + values and 2 - values. Then the subject stored 15 congruent items and 15 incongruent items, representing what is learned in an experiment. The familiarity of a stimulus x was determined by Equation 3.

$$fam_{old}(x) = \frac{B}{15} \sum_{i=1}^{15} sim(x, prior_i) + \frac{(1-B)}{30} \left(\sum_{i=1}^{15} sim(x, con_i) + \sum_{i=1}^{15} sim(x, inc_i) \right) \tag{3}$$

Here, $prior_i$, con_i , and inc_i represent the members of the distributions of expected items, studied congruent items, and studied incongruent items, respectively. The parameter B , which may take on values in the closed interval from 0 to 1, represents the relative influence of prior expectations. When $B = 0$, the recognition judgment is affected solely by what was studied, but greater values of B allow for greater contributions of expectations. To discover the predictions of integration theory for different expectation strengths, simulations were run for a range of B values, as shown in Figure 1. For each condition, predictions of $P(old)$ and d' are shown for both congruent and incongruent test items. When $B = 0$, of course, performance is the same for congruent and incongruent items. But as the strength of expectation increases, $P(old)$ increases for congruent items and decreases for incongruent items. Further, d' sharply decreases for congruent items while staying roughly constant for incongruent items. Thus, integration theory correctly predicts expectation effects ³.

3 Integration theory does not depend on the assumption that expectations are stored in terms of separate memory traces, as in this simulation. Instead, the stereotype itself might influence the judgments, perhaps after a prototype has been abstracted from many experiences. Another version of the simulation preloaded memory with the stereotype itself rather than with separate exemplars. This simulation computed familiarity as a weighted sum of similarity to the stereotype and similarity to the studied items. The predictions of this version are vir-

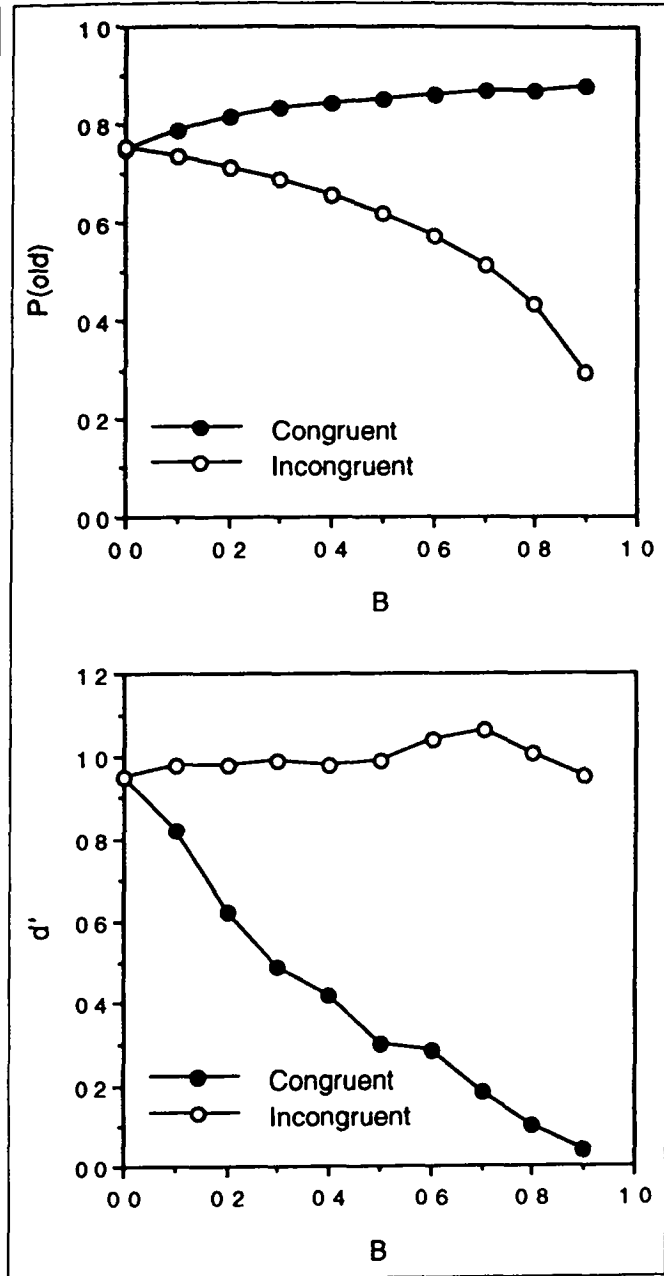


Fig 1 Predictions of integration theory for varying expectation strengths

What leads to the success of integration theory? As *B* increases in Equation 3, the familiarity of both old and new congruent items increases, while the familiarity of old and new incongruent items decreases. Thus, *P*(old), as determined by Equation 1, becomes increasingly greater for congruent items

tually the same as what is shown in Figure 1. In terms of predicting expectation effects, the two versions of integration theory are not identifiably different. (However, other experimental evidence has shown that prototype representation is inadequate, e.g., Fried & Holyoak, 1984; Medin, Altom, Edelson, & Freko, 1982; Nosofsky, 1992.)

compared with incongruent items. However, as *B* increases, familiarity is determined more by similarity to expectations and less by what was stored during the experiment. Thus, the difference in familiarity between old congruent items and new congruent items decreases, leading to the marked decrease in discriminability for congruent items. Integration theory can predict a *d'* as low as zero for congruent items, and indeed this result has been observed in some studies (Locksley, Stangor, Hepburn, Grosovsky, & Hoschstrasser, 1984; Woll & Graesser, 1982).

Weighting Theory

Weighting theory differs from integration theory in that its familiarity measure is not directly influenced by what is expected. Instead, the expectation is used to selectively weight the relative contributions of congruent and incongruent memory traces, as shown in Equation 4

$$fam_{old}(x) = \frac{A}{30} \sum_{i=1}^{15} sim(x, con_i) + \frac{(2-A)}{30} \sum_{i=1}^{15} sim(x, inc_i) \quad (4)$$

The *A* parameter may take on any value in the closed interval from 0 to 2. When *A* = 1, congruent and incongruent memory traces are weighted the same, and expectations have no effect. Values of *A* greater than 1 represent more influence by congruent items than by incongruent items, with *A* = 2 indicating the case in which familiarity is determined solely by similarity to congruent items. Likewise, values of *A* less than 1 indicate a relatively high contribution of incongruent items.

Figure 2 shows the results of simulations of weighting theory for values of *A* equal to and greater than 1. (When *A* was less than 1, weighting theory predicted that *P*(old) would be greater for incongruent items than for congruent items, clearly in contradiction to expectation effects.) As *A* increases from the condition in which expectations have no effect to conditions in which congruent items have greater weights, *P*(old) increases somewhat for congruent items and decreases markedly for incongruent items, thus accounting for the first half of expectation effects. The greater weights of congruent memory traces make congruent test items more familiar than incongruent test items. However, weighting theory fails to predict changes in discriminability due to stronger expectations. While this set of simulations showed that *d'* for incongruent items was usually slightly bigger than *d'* for congruent items, the simulations did not show the sharp decrease in *d'* for congruent items that is the other half of expectation effects. Further simulations with other parameter values also showed only small fluctuations in *d'* for congruent items, indeed, *d'* was sometimes predicted higher for congruent items than for incongruent items. The reason why weighting theory fails to predict the sharp decrease in *d'* is that even when expectations are strong (i.e., *A* is near 2), the familiarity of old congruent items must be greater than that of new congruent items.⁴

⁴ It is interesting to compare Tables A-1 and A-2 in terms of hit rates and false alarm rates for congruent items. While integration theory

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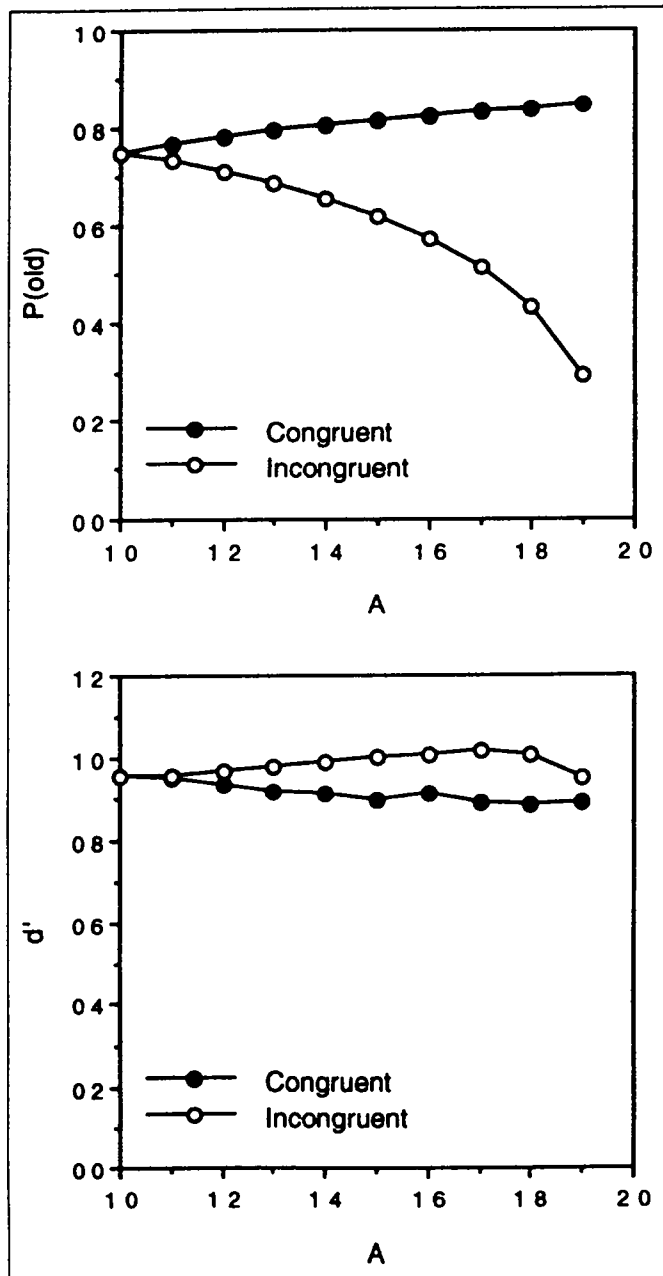


Fig 2 Predictions of weighting theory for varying expectation strengths

Distortion Theory

Distortion theory differs from integration theory in not allowing similarity to expectations to influence familiarity directly, and distortion theory differs from weighting theory because it weighs congruent and incongruent memory traces equally. The simulation for distortion theory also used Equation

can predict that the hit rate and false alarm rate will be about the same, weighting theory necessarily predicts that the hit rate will be greater than the false alarm rate, at any level of expectation strength

4, with the parameter A fixed at 1. To simulate distortion, memory traces were altered according to the following procedure. With independent probabilities D , each feature of a memory trace was "forgotten." The forgotten feature values were replaced with a + value from the stereotype. Thus, distortion had a real effect only on - values because a + would be effectively unchanged. The effects of distortion on incongruent and congruent memory traces were evaluated separately.

First, the incongruent memory traces were distorted, and the congruent memory traces were kept intact. Figure 3 shows the results of these simulations for values of D from 0 to 5. As D ,

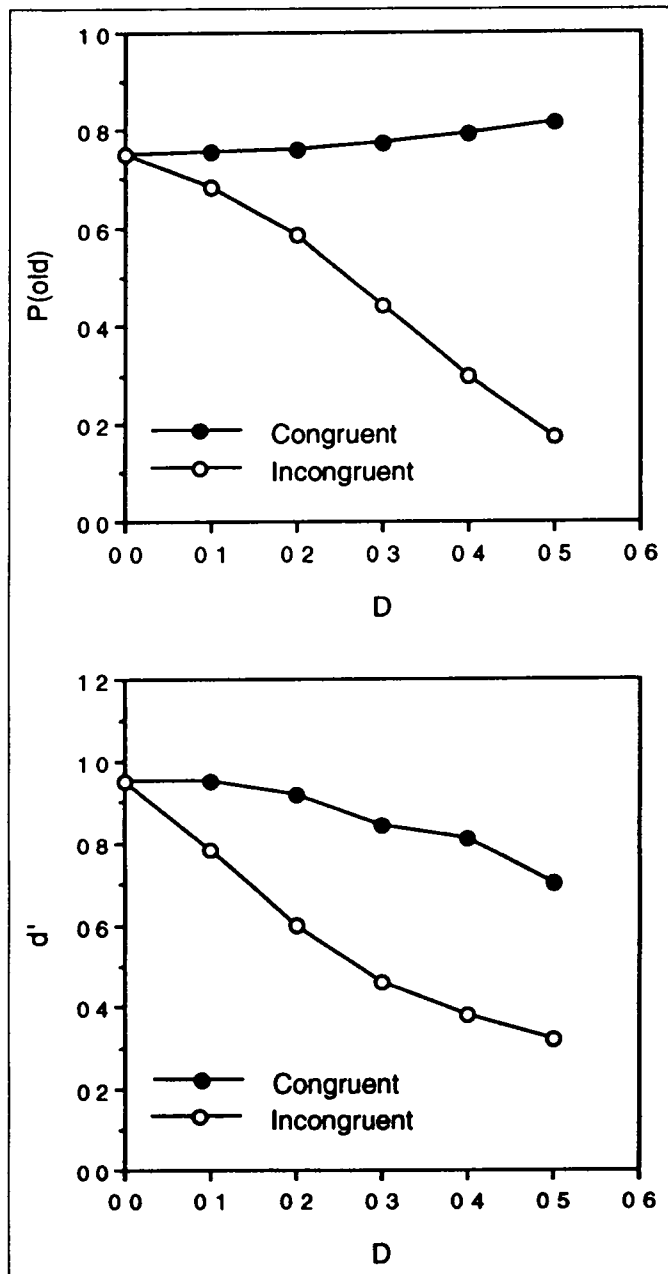


Fig 3 Predictions of distortion theory when incongruent items are distorted, for varying expectation strengths

the strength of expectations, increases, $P(\text{old})$ increases for congruent items and decreases for incongruent items, consistent with expectation effects. However, the simulation wrongly predicts that discriminability will be lower for incongruent items than for congruent items, and it wrongly predicts that discriminability for incongruent items will decrease as expectations grow stronger.

Second, the congruent memory traces were distorted, and the incongruent memory traces stayed the same. The rationale behind this simulation was that congruent items might be especially likely to activate the schema, and any unexpected features ($-$ values) of the congruent items could be changed to what is expected. Figure 4 shows the results of these simulations for values of D from 0 to 6. As the expectation strength increases, $P(\text{old})$ increases weakly for congruent items and remains constant for incongruent items. This result is unsatisfactory because no decrease in $P(\text{old})$ is predicted for incongruent items. Equation 4 shows that when $A = 1$, distortion theory predicts incorrectly that incongruent test items will remain familiar no matter how strong expectations grow. Figure 4 also indicates that the congruent-distortion simulation predicts the correct expectation effects for d' .

Therefore, neither incongruent distortion nor congruent distortion alone can predict expectation effects. Further simulations, with distortion on both kinds of memory traces, also failed to predict expectation effects, instead predicting that d' for incongruent items would decrease sharply as strength of expectation increased.

SET-SIZE EFFECTS

Now that integration theory has been shown to be superior to the other two theories in predicting expectation effects, applications of integration theory are considered briefly. The recognition model presented here can also account for the effects of another common experimental manipulation, varying the ratio of congruent to incongruent items. This manipulation is theoretically interesting because, consistent with integration theory, memorizing a large number of incongruent items could have effects like those of prestored, expected memory traces. Storing a large number of incongruent items ought to increase $P(\text{old})$ for incongruent items and decrease d' for incongruent items. Indeed, Stangor and McMillan's (1992) meta-analysis found that increasing the number of incongruent items relative to congruent items had an effect opposite to expectation effects.

This manipulation was simulated using integration theory. The total number of stored items per subject remained at 30, but the ratio of congruent to incongruent items was varied. The value of the B parameter was set at the intermediate value of 4. Figure 5 shows the results. Increasing the number of incongruent items relative to congruent items increases $P(\text{old})$ for incongruent items but decreases their d' . Thus, the recognition model, with integration theory's assumptions, can also account for set-size effects.

FREE RECALL AND CATEGORIZATION

Stangor and McMillan's (1992) meta-analysis showed also that free-recall measures act like $P(\text{old})$, in that congruent items

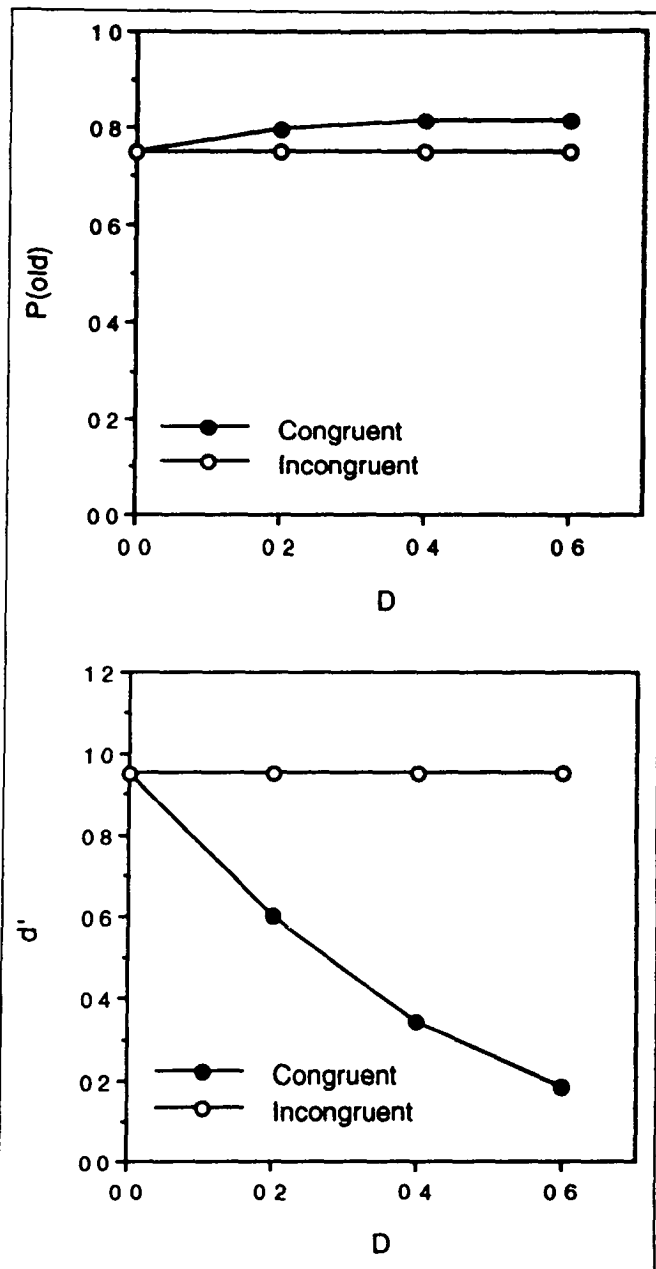


Fig 4 Predictions of distortion theory when congruent items are distorted, for varying expectation strengths

are more likely to be recalled than incongruent items when expectations are strong. Integration theory could explain this result by assuming that similar memory traces tend to serve as retrieval cues for each other (Gillund & Shiffrin, 1984). Thus, the expected memory traces would be better retrieval cues for the congruent items than for the incongruent items, and the likelihood of recall would be greater for congruent items. This integration approach also suggests that expected memory traces themselves sometimes might be mistakenly recalled in place of studied items. In fact, Graesser (1981) observed such intrusion errors due to expectations.

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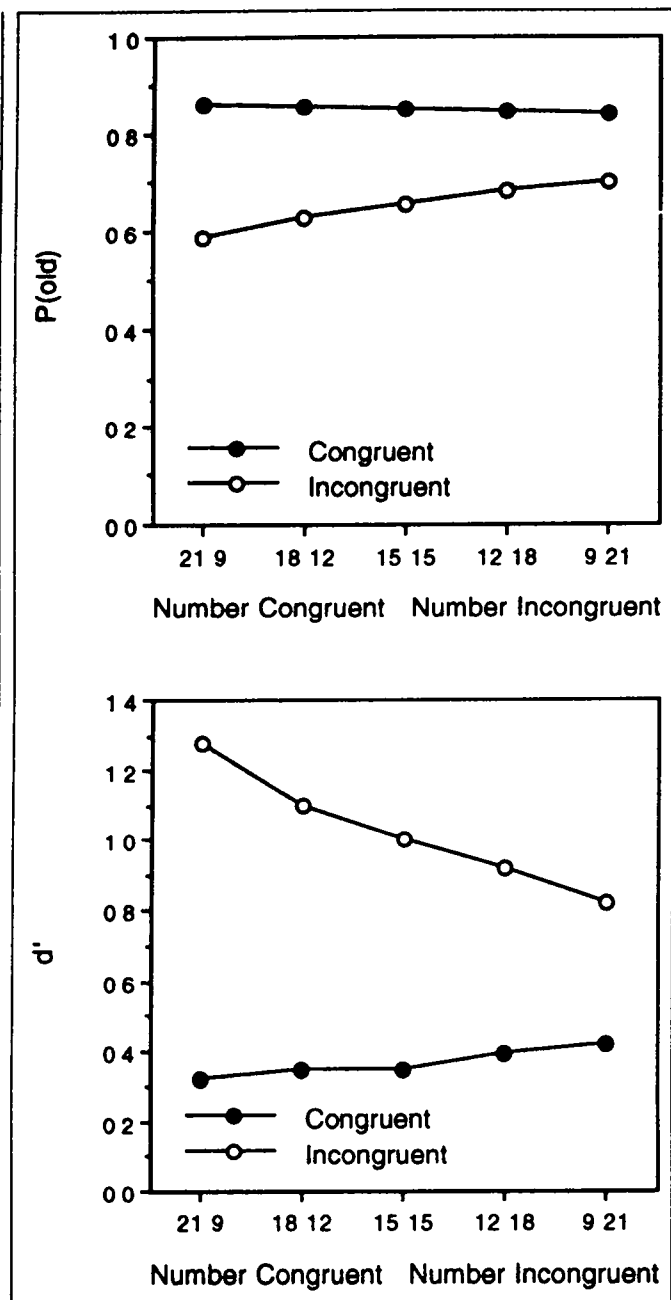


Fig 5 Predictions of integration theory for varying ratios of congruent items to incongruent items

Expectations also have substantial effects on category learning, in that categorization is influenced both by observed category members and by more general knowledge (Murphy & Medin, 1985). To explain these effects, Murphy and Medin suggested that people's theories affect categorization, but they did not propose a mechanism for combining theories with memory for examples. Perhaps one function of theories is to facilitate generation or imagining of expected items that have not been experienced directly. In this way, theories would serve as a "front end" to an exemplar-based categorization system, which

would be sensitive to two kinds of exemplars, expected and observed. Thus, integration theory is not intended as an alternative to theory-based categorization, but rather as a possible bridge between theories and categorization.

CONCLUSION

It is clear that of the three theories of expectation effects, only integration theory succeeds at predicting the expectation effects for recognition memory. Integration theory also provides a unified explanation for the manipulations that strengthen expectation effects: increasing expectation strength, memory load, and retention interval and decreasing study time. All of these situations may be explained by more reliance on memory for what is expected as opposed to memory for what is observed. Neither weighting theory nor distortion theory can account for expectation effects, but integration theory correctly and necessarily predicts expectation effects.

These simulations were intended to describe a neutral task of memorizing instances and then making judgments. In the terminology of Hastie and Park (1986), these were simulations of *memory-based* rather than *on-line* tasks. However, people are probably capable of performing many other kinds of processing on these instances, which might include weighting or distortion. For example, Hastie and Kumar (1979) instructed their subjects to form evaluative impressions of various person descriptions, rather than to simply study them. These subjects recalled incongruent information better than congruent information, apparently because they spent more effort evaluating the inconsistent information. In principle, other processing mechanisms could be added to the present recognition framework. Indeed, Hastie (1988) has simulated impression-formation tasks with assumptions including selective weighting. However, the conclusion remains that solely integration theory can explain the most basic effects of expectations on recognition memory under the simplest study conditions.

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REFERENCES

Alba, J. W., & Hasher, L. (1983). Is memory schematic? *Psychological Bulletin*, 93, 203-231.

Anderson, N. H. (1991). Stereotype theory. In N. H. Anderson (Ed.), *Contributions to information integration theory, Vol. II: Social* (pp. 183-240). Hillsdale, NJ: Erlbaum.

Brewer, W. F., & Treyens, J. C. (1981). Role of schemata in memory for places. *Cognitive Psychology*, 13, 207-230.

Estes, W. K. (in press). *Classification and cognition: The Fifth Paul M. Fitts Memorial Lectures*. New York: Oxford University Press.

Fried, L. S., & Holyoak, K. J. (1984). Induction of category distributions: A framework for classification learning. *Journal of Experimental Psychology: Learning, Memory and Cognition*, 10, 234-257.

Gillund, G., & Shiffrin, R. M. (1984). A retrieval model for both recognition and recall. *Psychological Review*, 91, 1-67.

Graesser, A. C. (1981). *Prose comprehension beyond the word*. New York: Springer-Verlag.

Haste, R. (1988). A computer simulation model of person memory. *Journal of Experimental Social Psychology*, 24, 423-447.

Haste, R., & Kumar, A. P. (1979). Person memory: Personality traits as organizing principles in memory for behaviors. *Journal of Personality and Social Psychology*, 37, 25-38.

Haste, R., & Park, B. (1986). The relationship between memory and judgment depends on whether the judgment task is memory-based or on-line. *Psychological Review*, 93, 258-268.

Heit, E. (1992). Categorization using chains of examples. *Cognitive Psychology*, 24, 341-380.

Hintzman, D. L. (1986). 'Schema abstraction' in a multiple-trace memory model. *Psychological Review*, 93, 411-428.

Hintzman, D. L. (1988). Judgments of frequency and recognition memory in a multiple-trace memory model. *Psychological Review*, 95, 528-551.

Jones, C. M., & Heit, E. (in press). An evaluation of the total similarity principle: Effects of similarity on frequency judgments. *Journal of Experimental Psychology: Learning, Memory, and Cognition*.

Locksley, A., Stangor, C., Hepburn, C., Groszovsky, E., & Hoshtrasser, M. (1984). The ambiguity of recognition memory tests of schema theories. *Cognitive Psychology*, 16, 421-448.

Medin, D. L., Altom, M. W., Edelson, S. M., & Freko, D. (1982). Correlated symptoms and simulated medical classification. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 8, 37-50.

Medin, D. L., & Schaffer, M. M. (1978). Context theory of classification learning. *Psychological Review*, 85, 207-238.

Metcalfe, E. J. (1985). Levels of processing: encoding specificity, elaboration, and CHARM. *Psychological Review*, 92, 1-38.

Murdock, B. B. (1982). A theory for the storage and retrieval of item and associative information. *Psychological Review*, 89, 609-626.

Murphy, G. L., & Medin, D. L. (1985). The role of theories in conceptual coherence. *Psychological Review*, 92, 289-316.

Nosofsky, R. M. (1988). Exemplar-based accounts of relations between classification, recognition, and typicality. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 14, 700-708.

Nosofsky, R. M. (1992). Exemplars, prototypes, and similarity rules. In A. M. Healy, S. F. Kosslyn, & R. M. Shiffrin (Eds.), *From learning theory to connectionist theory: Essays in honor of William K. Estes* (pp. 149-167). Hillsdale, NJ: Erlbaum.

Smith, D. A., & Graesser, A. C. (1981). Memory for actions in scripted activities as a function of typicality, retention interval, and retrieval task. *Memory & Cognition*, 9, 550-559.

Smith, E. R., & Zarate, M. A. (1992). Exemplar-based models of social judgment. *Psychological Review*, 99, 3-21.

Stangor, C., & McMillan, D. (1992). Memory for expectancy-congruent and expectancy-incongruent information: A review of the social and developmental literatures. *Psychological Bulletin*, 111, 42-61.

Taylor, S. E., & Crocker, J. (1978). Schematic bases of social information processing. In E. T. Higgins, C. P. Herman, & M. P. Zanna (Eds.), *Social cognition: The Ontario symposium* (pp. 89-134). Hillsdale, NJ: Erlbaum.

Woll, S. B., & Graesser, A. C. (1982). Memory discrimination for information: typical or atypical of person schemata. *Social Cognition*, 1, 287-310.

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APPENDIX

Table A-1 Hit rates (HR) and false alarm rates (FA) for integration theory

B	Congruent items		Incongruent items	
	HR	FA	HR	FA
0	89	61	89	61
1	89	68	88	58
2	89	73	87	56
3	89	77	85	52
4	89	79	83	49
5	88	81	80	44
6	89	83	77	38
7	88	85	71	32
8	88	86	62	24
9	88	87	45	14

Table A-2 Hit rates (HR) and false alarm rates (FA) for weighting theory

A	Congruent items		Incongruent items	
	HR	FA	HR	FA
10	89	61	89	61
11	90	63	88	59
12	91	65	87	55
13	91	67	85	52
14	92	69	83	48
15	92	70	80	44
16	93	71	76	39
17	93	73	71	32
18	94	74	62	24
19	94	75	45	14

Table A-3 Hit rates (HR) and false alarm rates (FA) for distortion theory when incongruent items are distorted

D	Congruent items		Incongruent items	
	HR	FA	HR	FA
0	89	61	89	61
1	89	61	82	55
2	89	62	70	47
3	89	65	53	35
4	90	68	36	24
5	90	72	21	14

Modeling Expectations

Table A-4 Hit rates (HR) and false alarm rates (FA) for distortion theory when congruent items are distorted

<i>D</i>	Congruent items		Incongruent items	
	HR	FA	HR	FA
0	89	61	89	61
2	88	72	89	61
4	86	77	89	61
6	84	79	89	61

Table A-5 Hit rates (HR) and false alarm rates (FA) for integration theory, for varying ratios of congruent items to incongruent items

Ratio	Congruent items		Incongruent items	
	HR	FA	HR	FA
21 9	89	82	82	36
18 12	89	81	82	43
15 15	89	81	83	48
12 18	89	80	84	53
9 21	88	79	84	56

