Edited by
Henri Cohen and Claire Lefebvre

ELSEVIER

Handbook of
Categorization in
Cognitive Science

Second Edition

CHAPTER

31

The Construction of Category Membership Judgments: Towards a Distributed Model

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OUTLINE

Abstract

The classification of objects to natural categories displays a great deal of crossperson consensus and within-person consistency. At the same time, categorization also exhibits some degree of within-person instability and cross-person variability.

We attempted to gain insight into the stable and variable contributions to category membership judgment by examining confidence judgments and response latency for one's decision whether an object belongs or does not belong to a given category. According to an extension of the Self-Consistency Model (SCM) (Koriat, 2012), category membership decisions are constructed on the fly on the basis of a small set of cues sampled sequentially from a population of cues associated with the object-category item. This population is largely shared by participants with the same background. The decision is based on the balance of evidence in favor of a positive or a negative response, and confidence is based on the consistency with which that decision was supported across the accessed cues. The results confirmed several predictions: (1) Consensual responses were endorsed with higher confidence and shorter response latency than nonconsensual responses with the differences between the two types of responses increasing with item consensus— the proportion of participants who made the majority response for the item. (2) When the task was repeated several times, confidence and response speed were higher for each participant's more frequent decision than for the less frequent decision. (3) Results suggested that confidence in a category membership decision reflects the participant's assessment of the likelihood that the same decision will be reached in future encounters with the item. (4) Finally, the context that was provided for the category membership decision was found to bias the decision reached, but confidence also changed correspondingly, suggesting that context affected the sampling of cues underlying the decision. Altogether, the results provide support for the model, and indicate that confidence and response latency can track the sources of stability and variability in category membership decisions.

31.1   INTRODUCTION

In the course of history, philosophers and psychologists have speculated about the structure of categories and how the features of a semantic category are defined. Their views have changed over the years. Initially, categories were thought to have distinct boundaries and unambiguous definitions that can specify clearly which exemplars count as members of a category. This assumption constitutes the core of the so-called classical view of concepts. However, the empirical study of categorization behavior has yielded evidence that posed difficulties to this notion, leading to alternative views to the classical view.

In this chapter, we propose a sampling view of the process underlying human categorization. This view underlies the Self-Consistency Model (SCM) of subjective confidence (Koriat, 2012). The model was originally developed to explain the basis and accuracy of confidence judgments in a binary decision, but embodies several rudimentary assumptions that apply to many tasks in which participants are required to make binary decisions. The model assumes that when people face a two-alternative forced-choice (2AFC) item, it is by retrieving a small number of cues from a large base of cues that they reach a

decision. The choice is based on the balance of evidence in favor of the two options, and confidence in the choice is based on the consistency with which the chosen response is supported across the sampled cues. The application of the model to a variety of tasks (see Koriat, 2012; Koriat & Adiv, 2016) indicated that confidence and response latency can track the stable and variable components of the decision. The extension of the model to category membership decisions (Koriat & Sorka, 2015) has yielded evidence in support of the viability of this extension, suggesting that the speed and confidence associated with category membership decisions can provide insight regarding the processes underlying categorization behavior.

In this chapter we first review the assumptions underlying the classical view of categories, and mention the results that challenge these assumptions. Next, we examine how alternative views to the classical view have attempted to account for these results. We then introduce our own proposal and indicate how it differs from other views in the field. Finally, we summarize results most of which are presented in Koriat and Sorka (2015), which support our general view.

31.2   THE CLASSICAL VIEW

The classical view of categorization is based on ideas developed in philosophy and logic, dating back to Aristotle (for a detailed discussion see Smith & Medin, 1981). It maintains that a concept can be defined by a set of fundamental features that are shared by all instances of that concept (Medin, 1989). These features are individually necessary and jointly sufficient for determining which instances are members of the concept. Furthermore, if all the features exist in a certain instance, then it must be a member of the concept; every instance that has the specific set of attributes is essentially a member of that concept. This view implies that categorization is rule-based.

The classical view has two main implications. First, concepts are represented as a collection of features that apply to all of the instances of the concept. The implication is that when a person is asked to judge whether an object is a member of the concept, the summary description of the concept is consulted to determine the decision.

The second implication is that membership in a concept is clear-cut. If a certain instance satisfies all of the attributes of a specific concept, the instance must be a member of that concept; and if it lacks only one attribute, it is not a member of that concept. Thus, there is no ambiguity in concept membership: concept boundaries are well defined and rigid.

The classical view has been the dominant view up until the 1970s, when it was subjected to criticisms that have intensified since.

Extensive empirical research has documented (1) difficulties in specifying a set of defining attributes for natural concepts (Ashcraft, 1978; Hampton, 2009; Rosch & Mervis, 1975), (2) gradedness in category membership (Barr & Caplan, 1987; Hampton & Gardiner, 1983; McCloskey & Glucksberg, 1978; Oden, 1977; Rosch, 1973; Rosch & Mervis, 1975), (3) cross-person and within-person inconsistency in categorization (Barr & Caplan, 1987; Estes, 2003; Hampton, 1979,1998, 2007, 2009; McCloskey & Glucksberg, 1978), and (4) contextual influences on categorization judgments (Anderson & Ortony, 1975; Barsalou, 1987, 1989; Hampton, 2011; Medin, Lynch, Coley, & Atran, 1997; Roth & Shoben, 1983; see Murphy, 2002). The results challenged the classical view, and motivated alternative views to now be considered.

31.3   SUBSEQUENT PROPOSALS

One alternative to the classical view is the prototype theory of concepts, which was proposed by Rosch and Mervis (1975). The prototype view rejects the assumption of essential features that must exist in each instance of a concept. Rather, the features of the prototype description are typical to the concept, so that the more typical attributes exist in an entity, the greater the likelihood of considering it as a member of the concept. The prototype can be a representation containing characteristic features, or it can be an abstraction of an actual instance of the concept— the best example. For several researchers, the prototype is the list of the characteristic features of the concepts (see e.g., Hampton, 1979; Rosch, 1978). For others, the best example of the concept is the prototype abstraction of that concept. That is, the prototype is the representation of a specific instance of the concept (e.g., Rosch, 1978).

Another alternative to the classical view is the exemplar-based view. According to this view, concepts are represented by particular instances of the concept. Thus, instead of having a mental description, a list of all the characteristic features of a certain category, people need only to store at least some of the exemplars of the category they have encountered in the past. When encountering a new instance, people compare it to previously stored instances, called exemplars. Similar to the prototype view, the exemplar view assumes that there are no necessary attributes for each concept, and therefore it is not surprising that people find it difficult to list a set of essential and defining features of a category. The exemplar view can also account for the difficulty in classifying borderline instances. These instances are either similar to exemplars from several categories or are dissimilar enough to any classified exemplar (Medin & Smith, 1984).

Both the prototype view and the exemplar view embody the assumption that categories are defined in terms of family similarity rather than in terms of a set of criterial features. The implication is that category membership is graded rather than all or none. It should be mentioned that hybrid models that include both rule-based and similarity-based categorization have also been proposed (see Smith & Sloman, 1994).

31.4   OUR PROPOSAL

The model to be presented below is based on the assumption that category membership decisions are generally constructed on the fly depending on the cues and considerations that are accessible at the time of the judgment (see Barsalou, 1987). A similar assumption in attitude research underlies the attitude-as-construction view, which assumes that attitudinal judgments are formed on the spot. Therefore, they can vary depending on the person's current goals and mood, and depending on the context in which the judgment is made (Bless, Mackie, & Schwarz, 1992; Schwarz, 2007, 2008; Schwarz & Strack, 1991; Tourangeau, 1992).

Researchers in the area of judgment and decision making also proposed a similar view with regard to personal preferences (Lichtenstein & Slovic, 2006; Slovic, 1995). Several observations have indicated that preferences can vary with the task, the context, and the goals of the respondents (see Bettman, Luce, & Payne, 1998; Shafir, Simonson, & Tversky, 1993; Warren, McGraw, & Van Boven, 2011). These observations gave rise to the idea that preferences too are constructed in the process of elicitation rather than retrieved ready-made from memory.

We propose that in the same way, category membership judgments are constructed on the spot. Current models of the process underlying categorization judgments assume a principled process underlying these judgments. This is true of both the prototype view and the exemplar view. Unlike these views, we assume that category membership judgments are driven by a process that is largely associative, based on whatever cues and considerations come to mind at the time of making a judgment. Indeed, a think-aloud study (Koriat & Sorka, 2015) suggested that the cues that people rely on in making their judgments tend to be of many different sorts. Many of the considerations mentioned by participants would not be considered logical or rational. For example, for the question "Is egg an animal?" the following considerations were taken to support a positive answer: "eggs can be eaten just like animals" and "eggs come from chicken." Other considerations that were seen to support a negative answer were "before eggs are hatched, they do not have organs," and "some plants have egg-like reproductive parts". People simply make use of whatever cues come to mind that

can tip the balance in favor of one of the two response options. Of course, some of the cues consist of hunches, associations, and images that cannot be expressed in a propositional form.

The limitations of the cognitive system prevent people from drawing too large a sample from their memory because they need to aggregate information across the accessed cues to reach a binary decision. Therefore, the set of accessible cues in each occasion represents only a small subset of the potential, available cues. As a consequence, category membership decisions may change from one occasion to another, particularly when the context changes.

In addition, we assume that cues are sampled sequentially one after the other, and the implication of each cue for the decision is evaluated on the spot. The sampling of cues is terminated when the person feels that the retrieved cues clearly tip the "balance of evidence" (Vickers, 2001) in favor of one option rather than the other.

A critical assumption, however, is that the population of available cues associated with each category membership item is largely shared by people with the same experience. This assumption is consistent with research on the wisdom-of-crowds (Surowiecki, 2005). Indeed, research on categorization has yielded a great deal of similarity across people, to the extent of giving rise to the classic view of categorization, which assumed that categorization is rule- based. Thus, although the sample of accessible cues for a given item may differ from one person to another and from one occasion to another for the same person, the population of cues from which the cues are sampled is assumed to be largely the same across people and occasions.

The portrayal of the categorization process sketched above implies a distributed model in which people sample cues from a rich population of cues that is associated with the object-category item. The assumption that cues are sampled from the same population is responsible for the cross-person consensus and for the within-person consistency in category membership judgments. In turn, the assumption that each decision is based on a small set of items drawn more or less randomly from the same network of cues is responsible for the variability in these judgments across people and across occasions. In what follows, we describe the SCM in order to show how confidence judgments and response latency can help track the stable and variable contributions to category membership judgments.

31.5 THE SELF-CONSISTENCY MODEL OF SUBJECTIVE CONFIDENCE

SCM was originally developed to explain the accuracy of confidence judgments for binary questions for which the answer has a truth value

(Koriat, 2008, 2011). The model, however, has since been extended to 2AFC questions for which the answer does not have a truth value. This extension focused on predictions that derive from SCM's assumptions about the *basis* of confidence judgments. Indeed, results consistent with these predictions have been obtained for questions tapping social attitudes (Koriat & Adiv, 2011), social beliefs (Koriat & Adiv, 2012), and personal preferences (Koriat, 2013). As will be reviewed below, these predictions also received some support for category membership decisions, thus testifying for the generality of the model.

Underlying SCM is the metaphor of the person as an intuitive statistician (Gigerenzer & Murray, 1987; Peterson & Beach, 1967; see McKenzie, 2005). When people have to assess their confidence in their decision, it is by replicating the decision process several times that they appreciate the extent of certainty or uncertainty involved. Like statistical level of confidence, subjective confidence is based essentially on self-consistency: the extent to which different "observations" converge in supporting the same decision. These "observations" consist of cues drawn from memory and their implications for the decision. Selfconsistency represents a crude mnemonic cue that reflects the amount of deliberation and conflict experienced in making a choice, and can be captured by the agreement among the sampled cues in favoring that choice (see Alba & Marmorstein, 1987; Armelius, 1979; Brewer & Sampaio, 2012; Kruglanski & Klar, 1987; Slovic, 1966). Subjective confidence can be said to reflect an assessment of reproducibility—the likelihood that a new sample will yield the same choice.

Koriat (2012) used a simulation experiment to test the predictions from a very crude instantiation of SCM. In that instantiation, it was assumed that for each 2AFC item, a maximum of seven cues are sampled sequentially from memory, and each cue yields a binary subdecision that favors one of the two response options. However, if three successively retrieved cues yield the same subdecision, the retrieval of cues is terminated, and that subdecision determines the decision (see Audley, 1960). Confidence in the decision reached is based on self-consistency—the extent to which the decision is supported across the retrieved cues. A simple index of self-consistency was used, defined as $1 \sim y/v\$$ (range 0.5—1.0), when p and q designate the proportion of cues favoring the two choices, respectively.

In the simulation experiment, it was assumed that each item can be characterized by a population of cues, with p_{maj} denoting the proportion of cues that support the majority decision. A vector of nine binomial populations that differ in p_{maj} was assumed, with p_{maj} varying from 0.55 to 0.95, in steps of 0.05. For each such population, it was possible to compute the pc_{maj}—the probability with which the majority alternative (the one that corresponds to the majority value in the population) will be chosen, and also the mean confidence in that choice.

In parallel, it was possible to calculate the mean confidence in the minority decision when it is made. The results of the simulation experiment yielded a pattern that appears in the inset of Fig. 31.1. In that inset, the self-consistency index is plotted as a function of pc_{maj} for majority and minority decisions. A very similar pattern was obtained for the average number of cues sampled before reaching a decision. This number was assumed to capture response latency.

The predicted pattern is what has been labeled by Koriat, Adiv, and Schwarz (2016) the prototypical majority effect (PME):

1. Majority responses should be endorsed with greater confidence, and should be expressed with shorter latencies than minority responses.
2. The difference between majority and minority responses in both confidence and response speed should increase as a function of the size of the majority.

Basically, SCM predicts that for any given item, confidence should differ depending on which alternative is chosen: when a random sample of cues happens to favor the majority alternative, confidence
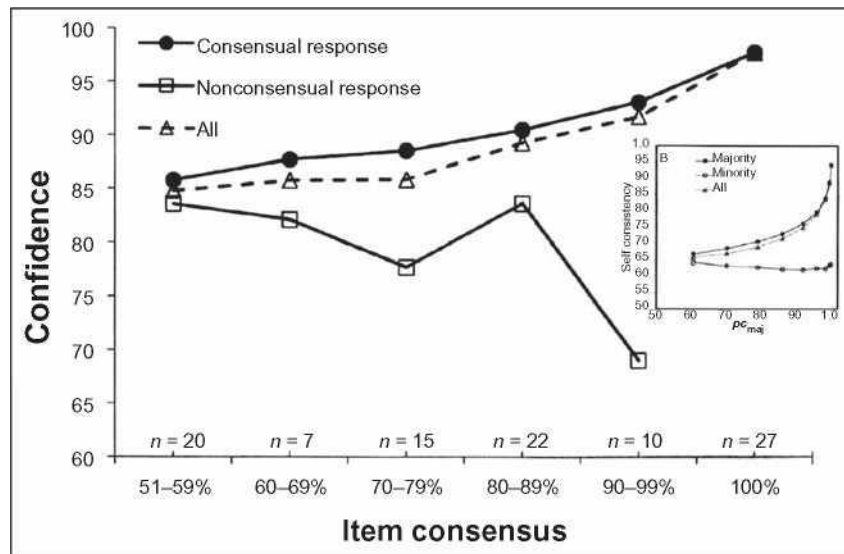
FIGURE 31.1 Mean confidence judgments for consensual and nonconsensual responses and for all responses combined (All) as a function of item consensus—the percentage of participants who made the consensual response (Experiment 1). Indicated also is the number of items (n) in each category.
Source: Reproduced with permission from Koriat, A., & Sorka, H. (2015). The construction of categorization judgments: Using subjective confidence and response latency to test a distributed model. Cognition, 134, 21 − 38. Copyright © 2014 by Elsevier. The inset presents the predicted pattern (see text). It is reproduced with permission from Koriat and Adiv (2011). Copyright © 2011 by Guilford Press.

should be higher than when it happens to favor the minority alternative. This is because samples of cues that favor the majority choice should have smaller standard deviations, and hence higher selfconsistency on average, than samples that favor the minority choice.

31.6   EMPIRICAL EVIDENCE

In what follows, we present a brief review of the results of a study that provided a test of the predictions derived from SCM for category membership decisions. The procedure of the experiments was similar to that used in several previous experiments that tested the SCM predictions for different tasks. Participants were presented with 2AFC items involving category membership judgments. On the basis of the experimental results, the choice that was made by the majority of participants for each item was defined as the majority (or consensual) response for that item. The other choice was defined as the minority (or nonconsen- sual) response. Item consensus (50—100%) was defined for each item as the percentage of participants who made the majority response for that item. Confidence was calculated for majority and minority responses for each item consensus category.

31.6.1   Experiment 1: A Paper-and-Pencil Study

Experiment 1, which was a paper-and-pencil study, will be used to illustrate the predictions and how they were tested. In that experiment, 21 students, native English speakers, were presented with 102 candidate exemplars divided into nine categories. These were chosen from Barr and Caplan (1987) and McCloskey and Glucksberg (1978) to represent a wide range of typicality and membership ratings. The candidate exemplars of each category appeared in the same page, and each category-exemplar pair appeared such that the candidate exemplar was printed on the left- hand side, and the category name appeared on the right-hand side (e.g., apple—FRUIT). Participants were asked to decide whether the noun represents a member of the category by circling *yes* or *no,* and to indicate their confidence on a 0—100 scale (they were allowed to mark U for "unfamiliar," and the responses to these items were eliminated from the analysis).

Item consensus averaged 80.8% across items (range 52—100%), and for 27 items, all participants gave the same response. Fig. 31.1 presents mean confidence judgments for consensual and nonconsensual responses plotted for different classes of item consensus. The figure also presents the mean confidence across both responses. Mean

confidence judgments increased monotonically with item consensus, consistent with the idea that self-consistency should increase with the polarity of the population of cues associated with an item. The 27 full- consensus items yielded the highest mean confidence (97.7%). For the remaining items, confidence was consistently higher for the consensual answers (averaging 88.8% across the 74 items) than for the nonconsen- sual answers (averaging 81.9%). A detailed analysis of the results (see Koriat & Sorka, 2015) suggested that the discrepancy in confidence between consensual and nonconsensual responses increased with item consensus.

31.6.2 Experiment 2

We turn next to the results of a second experiment that yielded a wider range of results. Experiment 2 was a computerized experiment that allowed the testing of predictions about response latency. In addition, it included seven presentations of the same list of items, so that predictions of SCM could also be tested in a within-individual analysis. The experiment included 100 pairs, 10 object-category pairs for each of 10 categories. The seven administrations of the categorization task were divided between two sessions that took place 1 week apart (four presentations in Session 1 and three in Session 2 with filler tasks between presentations). Response latency—the interval between the presentation of the pair and the response—was measured, and participants indicated their confidence by sliding a pointer on a 0-100 slider using the mouse.

31.6.2.1   *The Relationship of Confidence and Response Latency to Cross-Person Consensus*

Focusing on the results from the first presentation, we examined the predictions of SCM for the differences between consensual and noncon- sensual answers in confidence and latency. The results are presented in Fig. 31.2A (confidence) and Fig. 31.2B (latency). As in Experiment 1, confidence was very high (96%) for the 15 full-consensus items. For the remaining items, confidence was significantly higher for the consensual responses (84.6%) than for the nonconsensual responses (75.3%). In addition, detailed analyses confirmed that the difference in confidence between consensual and nonconsensual responses increased significantly with item consensus.

Basically the same pattern was observed for response speed: mean response speed increased with item consensus. Consensual responses were made faster than nonconsensual responses, with the difference increasing with item consensus. Note that this pattern is consistent with what Bassili (2003) called the "Minority Slowness Effect" which,
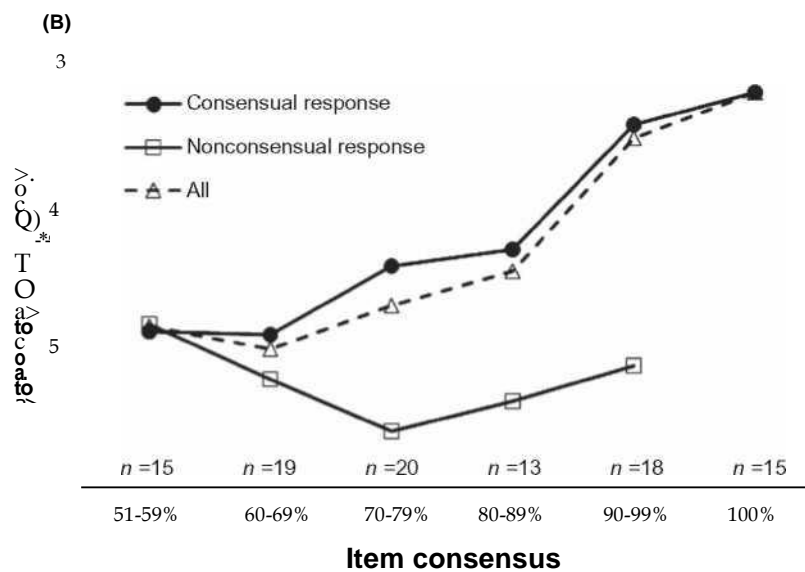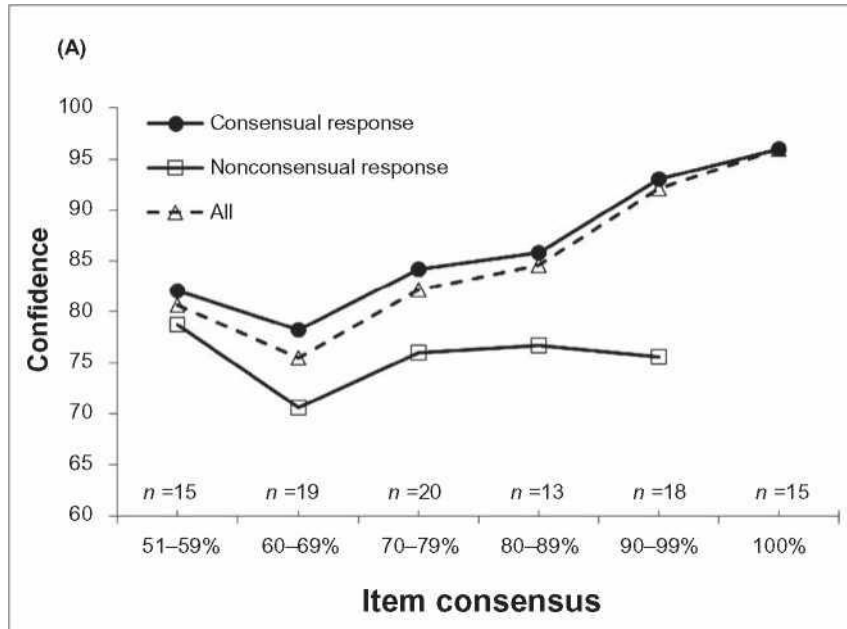
FIGURE 31.2 Mean confidence judgments (A) and response latency (B) in Presentation 1 of Experiment 2 for consensual and nonconsensual responses and for all responses combined as a function of item consensus (the percentage of participants who chose the consensual response). Indicated in the figure is also the number of items (n) in each item consensus category. *Source: Reproduced with permission from Koriat, A., & Sorka, H. (2015). The construction of categorization judgments: Using subjective confidence and response latency to test a distributed model.* Cognition, 134, 21 – 38. *Copyright © 2014 by Elsevier.*

according to him, reflects the inhibition that participants feel when they express a view that departs from the majority opinion. However, Koriat et al. (2016) argued that a PME pattern for both response speed and confidence can result from the internal process underlying choice and confidence independent of any social pressure.

We should note that the pattern of results depicted in Fig. 31.2 was preserved when confidence and response speed were first standardized to neutralize chronic individual differences in confidence and response speed. Also, the consensual—nonconsensual differences were obtained even in a between-individual analysis: for each item, individuals who made the consensual choice tended to express greater confidence and to respond faster than those who made the nonconsensual response. Thus, the consensual—nonconsensual differences reflect differences between different *responses* rather than differences between individuals or differences between items.

31.6.2.2 The Relationship of Confidence and Response Latency to Within-Person Consistency

Because the task was presented seven times, we could test the predictions of SCM in a within-individual analysis. We classified all items for each participant into those that were made more frequently across the seven presentations and those that were made less frequently. Fig. 31.3A presents mean confidence for the participant's frequent and rare responses as a function of item consistency—the number of times that the frequent response was chosen. Confidence was highest for the responses that were repeated across all presentations (90.0%). For the remaining items, confidence was significantly higher for the participant's frequent responses (73.9%) than for the participant's rare responses (62.7%), with the difference increasing with item consistency. A similar pattern was observed for response speed (Fig. 31.3B). Thus, participants were less confident and responded more slowly when their response deviated from their own modal response.

31.6.2.3 Confidence and Response Latency as Predictors of Reproducibility

As noted earlier, like statistical level of confidence, subjective confidence was assumed to represent an assessment of reproducibility—the likelihood that a new sample of cues drawn from the same population will yield the same choice. Indeed, in a number of studies in which the same task was presented several times, confidence in the response to an item in its first presentation predicted the likelihood that the same response will be made in subsequent presentations (Koriat, 2011, 2013; Koriat & Adiv, 2011, 2012). This was also true for category membership decisions in Experiment 2, as can be seen in Fig. 31.4.
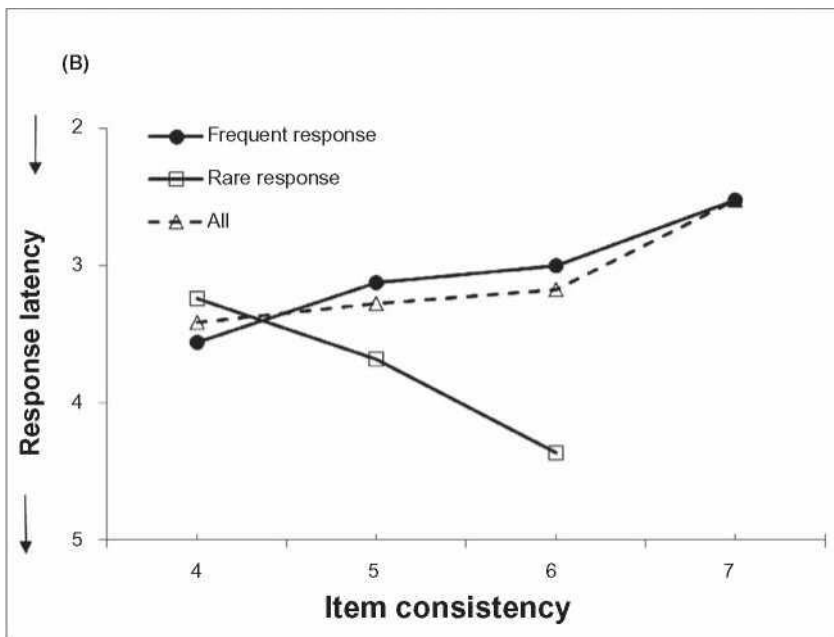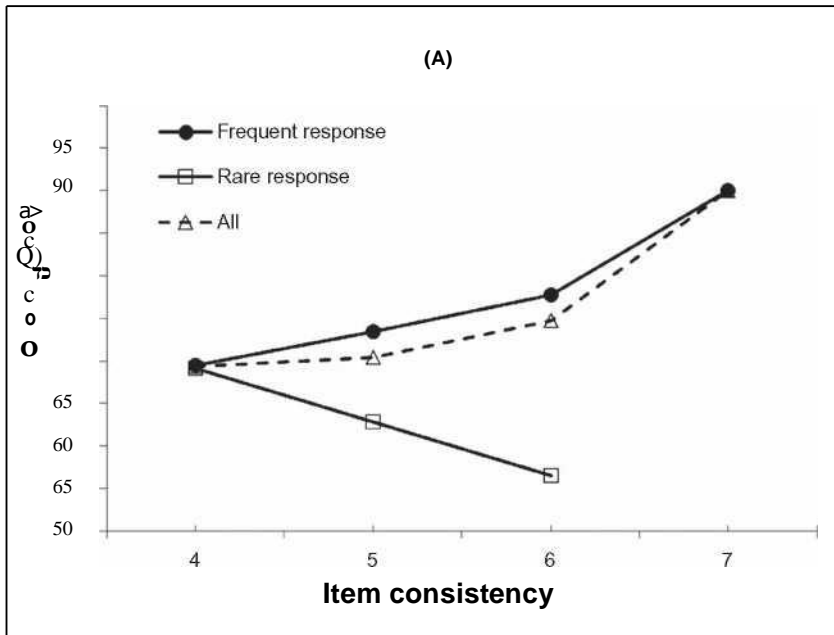
FIGURE 31.3 Mean confidence judgments (A) and response latency (B) for each participant's frequent and rare responses and for all responses combined as a function of item consistency (the number of times that a response was made across the seven presentations). *Source: Reproduced with permission from Koriat, A, & Sorka, H. (2015). The construction of categorization judgments: Using subjective confidence and response latency to test a distributed model.* Cognition, 134, *21 – 38. Copyright © 2014 by Elsevier.*
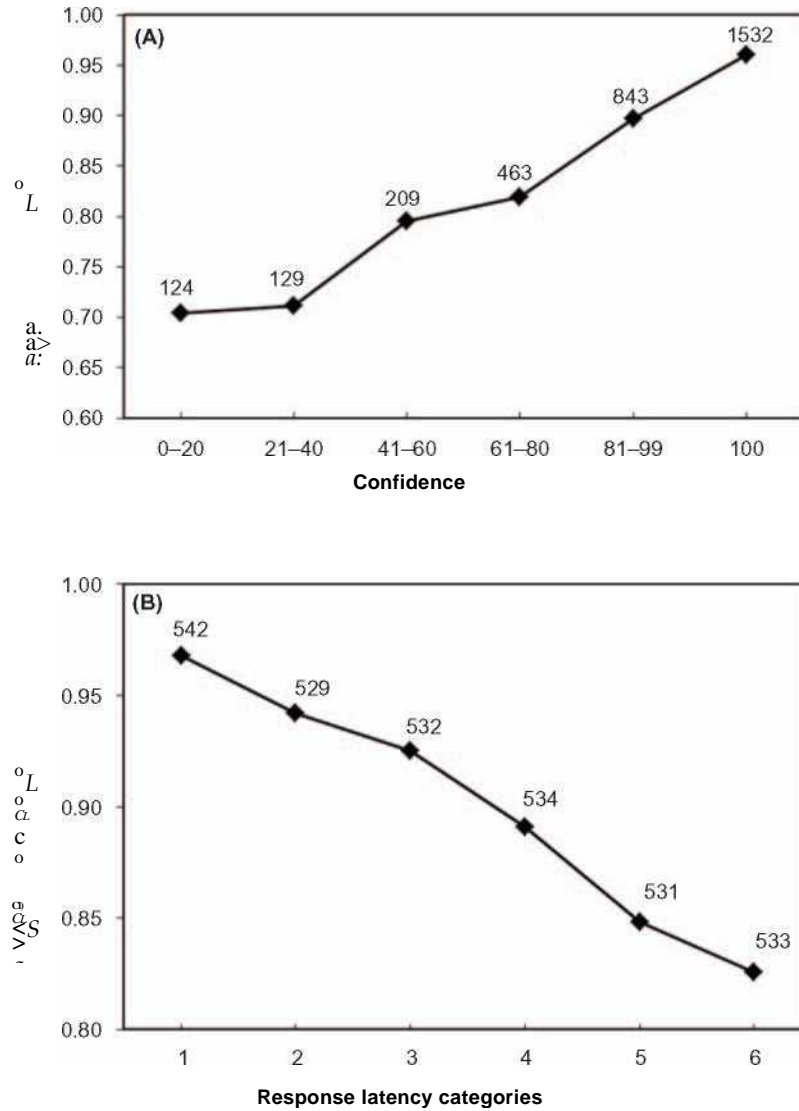
FIGURE 31.4   (A) presents the likelihood of repeating the Presentation-1 choice across the subsequent six presentations (repetition proportion) for each of the six confidence categories. (B) plots repetition proportion as a function of presentation-1 response latency. Indicated in the body of this figure is also the number of observations in each category. *Source: Reproduced from Sorka, H. (2013).* The construction of categorization judgments: Using subjective confidence to test a distributed model *(Master's thesis, University of Haifa, Israel). Retrieved from http://nprimofe.haifa.ac.il/NHAU:books_and_more:hau_aleph001816043, Sorka (2013).*

In Fig. 31.4A, the confidence judgments in Presentation 1 were grouped into six categories, and the proportion of response repetitions— the likelihood of making the same response over the subsequent six presentations—is presented for each category. The results in this figure were obtained by pooling data across participants and items. It can be seen that response repetition increased monotonically with confidence in Presentation 1; the Spearman rank-order correlation over the six values was 1.0. A similar analysis was carried out for response latency (Fig. 31.4B). The results indicated that response repetition decreased with increasing response latency, the Spearman rank-order correlation across the six points was —1.0. Similar results were obtained in all the studies in which the task was administered several times (see Koriat, 2011, 2013; Koriat & Adiv, 2011, 2012).

31.7   THE EFFECTS OF CONTEXT ON CATEGORY MEMBERSHIP DECISIONS

Previous research has indicated that category membership decisions can be influenced by the context or perspective in which the decision is made (Barsalou, 1987; Hampton, 2011; Medin et al., 1997; Roth & Shoben, 1983). According to SCM, context can affect category membership decisions by biasing the sample of cues retrieved. Therefore, confidence and response latency should mirror the effects of context on category membership decisions: decisions that are compatible with a given context should be endorsed with higher confidence than decisions that are incompatible with that context.

To examine the effects of context on categorization, we presented participants with short passages depicting different contexts, followed each by a categorization judgment. The task included 10 questions, each appearing with two different types of contexts, neutral or biasing, across two blocks. The neutral context was intended to prime the consensual response for that item as was found in Experiment 2 (without context). The biasing context, in contrast, was intended to induce the nonconsensual response. Table 31.1 presents, as examples, two of the questions used along with their neutral and biasing passages and the response that they were intended to prime. The task was administered in a paper-and-pencil format. Participants were asked to imagine themselves being in the situation described in each passage, and to answer the category membership question according to the situation described. They circled *yes* or *no* and indicated their confidence in their decision on a 0—100 scale.

Context was found to affect category membership decisions: the percentage of nonconsensual responses was significantly higher for the

31. CATEGORIZATION: A DISTRIBUTED MODEL Examples of the Materials Used in

TABLE 31.1
Experiment 3

	Is Dancing a Sport? Consensual Response YES
Primed Context	Scenario
Neutral	Your sister is a salsa dancer. She practices almost every day and travels to competitions abroad. She is a perfectionist and she is a sore loser. Every time she loses she shuts herself in her room for days and thinks that she should retire. You think it makes life very difficult for her.
Biasing	Your grandfather had a stroke that limited his mobility. As a consequence, he moved into a nursing home. When you visit him you mostly play chess and he usually wins. You love him for his serenity, his smile, and you miss the way he used to dance. You wish you had more time together.

	Is Architecture a Science? Consensual Response NO
Primed Context	Scenario
Neutral	You are visiting Barcelona with your best friend. You really want to go to the Picasso exhibition while your friend wants to visit the Sagrada Familia cathedral. The cathedral is the masterpiece of Gaudi and the lavish decorative elements of the building were sculpted by the architect himself. However, the exhibition is a rare opportunity to view Picasso's original paintings from different periods of his work. You want to accompany your friend, but also to enjoy the trip.
Biasing	You have applied to the Architecture Department at the University. The classes will start in a month. During the first year of the degree you are required to complete courses in physics, structural engineering and building codes. The problem is that you've never been good with calculations and you're a little afraid of these courses.

For each question, the table indicates the consensual choice in Experiment 2, and presents the neutral passage, which was intended to prime that response, and the biasing passage, which was intended to prime the alternative, nonconsensual response.

biasing context (64.2%) than for the neutral context (42.2%). In parallel, confidence judgments mirrored the effects of context on categorization. As can be seen in Fig. 31.5, the neutral context yielded the typical finding: confidence was higher for the consensual response (80.2) than for the nonconsensual response (72.0). In the biasing context, in contrast, confidence was significantly higher for the nonconsensual response (82.7) than for the consensual response (72.0). The results illustrate what happens when a minority response becomes a majority: the induced context reversed the consensual—nonconsensual difference that has been observed so far for confidence judgments (see Koriat et al., 2016). The results are consistent with the idea that context may affect categorization by biasing the sampling of cues retrieved,
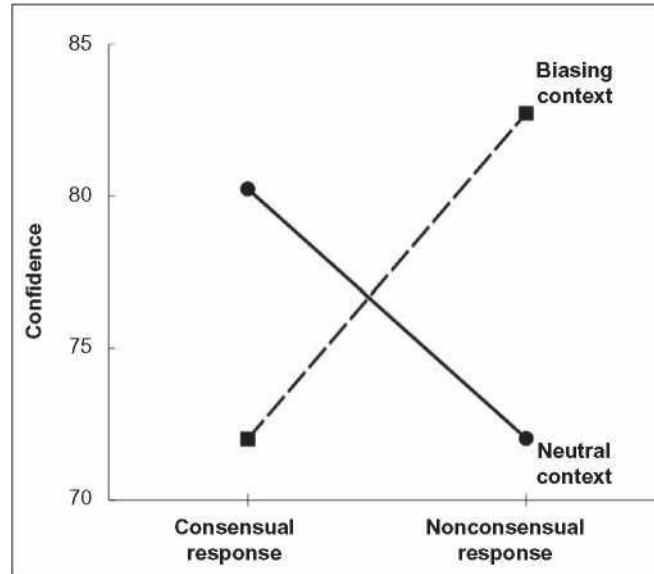
FIGURE 31.5 Mean confidence judgments for normatively consensual and normatively nonconsensual responses for the neutral and biasing contexts in Experiment 3.[1]

and that the effects of context should also be reflected in confidence judgments.

31.8   CONCLUSION

The results reviewed in this chapter are consistent with the distributed model according to which categorization decisions are based on the sampling of cues from a rich network of cues that is associated with the object—category pair. When the sample drawn supports the consensual choice, the one that is favored by the "collective wisdom," confidence is higher and response latency is shorter than when the retrieved sample supports the nonconsensual choice. In addition, the difference in confidence between consensual and nonconsensual responses increases with the "size of the majority"—the extent to which the consensual response is preferred across people over the nonconsensual response.

[1]Fig. 31.5 differs from Figure 7 in Koriat and Sorka (2015). Although both Figures are based on the results reported in the text of that article, the results for the neutral context were incorrectly plotted in Figure 7 in that article.

It is important to note that the pattern of results depicted in Fig. 31.1 and Fig. 31.2A for confidence judgments has been observed across tasks from a variety of domains, including word matching, general information, perceptual judgments, social attitudes, social beliefs, personal preferences, and the predictions of others' responses. A similar pattern to that depicted in Fig. 31.2B has also been observed in those studies in which response latency was measured (for reviews, see Koriat & Adiv, 2016; Koriat et al., 2016).

In addition, in several of these studies, the task was presented several times. The results yielded the same general pattern as that depicted in Fig. 31.3: the more frequently chosen response across repetitions tended to be associated with higher confidence and shorter response latency than the less frequently chosen response (see Koriat et al., 2016). Altogether, these results suggest that the sampling view assumed by SCM has some generality, and applies also to category membership judgments.

Other models of categorization postulate some general principle underlying the information that is used in determining categorization decisions (see Brooks, 1978; Hampton, 1979; Nosofsky, 1988, 1991; Rosch, 1978; Rosch & Mervis, 1975). SCM, in contrast, assumes that the cues underlying category membership judgments may be of many different sorts. They are retrieved associatively in a quasirandom fashion, and participants rely on whatever cues come to mind at the time of making a decision. In fact, SCM has evaded the question of the content of the cues used. Other authors also considered the possibility of a multiplicity of features underlying categorization (e.g., Hampton, 1998, 2012; Medin, 1989; Rosch, 1973; Smith, Patalano & Jonides, 1998).

The predictions of SCM are consistent with those made by other researchers as far as inter-item differences are concerned (e.g., Estes, 2004; Hampton, 1998; McCloskey & Glucksberg, 1979). In fact, much of the theoretical work on categorization judgments has concerned interitem differences in typicality ratings, cross-person consensus, and within-person consistency. In SCM, inter-item differences have been conceptualized in terms of p_{maj}, the proportion of cues that support the majority choice, and indeed, the results indicate that mean confidence and mean response speed (see "All" in Figs 31.1-31.3) generally increase with degree of consensus and consistency. The unique prediction of SCM, however, concerns differences between different *choices*. None of the current theories has faced the challenge of explaining why different people make different responses to the *same* item, and why the same person makes different responses to the same item on different occasions. It is the combination of two assumptions that allows accounting for both the stability and variability components of category

membership decisions. First, each object—category pair is associated with a commonly shared population of cues. Second, category membership decisions are assumed to be based in each occasion on a small sample of cues drawn from that population. The combination of the two assumptions also indicates how the polarity of the cues associated with each item (p_{maj}) constrains the variability that can occur in category membership decisions either across people or across occasions. Of particular importance is the finding that the context for category membership judgments can reverse the pattern of results observed for confidence so that a normatively minority choice, when induced by context, is endorsed with higher confidence than the normatively majority choice.

Acknowledgment

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SECOND EDITION

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