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Ready to Learn: Incidental Exposure Fosters Category Learning

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Abstract

Our knowledge of the world is populated with categories such as dogs, cups, and chairs. Such categories shape how we perceive, remember, and reason about their members. Much of our exposure to the entities we come to categorize occurs incidentally as we experience and interact with them in our everyday lives, with limited access to explicit teaching. This research investigated whether incidental exposure contributes to building category knowledge by rendering people "ready to learn"—allowing them to rapidly capitalize on brief access to explicit teaching. Across five experiments (N = 438 adults), we found that incidental exposure did produce a ready-to-learn effect, even when learners showed no evidence of robust category learning during exposure. Importantly, this readiness to learn occurred only when categories possessed a rich structure in which many features were correlated within categories. These findings offer a window into how our everyday experiences may contribute to building category knowledge.

Keywords

category learning, incidental learning, unsupervised category learning, category structure, open data

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Our knowledge about the world is richly populated with categories. For example, we often think about dogs as in some way equivalent, despite substantial differences between them in color, size, and other features. Moreover, this equivalence guides the way we perceive, remember, and reason about dogs. For instance, when learning that one dog has a four-chambered heart, we can infer that other dogs do as well. Importantly, we rarely pursue a goal to form these categories or are explicitly taught about them. Even when learning categories early in development, people may have only occasional, limited access to explicit information about category membership, such as a person pointing at a dog while saying, "Look at that dog!" (Yu & Ballard, 2007). More often, we incidentally encounter members of categories while pursuing our everyday goals. Here, we examined contributions of these incidental experiences to building category knowledge and identified conditions under which incidental experiences contribute to category learning.

How Does Incidental Exposure Contribute to Category Learning?

Much of the current understanding of category learning comes from research in which learners are explicitly taught categories (or explicitly told to form categories; e.g., Pothos & Chater, 2005; Zeithamova & Maddox, 2009). For example, in *supervised-classification* studies that comprise the bulk of category-learning research, learners receive a wealth of information: (a) the fact that the stimuli belong to a specified (typically small) number of categories, (b) category labels, and (c) corrective feedback following classification decisions (e.g., Kruschke, 1992; Nosofsky, 2011). Similar teaching is provided in *inference training*, in which learners infer

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missing features of category stimuli and are given corrective feedback (e.g., Markman & Ross, 2003).

However, explicit teaching is likely limited in real-world experiences. Instead, much of our experience with categories is likely both unsupervised and incidental. This experience is unsupervised because no explicit teaching is provided and incidental because it occurs without a goal to learn categories (Billman & Knutson, 1996; Clapper, 2006; Clapper & Bower, 1994, 2002; Love, 2002). Additionally, category membership may or may not be related to the other goals we pursue while acquiring these experiences. For example, if we see a person playing with a dog in a park, incidental exposure to this member of the dog category may be related to a goal to determine whether the person is playful or unrelated to a goal to get fresh air. How do these unsupervised incidental experiences contribute to category learning?

Prior research has focused on whether incidental exposure fosters one aspect of learning about categories: detecting correlations between features that characterize many real-world categories (e.g., features such as fur, four legs, and snout are correlated in the dog category; Malt, 1995; Malt & Smith, 1984; Rosch et al., 1976). This research has yielded mixed results. Some evidence suggests that people do learn correlations between features from incidental exposure (Billman & Knutson, 1996; Gabay et al., 2015; Holt et al., 2015), especially when categories are dense in structure (i.e., when many features are correlated with membership). Conversely, other evidence suggests that correlations may go undetected even for dense categories (Clapper, 2006; Clapper & Bower, 1994, 2002).

However, human category knowledge goes well beyond detecting correlations. Instead, we discriminate between categories (e.g., dogs vs. cats), recognize new members of known categories, associate categories with labels (e.g., "dog"), describe characteristic features of categories (e.g., Cree & McRae, 2003; Malt & Smith, 1984; McRae et al., 2005), and so on. How does incidental exposure contribute to building this rich category knowledge?

Here, we investigated whether incidental exposure to categories contributes to category learning by rendering people ready to learn categories from even brief access to explicit teaching (for a similar assessment of learning in pigeons, see Castro et al., 2018). Such a ready-to-learn effect would represent a vital synergy in category learning between everyday extensive incidental exposure and limited access to explicit information.

We further considered how incidental exposure may foster readiness to learn. First, we examined whether readiness to learn depends on category structure. Does incidental exposure foster readiness to learn any category or only richly structured (dense) categories? We expected the latter, given that learning sparse categories with few category-relevant features may occur only when learners pursue a goal to form categories that prompts them to search for and selectively attend to these features (Kloos & Sloutsky, 2008; Perry & Lupyan, 2014; Rehder & Hoffman, 2005; Sloutsky, 2010). Second, we investigated whether readiness to learn depends on robust implicit category learning during incidental exposure. Alternatively, readiness to learn may transpire without such learning, such as via the passive storage of exemplars in memory that form a foundation for subsequent learning (see the General Discussion and the Supplemental Material available online).

Statement of Relevance

No two things that we see in the world around us are identical. Yet we often treat different things as being of the same kind, or belonging to the same "category." For example, we think of different dogs as belonging to the category of dogs, and this guides how we perceive, reason about, and remember dogs. However, we rarely receive explicit information about category membership. Instead, much of our everyday exposure to the things that we categorize is incidental, such as when we happen to pass a dog on the street. The present studies investigated the contributions of such incidental exposure to category learning. Our findings revealed conditions in which incidental exposure contributes to category learning by rendering people ready to learn categories rapidly from brief access to explicit information. This research thus offers a new approach to illuminating how our everyday experiences may shape the categories that we learn.

Present Study

In five experiments, participants first completed a cover task in which they were exposed to either exemplars of categories (*category exposure*) or unstructured baseline stimuli (*baseline exposure*). Subsequently, participants were explicitly taught the categories to which participants in the category-exposure condition had been exposed. We assessed whether incidental exposure to categories fostered readiness to learn by facilitating subsequent explicit category learning.

To further illuminate the contributions of incidental exposure to category learning, we investigated whether the ready-to-learn effect depended on category structure

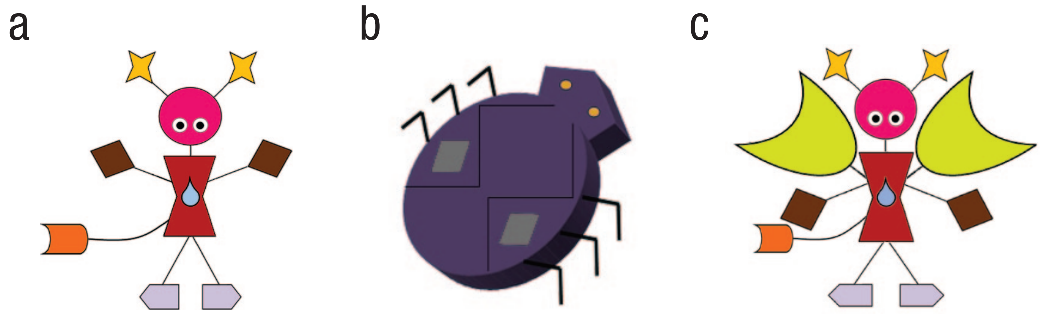

Fig. 1. Examples of (a) a category exemplar in Experiments 1 to 4, (b) a baseline stimulus in Experiments 1 and 2, and (c) a category exemplar in Experiment 5. Baseline stimuli in Experiments 3 to 5 had the same features as category exemplars.

and robustness of implicit category learning during exposure. To investigate the role of category structure, we contrasted the effects of incidental exposure to dense categories, in which many features were correlated with membership, with exposure to sparse categories, in which few features were correlated. This was a vital contrast because learning sparse categories may require selective attention to category-relevant features, which may not be evoked by incidental exposure (Kloos & Sloutsky, 2008; Sloutsky, 2010).

Second, we investigated whether the ready-to-learn effect depended on robust implicit category learning during exposure. We investigated this question following the logic of prior implicit-learning paradigms, in which participants respond faster to events that they implicitly learn to be predictable (e.g., in contextual-cuing or serial reaction time [RT] tasks, responses to stimuli are speeded when they are predicted by other stimuli; Chun & Jiang, 1998; Goujon et al., 2015; Nissen & Bullemer, 1987; Schwarb & Schumacher, 2012). Specifically, Experiments 1 to 3 used a cover task in which participants made timed responses to events. For participants in the category-exposure condition, category membership was implicitly correlated with these events, such that implicit category learning could speed responses relative to those of participants in the baseline-exposure condition.

To anticipate the results, we found that incidental exposure to dense but not sparse categories did indeed foster subsequent readiness to learn. Importantly, the ready-to-learn effect transpired even when any implicit learning during exposure was not robust enough to influence participants' concurrent responses. To assess the generality of the ready-to-learn effect, we further investigated whether it transpires even when category membership is unrelated to cover task responses (Experiments 4 and 5) or contexts in which category exemplars appear (Experiment 5).

All recruitment criteria and procedures for these experiments were approved by the institutional review board at The Ohio State University, and all participants provided informed consent. Formal power analyses for all experiments are reported in the Supplemental Material. Scripts and data for all analyses can be found at https://osf.io/jrtfn/.

Experiment 1

Method

Participants. Participants were 139 adults recruited from Amazon Mechanical Turk (MTurk)[1] who were compensated at a rate of $8 per hour. Participants were randomly assigned to four between-subjects conditions, as described in the Design section below. This sample size was identified by taking prior experiments that used the categories from which the categories in this experiment were adapted (Deng & Sloutsky, 2012, 2015, 2016) and treating the sample sizes in those experiments as a conservative estimate of the sample size needed to detect condition differences in category learning.

Materials. The primary stimuli used in this experiment were exemplars from two categories: *flurps* and *jalets*. These exemplars were colorful images of creatures similar to those used in prior category-learning research conducted by Deng and Sloutsky (e.g., Deng & Sloutsky, 2012, 2015, 2016). The creatures were composed of seven binary-valued visual features including a head, antennae, body, hands, feet, tail, and button (Fig. 1a). In the constructed categories, some of these features correlated with each other and with category membership. Specifically, one feature (e.g., the color of the tail) was deterministically related to category membership; all flurps had one value of this feature (e.g., the orange tail), and all jalets had the other value (e.g., the blue tail). In addition, at least one feature was also probabilistically related to category membership (and thus with the deterministic feature); most flurps (80%) had one value of this feature,

Table 1. Structure of Dense-Category Exemplars Depicting Binary Values of Deterministic, Probabilistic, Irrelevant, and Context Features (Experiments 1–4)

	Exemplar									
Creature and feature	1	2	3	4	5	6	7	8	9	10
Flurp										
Deterministic	1	1	1	1	1	1	1	1	1	1
Probabilistic 1	0	0	1	1	1	1	1	1	1	1
Probabilistic 2	1	1	0	0	1	1	1	1	1	1
Probabilistic 3	1	1	1	1	0	0	1	1	1	1
Probabilistic 4	1	1	1	1	1	1	0	0	1	1
Probabilistic 5	1	1	1	1	1	1	1	1	0	0
Irrelevant	0	1	0	1	0	1	0	1	0	1
Context	1	1	1	1	1	1	1	1	1	1
Jalet										
Deterministic	0	0	0	0	0	0	0	0	0	0
Probabilistic 1	1	1	0	0	0	0	0	0	0	0
Probabilistic 2	0	0	1	1	0	0	0	0	0	0
Probabilistic 3	0	0	0	0	1	1	0	0	0	0
Probabilistic 4	0	0	0	0	0	0	1	1	0	0
Probabilistic 5	0	0	0	0	0	0	0	0	1	1
Irrelevant	0	1	0	1	0	1	0	1	0	1
Context	0	0	0	0	0	0	0	0	0	0

and most jalets (also 80%) had the other value. The remaining features were irrelevant to category membership because their two values occurred equally often in flurps and jalets. The overall frequency of the values of each feature was the same; only correlations between feature values and not raw frequency distinguished between deterministic, probabilistic, and irrelevant features. As described below, the proportion of features that were relevant and irrelevant to category membership was manipulated to generate a pair of categories with a dense category structure (shown in Table 1) and categories with a sparse structure (shown in Table 2).

In addition, in the exposure phase only (see the Procedure section below), stimuli appeared in one of two locations or *contexts* (i.e., a panel on the left or the right of the screen). Just as category membership was correlated with the visual features, category membership was also perfectly correlated with spatial context, such that flurps always appeared in one spatial context, and jalets always appeared in the other. This correlation with context was designed to allow us to measure implicit category learning during the exposure phase (see the Procedure section).

Dense-category exemplars. In dense categories, in addition to the deterministic feature, the values of five of the remaining features were probabilistically correlated with membership in a given category. Values of the one remaining feature were irrelevant to category membership. As noted above, category membership was also perfectly correlated with context in the exposure phase (see the Procedure section). This category structure is summarized in Table 1.

Sparse-category exemplars. Sparse categories contained the same features as the dense categories, but the proportion of features correlated with category membership was reduced. Specifically, in sparse categories, one feature was deterministic, one was probabilistic, and five were irrelevant. As in dense categories, membership in sparse categories was perfectly correlated with the context in which exemplars appeared in the exposure phase. This structure is summarized in Table 2.

Baseline stimuli. An additional set of creatures dissimilar in appearance from the category exemplars (Fig. 1b) was adapted from stimuli created by Badger and Shapiro (2012) for use as baseline stimuli. Like category exemplars, these stimuli were composed of binary-valued features and appeared in one of two contexts during the exposure phase. Unlike the category exemplars, the set of baseline exemplars did not have a category structure: Stimuli included all possible combinations of feature values and were uncorrelated with context.[2] See the Supplemental Material for further discussion of how these two types of baseline stimuli rule out alternative explanations for the ready-to-learn effect.

Table 2. Structure of Sparse-Category Exemplars Depicting Binary Values of Deterministic, Probabilistic, Irrelevant, and Context Features (Experiment 1)

	Exemplar									
Creature and feature	1	2	3	4	5	6	7	8	9	10
Flurp										
Deterministic	1	1	1	1	1	1	1	1	1	1
Probabilistic 1	1	1	1	1	1	1	1	1	0	0
Irrelevant 1	0	0	0	0	1	1	1	1	0	1
Irrelevant 2	0	1	1	1	0	0	0	1	0	1
Irrelevant 3	1	0	0	1	0	1	1	0	0	1
Irrelevant 4	1	0	1	0	1	0	1	0	1	0
Irrelevant 5	0	1	1	1	0	0	0	1	1	0
Context	1	1	1	1	1	1	1	1	1	1
Jalet										
Deterministic	0	0	0	0	0	0	0	0	0	0
Probabilistic 1	0	0	0	0	0	0	0	0	1	1
Irrelevant 1	0	0	0	0	1	1	1	1	0	1
Irrelevant 2	0	1	1	1	0	0	0	1	0	1
Irrelevant 3	1	0	0	1	0	1	1	0	0	1
Irrelevant 4	1	0	1	0	1	0	1	0	1	0
Irrelevant 5	0	1	1	1	0	0	0	1	1	0
Context	0	0	0	0	0	0	0	0	0	0

Design. This experiment had a nested between-subjects design, illustrated in Figure 2. This design determined (a) the items that participants saw during an initial exposure phase and (b) the categories that participants were taught during a subsequent explicit phase. First, each participant was randomly assigned to one of two structure conditions: dense or sparse. In the dense condition, participants were taught dense categories during the explicit phase, and in the sparse condition, participants were taught sparse categories during the explicit phase. Within each structure condition, there were two conditions in the exposure phase: (a) category exposure, in which participants were exposed to exemplars of the same category structure (i.e., dense vs. sparse) that they would later be taught in the explicit phase, and (b) baseline exposure, in which participants were exposed to baseline stimuli. This design afforded a test of whether learning dense or sparse categories from explicit instruction was facilitated by prior incidental exposure to these categories, relative to exposure to baseline stimuli. Each participant was randomly assigned to one of four combinations of structure and exposure conditions: (a) category exposure, dense structure (n = 35); (b) baseline exposure, dense structure (n = 35); (c) category exposure, sparse structure (n = 36); and (d) baseline exposure, sparse structure (n = 33).

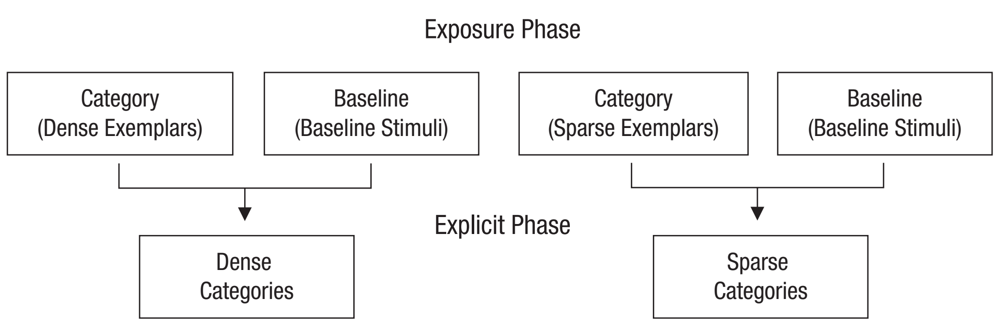

Fig. 2. Schematic depiction of the experimental design. The experiment consisted of an exposure phase followed by an explicit phase. The nested design determined the items that participants saw during these phases. First, participants were assigned to a structure condition that determined whether they learned dense or sparse categories during the explicit phase. Within each structure condition, each participant was assigned to one of two exposure-phase conditions, such that they saw either baseline stimuli or exemplars of the categories that they would subsequently learn in the explicit phase.

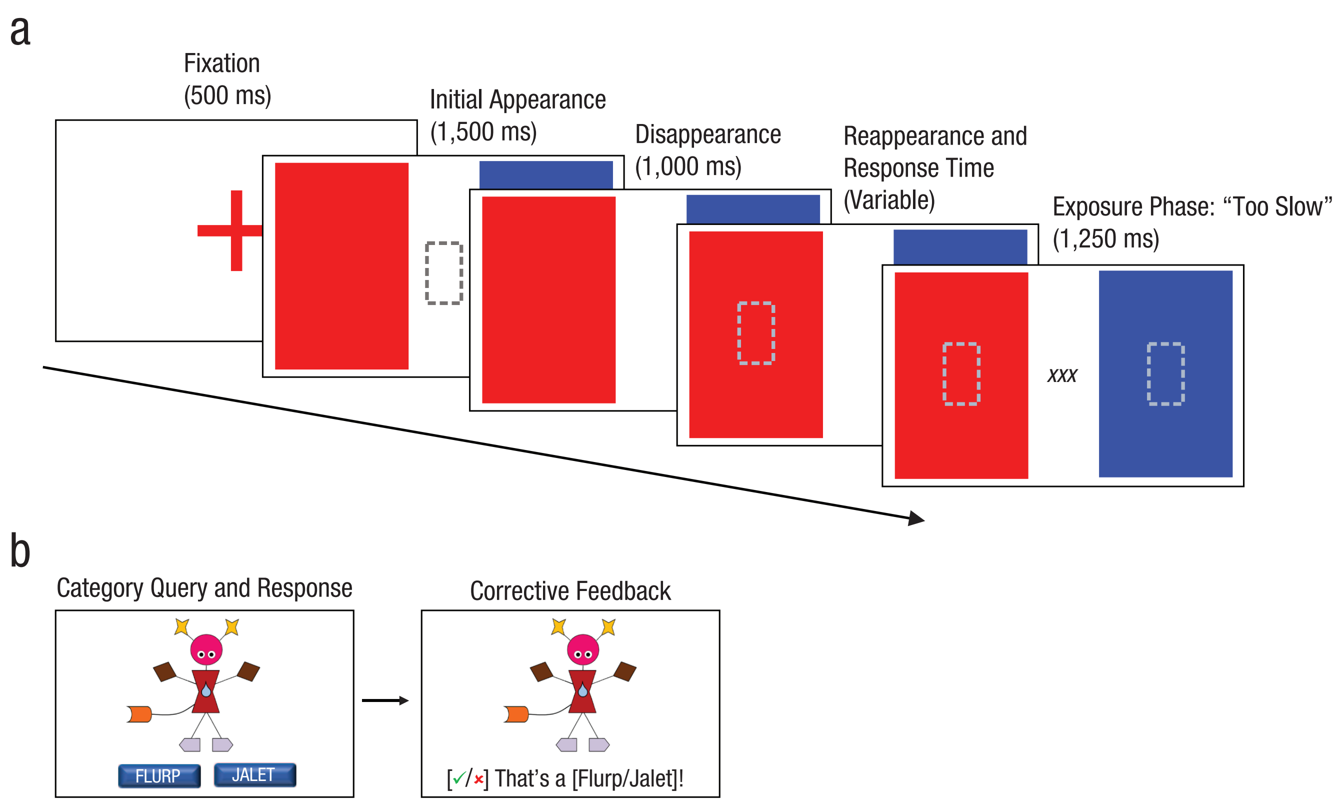

Fig. 3. Trial sequence and exemplars shown in the practice, exposure, and explicit phases of the color-jump game. In practice and exposure trials (a), an exemplar appeared in the center of the screen (the position is indicated here by dashed boxes) between a red panel on the left and a blue panel on the right. The exemplar then briefly disappeared and subsequently reappeared inside either the red or the blue panel. Participants had to indicate which panel the exemplar appeared in. In practice trials, a star appeared in place of the exemplar, and feedback indicated whether the participant was correct, incorrect, or too slow. In exposure trials, the exemplars appeared, and feedback was provided only when participants were too slow. In each trial of the explicit phase (b), participants had to identify whether an on-screen creature was a "flurp" or a "jalet." A green check mark appeared if they had categorized correctly, and a red X appeared if they had categorized incorrectly.

Procedure. Participants took part in the experiment online by following a link posted on MTurk. The experiment was created in and hosted by Gorilla Experiment Builder (Anwyl-Irvine et al., 2019). The experiment consisted of two phases: an exposure phase and an explicit phase.

Exposure phase. The exposure phase began with a practice version of the "color-jump game" cover task, which participants completed throughout the exposure phase. The purpose of this cover task was to provide incidental exposure to category exemplars or baseline stimuli and, as explained below, to provide a measure of implicit category learning. The practice version accustomed participants to the task and encouraged speeded responding. A schematic of this task is provided in Figure 3.

In the practice for the color-jump game, participants watched a star that initially appeared in the center of the computer screen between a red panel on the left and a blue panel on the right. The star then disappeared and "jumped" (i.e., reappeared) to either the left red panel or the right blue panel. Participants were instructed to watch where the star jumped and then press the "q" key if the star jumped to the left or the "p" key if it jumped to the right. Note that participants were instructed to respond after the star reappeared and never instructed to try to anticipate the location in which the star would reappear. Participants were informed that they would have only a short amount of time to respond and that they would receive feedback indicating whether they were correct, incorrect, or too slow. (As noted below, corrective feedback was provided only during practice.)

Participants then completed 20 practice trials. The star jumped equally often to the left and right, in a pseudorandomized order. The amount of time participants had to respond after the star reappeared started at 500 ms and then decreased in 25-ms increments every five trials; the allowance for the last five trials was 425 ms.

Following practice, participants continued to play the color-jump game, but the star was replaced by new stimuli. Within both the dense- and sparse-structure conditions, each participant was assigned to one of two exposure conditions: (a) category-exposure condition, in which the stimuli that jumped were exemplars of the same category that they would subsequently be explicitly taught in the explicit phase, or (b) baseline-exposure condition, in which the stimuli that jumped were baseline stimuli (Fig. 2). In the category-exposure condition, category membership was perfectly correlated with jump "context" (i.e., with whether they jumped to the red or blue panel) and thus with responses in the task. This correlation was designed to provide a measure of implicit category learning. Specifically, because implicitly learning to differentiate between categories would render jump location predictable, such learning may manifest as greater improvements in the speed of responses in the category-exposure condition compared with the baseline-exposure condition, where no implicit learning is possible. Such speedup in the category-exposure condition would be similar to other instances of implicit learning, including contextual-cuing and serial RT tasks (Chun & Jiang, 1998; Nissen & Bullemer, 1987). To keep any correlation between category membership and jump context implicit, we never told participants whether their responses were correct or incorrect and gave them feedback only when they responded too slowly.

Participants completed 80 trials (eight blocks of 10 trials) of the color-jump game. In the category-exposure condition, category exemplars were pseudorandomly assigned to blocks such that (a) an equal number of exemplars from each category occurred in each block, and (b) a given exemplar never appeared twice within a block.

To increase the potential speed and accuracy benefits of implicitly learning the categories in the category-exposure condition, for all participants, we increased the difficulty of the task by reducing the RT allowance from 425 ms by 25 ms every two blocks; for the final two blocks, the allowance was 350 ms. Participants were alerted to this reduction in RT allowance at the beginning of each block in which it occurred. Note that a subsequent experiment (Experiment 3) assessed this implicit learning without the reduction in RT allowance.

Explicit phase. In this phase, participants were explicitly taught the dense or sparse categories using a supervised category-learning task. The purpose of this phase was to investigate whether incidental exposure to categories in the exposure phase would improve participants' ability to capitalize on limited access to explicit teaching.

First, participants were informed that they would learn about two kinds of creatures: flurps and jalets. Participants were told that for each creature, they should identify whether they think it is a flurp or jalet by clicking on-screen buttons, after which they would receive corrective feedback (Fig. 3b). Participants then proceeded through 30 training trials of this task (three blocks of 10 trials each). This number of training trials was based on the trials typically needed to learn similar categories from explicit supervision in prior studies (Deng & Sloutsky, 2016). To generate 30 trials, we randomly assigned half of the category exemplars from each of the categories to appear twice, and the remaining half appeared once. These items were pseudorandomly assigned to blocks such that an equal number of exemplars from each category appeared in each block, and the repeated exemplars never appeared in the same block. Finally, the order of exemplars within blocks was randomized for each participant.

On each trial, participants were presented with a category exemplar on its own in the center of the screen, without the two jump contexts. Participants were asked whether each creature was a flurp or a jalet. After responding, participants received a message saying, "That's a [flurp/jalet]!" along with a picture of the exemplar they had just categorized. A green check mark appeared if they had categorized correctly, or a red X appeared if they had categorized incorrectly (Fig. 3b). The outcome measure of interest in this phase was how well participants learned to categorize the category exemplars over the course of the 30 trials.

Results

Overview. Analyses assessed the effects of incidental exposure to categories. First, we assessed whether participants showed evidence of robust implicit learning of the categories during the exposure phase. As a reminder, during the exposure phase, there was a cover task in which stimuli jumped to one of two locations, and participants indicated the jump location. The stimuli were either category exemplars whose category membership was correlated with the jump location context (category-exposure condition) or baseline stimuli (baseline-exposure condition). Therefore, implicit category learning during the exposure phase could have allowed participants who were exposed to category exemplars to correctly anticipate the location of the stimulus and respond faster than participants who were exposed to baseline stimuli (Chun & Jiang, 1998; Goujon et al., 2015; Nissen & Bullemer, 1987; Schwarb & Schumacher, 2012). Analyses thus estimated speedup over the exposure phase (i.e., slope in RT over trials) for participants in each exposure condition and compared speedup between conditions. Analyses using accuracy as the outcome variable revealed results similar to the results of analyses of RT and are included in scripts available on OSF.

Second, we assessed whether incidental exposure to categories during the exposure phase fostered subsequent readiness to learn categories in the explicit phase. Recall that each participant was assigned to one of two structure conditions such that in the explicit phase, some participants were explicitly taught dense categories, and others were taught sparse categories. Within each structure condition, we assessed the effects of exposure to category exemplars in the preceding exposure phase. Specifically, for each structure condition, we assessed whether category learning in the explicit phase was better in participants who had been exposed to category exemplars relative to participants who had been exposed to baseline stimuli. Additional analyses that assessed correlations between speedup in the exposure phase and category learning in the explicit phase are reported in the Supplemental Material.

Because both differences and similarities between conditions would be informative about the effects of incidental exposure to categories, all assessments were performed as hierarchical Bayesian analyses using the *rstan* package (Version 2.21.2; Stan Development Team, 2020), the *bayestestR* package (Version 0.11.5; Makowski et al., 2019), and the *loo* package (Version 2.4.1; Vehtari et al., 2017) in the R programming environment (R Core Team, 2017). In these analyses, hierarchical Bayesian models were used to predict each participant's outcome variable (i.e., RT across trials in the exposure phase and accuracy across trials in the explicit phase) on the basis of participant-level parameters (i.e., intercept and slope for trial number for a participant's RT in the exposure phase and accuracy in the explicit phase). These models were hierarchical because values for participant-level parameters were sampled from distributions based on the participant's condition. In Bayesian model fitting, samples are drawn from regions of parameter space (the posterior distribution) that make accurate predictions for outcome variables. Therefore, if participants in different conditions tend to be best fitted by different parameter values, the posterior distributions for conditions will tend to differ.

Thus, the analyses below evaluated condition differences and similarities in two ways (for a similar analysis pipeline, see Kruschke, 2014). First, in analyses of the explicit phase only, we used leave-one-out cross-validation (Vehtari et al., 2017) to compare (a) the fits of models in which different parameter values (i.e., intercept and slope) were drawn from different distributions across conditions with (b) the fits of models in which parameter values were drawn from the same distribution. This comparison was designed to identify the parameters for accuracy across explicit phase trials that differed between conditions. Identifying which parameters differed between conditions disentangled whether (a) conditions were associated with different initial levels of accuracy (which would transpire as differences in intercepts) and/or (b) conditions were associated with different rates of category learning (which would transpire as differences in slopes). This comparison was not conducted for analyses of the exposure phase because only differences between conditions in decrease in RT (i.e., slope) were of interest.

Second, for analyses of both the exposure and the explicit phases, we calculated differences between the distributions for different conditions. To capture the range of most probable values for differences between conditions, we calculated the highest density intervals (HDIs) for the distributions of differences. This interval is the range of a distribution that contains some specified percentage of probable values. For example, the 89% HDI for a distribution of values (e.g., a distribution of differences between conditions) is the portion of the distribution that contains 89% of the probable values. The interpretation of such intervals is simply the probability that the "true" value falls within the range, for example, that there is an 89% probability that the value falls within the 89% HDI. Because there is currently no convention regarding the percentage to use as the basis for inferences, we followed some Bayesian statisticians in reporting 89% HDIs (Makowski et al., 2019; McElreath, 2020).

Exposure phase. Analyses of the exposure phase assessed whether exposure to category exemplars (category-exposure condition) affected performance during the exposure phase differently from exposure to baseline stimuli (baseline-exposure condition). Specifically, we conducted separate analyses of the dense- and sparse-structure conditions, which assessed whether participants in the category-exposure condition showed an advantage in which they sped up (decreased in RT) across trials more than participants in the baseline-exposure condition. Change in RT over the exposure phase is shown in Figure 4.

To conduct these analyses, we constructed a hierarchical Bayesian model in which each participant's RT across trials was predicted as the outcome of a linear regression with an intercept and a slope for trial number. Note that we used linear regression because the progressive reductions in RT allowance caused changes in RT across trials to be approximately linear.[3] We used this model to assess the effects of category versus baseline exposure within each structure condition. For each participant, we estimated an intercept and slope for RT across trials. Critically, participant slopes were drawn from one of two

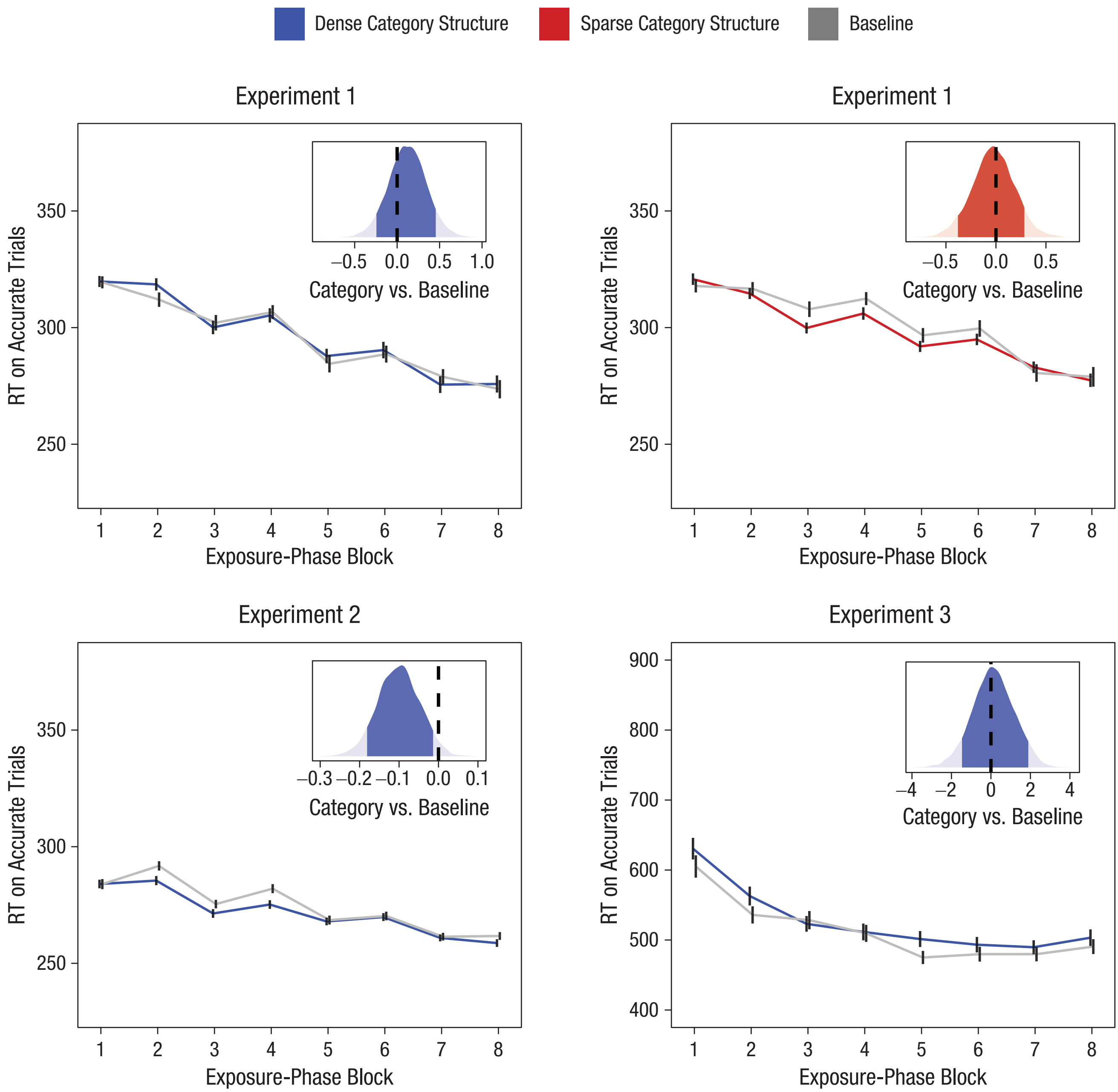

Fig. 4. Mean reaction time (RT) in trials with accurate responses, separately for each block of the exposure phase in Experiments 1 to 3. Results are shown separately for trials with dense and sparse category structures in Experiment 1 and trials with dense category structures in Experiments 2 and 3, all compared with RT to baseline exposure. Error bars depict standard errors of the mean. Insets depict the distribution of differences in RT speedup between the category- and baseline-exposure conditions; differences greater than 0 indicate an advantage for the category-exposure condition. The solid region in each distribution depicts the 89% highest density interval.

distributions on the basis of whether the participant was in the category- or baseline-exposure condition. These distributions were given the same weak prior probability distributions. If RTs for participants in the category-exposure condition decreased more than RTs for participants in the baseline-exposure condition, then we would find larger, negative slopes for RT across trials for participants in the category-exposure condition. This tendency for larger negative slopes would transpire as larger negative means for the posterior distribution of slopes in the category-exposure condition. To test whether this tendency was present, we calculated the difference between the means of the distributions for the category- and baseline-exposure conditions for each sample from the posterior distribution. To produce positive values when this difference was in the direction of interest (i.e., when there were larger negative slopes for participants in the category-exposure than the baseline-exposure condition), we calculated the difference as the mean of the distribution for participants in the baseline-exposure condition minus the mean of the distribution for participants in the category-exposure condition. For example, if slopes were indeed more negative for participants in the category-exposure condition (e.g., –3) than for participants in the baseline-exposure condition (e.g., –1), this difference would be positive, for example, –1 – (–3) = 2, whereas if slopes were less negative for participants in the category-exposure condition (e.g., –1 vs. –3), this difference would be negative, for example, –3 – (–1) = –2. Thus, positive differences would indicate that participants who were exposed to category exemplars decreased more in RT (i.e., had larger negative slopes) than participants exposed to baseline stimuli.

Slopes for RT were similar for the category-exposure condition and the baseline-exposure condition, for both the dense- and sparse-structure conditions. Specifically, the 89% HDI for differences between the slope distributions for category exposure and baseline exposure included 0 for both the dense-structure (89% HDI = [–0.24, 0.48]) and sparse-structure (89% HDI = [–0.33, 0.31]) conditions. Thus, incidental exposure to categories did not foster implicit category learning that was robust enough to manifest in responses during the exposure phase (see the Supplemental Material for additional analyses and discussion).

Explicit phase. Categorization accuracy in the explicit phase is depicted in Figure 5. Note that visualizing binary accuracy data requires aggregating data across trials and blocks, which can obscure the nature of category-learning curves that unfold trial by trial (see the Supplemental Material for a demonstration of the effect of aggregation). Therefore, Figure 5 depicts both the aggregated data and trial-by-trial learning curves. The main analysis of the explicit phase assessed whether exposure condition (category vs. baseline) affected participants' ability to learn to accurately categorize the exemplars over the course of this phase. Specifically, we tested whether intercepts or slopes for categorization accuracy differed between the category- and baseline-exposure conditions for participants who learned either dense or sparse categories in the explicit phase.

To conduct this test, for each participant, we predicted categorization accuracy across trials as the outcome of a logistic regression with an intercept and a slope for trial number (for a similar approach, see Zettersten & Lupyan, 2020). Effects of exposure condition might transpire in two ways. First, differences between the intercepts for participants in different exposure conditions, if found, would indicate that from the beginning of the explicit phase, participants in one exposure condition categorized more accurately than participants in another exposure condition. If better initial categorization accuracy transpired in the category-exposure condition, this difference would imply that participants in the category-exposure condition began the explicit phase already differentiating between the categories. Alternatively, differences between the exposure conditions in slopes, if found, would indicate that participants in one exposure condition learned to categorize in the explicit phase more rapidly than participants in the other exposure condition. Therefore, we generated four hierarchical Bayesian models. Across models, intercepts, slopes, both, or neither were sampled from one of four distributions: (a) category exposure, dense structure; (b) baseline exposure, dense structure; (c) category exposure, sparse structure; and (d) baseline exposure, sparse structure. A comparison of these models using approximate leave-one-out cross-validation indicated that the data were best fitted by the model in which slopes, but not intercepts, were taken from different distributions. Therefore, subsequent analyses were conducted using this model.

We used this model to test whether category-learning slopes in the category-exposure condition differed from slopes in the baseline-exposure condition for either dense or sparse categories. For each sample from the posterior distribution, we calculated the mean of the category-exposure distribution minus the mean of the baseline-exposure distribution. We calculated this difference separately within the dense and sparse conditions. Larger positive differences would indicate that participants in the category-exposure condition had steeper category-learning slopes than participants in the baseline-exposure condition.

As shown in Figure 6, for dense categories, category-learning slopes were steeper for participants in the category-exposure than in the baseline-exposure condition (i.e., the 89% HDI for differences between slope distribution was [0.02, 0.10]). In contrast, for sparse categories, category-learning slopes were similar in the category and baseline conditions (i.e., the 89% HDI for differences between slope distributions was [–0.05, 0.03]). These results provide evidence that incidental exposure to dense but not sparse categories led to steeper category-learning slopes when participants learned categories from brief access to explicit teaching. In contrast, additional analyses presented in the Supplemental Material provide evidence that, when learning could be driven only by explicit teaching (in the baseline-exposure condition), sparse categories were, if anything, slightly easier to learn than dense categories.

This experiment provides evidence that incidental exposure to categories results in the ready-to-learn effect:

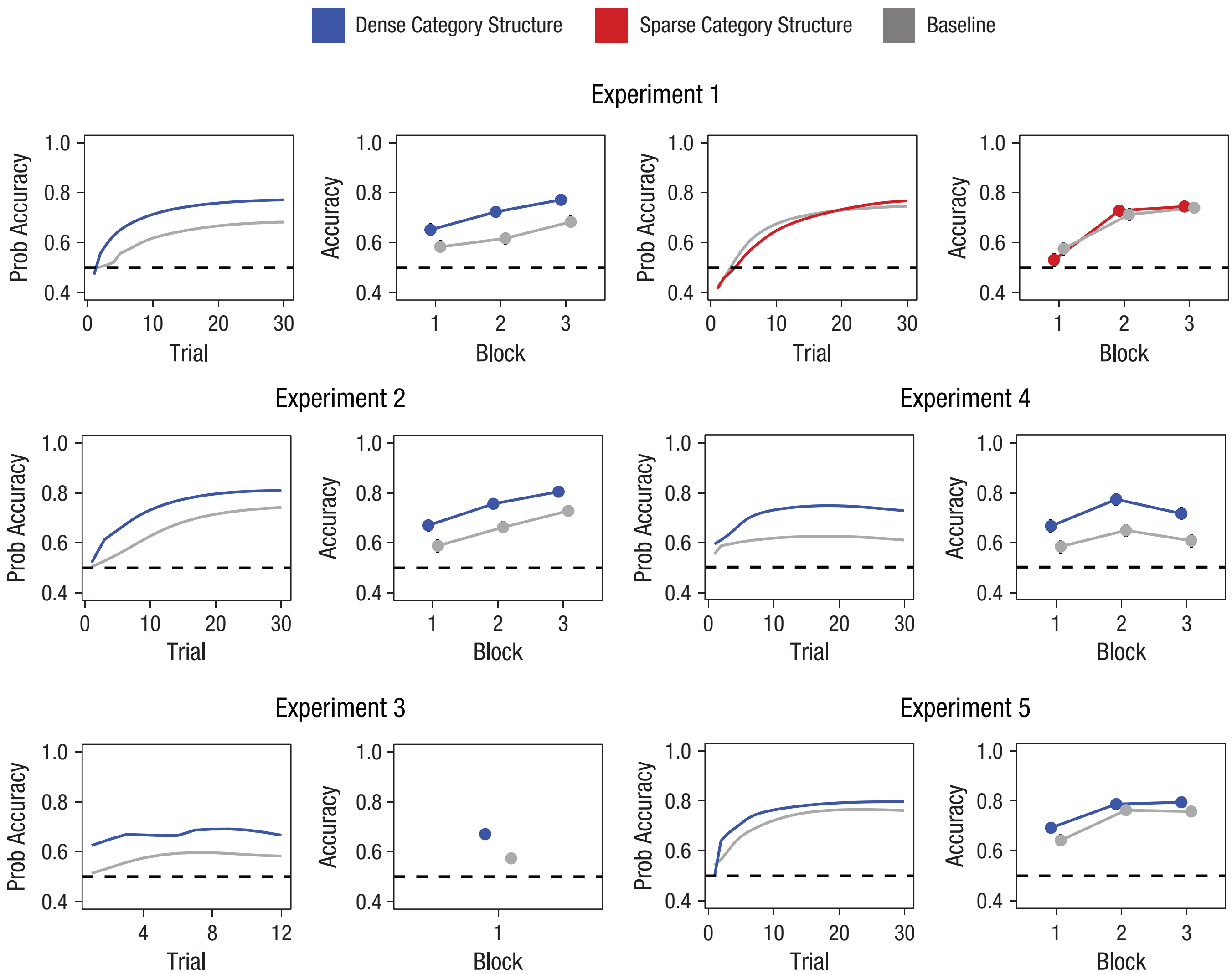

Fig. 5. Category learning in the explicit phase in Experiments 1 to 5. Learning is depicted in two graphs for each experiment and category-structure condition; trial-by-trial learning curves are shown on the left, and accuracy aggregated across trials within each block is shown on the right. Trial-by-trial learning curves were generated in two steps. First, we used a nonhierarchical model to predict trial-by-trial accuracy for each participant as the outcome of a logistic regression with an intercept and a slope for trial number. Second, we used estimated intercepts and slopes to plot trial-by-trial learning curves averaged across participants in each condition. Trial-by-trial learning curves thus depict the estimated probability of an accurate response ("Prob Accuracy") on each trial. For aggregated data, error bars depict standard errors of the mean.

Participants who were exposed to dense (but not sparse) categories learned faster from limited access to explicit teaching than participants who were exposed to baseline stimuli. Importantly, this ready-to-learn effect transpired in spite of the finding that participants did not show evidence of robust category learning during incidental exposure (further details and analyses are provided in the Supplemental Material). As we discuss below, finding a learning advantage in the explicit phase coupled with no evidence of robust learning in the exposure phase is consistent with large literature on latent learning in nonhuman animals (for a review, see Spear et al., 1990). Moreover, a supplemental experiment reported in the Supplemental Material provides evidence that this finding did not transpire simply because participants treated the exposure phase as supervised category learning. This experiment showed that when participants were prompted to treat the exposure phase as supervised category learning, patterns differed in multiple ways: (a) In the exposure phase, there was greater speedup in the category-exposure than in the baseline-exposure condition, and (b) in the explicit phase, participants in the category-exposure condition had higher intercepts rather than steeper slopes, indicating that participants in the category-exposure condition began the explicit phase already differentiating between the categories.

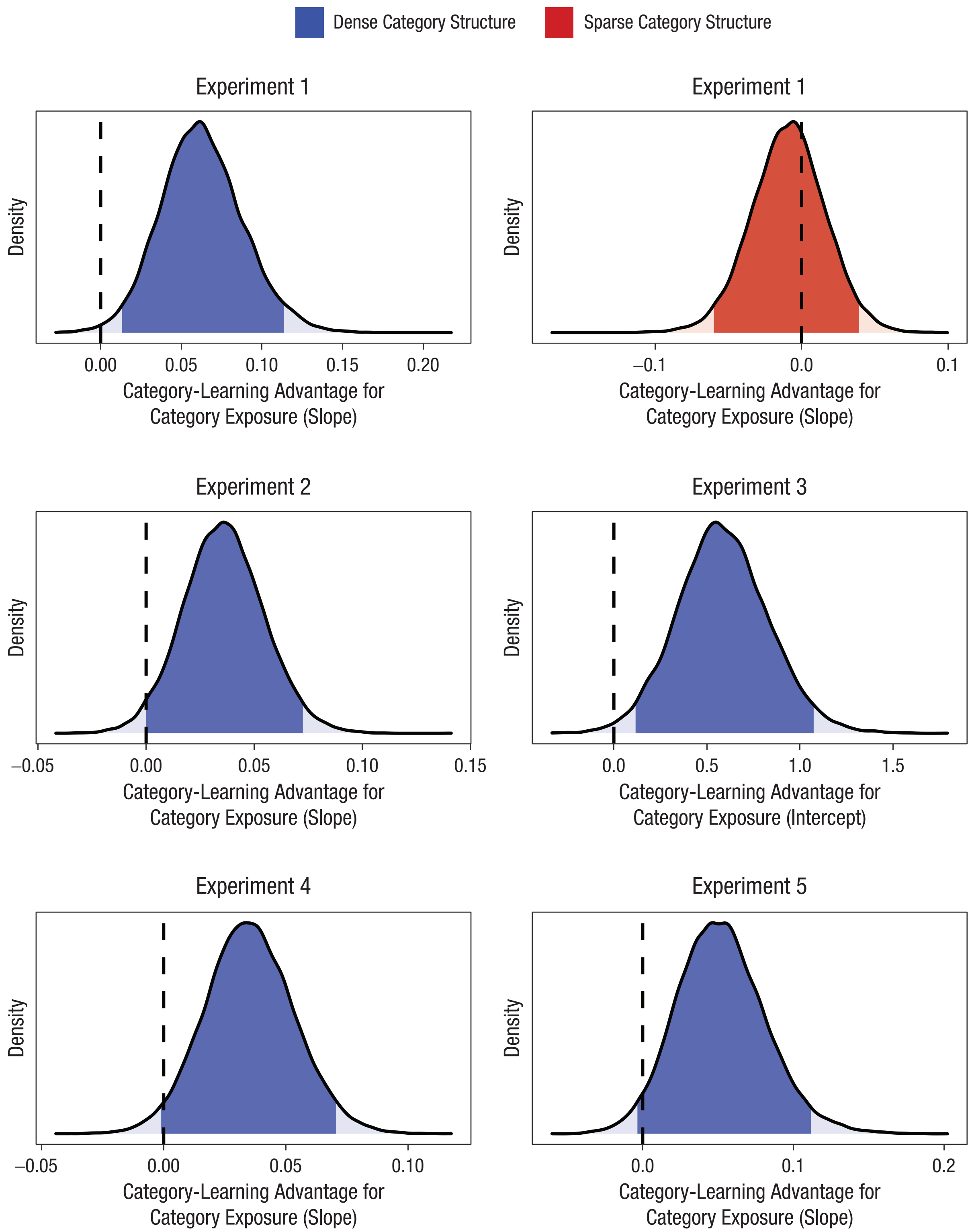

Fig. 6. Posterior distributions of category-learning differences between the category- and baseline-exposure conditions in the explicit phases of Experiments 1 through 5. The solid region in each distribution denotes the 89% highest density interval. Zero indicates no difference between the category- and baseline-exposure conditions; values greater than 0 indicate better category learning in the category- than in the baseline-exposure condition, whereas values less than 0 indicate the opposite pattern.

To examine the robustness of the ready-to-learn effect, we conducted Experiment 2. Experiment 2 was a replication of the dense-structure condition of Experiment 1, designed to test whether the same findings would transpire in a new sample of participants recruited from a different population.

Experiment 2

Method

Participants. Participants were 72 adults recruited from the undergraduate population at The Ohio State University who participated for course credit.

Materials, design, and procedure. The materials, design, and procedure were identical to those used in the dense-structure condition of Experiment 1. Each participant was randomly assigned to one of two exposure conditions: category (n = 37) or baseline (n = 35).

Results

Data from Experiment 2 were submitted to the same hierarchical Bayesian analyses used in Experiment 1.

Exposure phase. Change in RT over the exposure phase is shown in Figure 4. As in Experiment 1, analyses of the exposure phase tested implicit category learning in terms of whether participants in the category-exposure condition had larger decreases in RTs than participants in the baseline condition. As a reminder, implicit category learning could speed responses in the category-exposure condition because category membership was perfectly correlated with cover task events to which participants responded. However, this was not the case: The analyses of RT slopes in the exposure phase did not find steeper slopes in the category-exposure condition. If anything, the opposite was the case; RT slopes were somewhat steeper in the baseline than in the category-exposure condition (89% HDI = [–0.19, –0.02]).

Explicit phase. Category learning is depicted in Figure 5. As in Experiment 1, the model that best fitted the data in the explicit phase was one in which slopes but not intercepts for categorization accuracy came from different distributions based on exposure condition. Therefore, we followed the same approach as in Experiment 1 to compare the distribution of slopes in the category- and baseline-exposure conditions. As shown in Figure 6, category-learning slopes were steeper for participants in the category-exposure condition (i.e., the 89% HDI for differences between slope distributions was [0.01, 0.07]). These results replicate the evidence from Experiment 1 that incidental exposure to dense categories improved category learning from brief access to explicit teaching.

Experiment 3 tested the robustness of these findings by introducing two methodological refinements. First, it could be argued that the advantage of the category-exposure condition over the baseline-exposure condition was not due to exposure to exemplars from dense categories per se but occurred because this exposure familiarized participants in the category-exposure condition with the features of the category stimuli. Even though this possibility is inconsistent with the lack of a ready-to-learn effect for participants who were exposed to sparse categories (and thus were also familiarized with features of the category stimuli), we deemed it necessary to examine the familiarity possibility explicitly. To do so, in Experiment 3, we used a baseline condition in which participants were exposed to stimuli containing the same features as category members, but without category structure. Second, to rule out the possibility that the lack of evidence for implicit category learning during incidental exposure transpired because the RT limits forced changes in RT in the category- and baseline-exposure conditions to be similar, we eliminated these limits in Experiment 3. In addition, because the explicit phase served as a check that the ready-to-learn effect would transpire with these methodological refinements, we kept the study short (see Note 1) by limiting the explicit phase to a single block.

Experiment 3

Method

Participants. Participants were 87 adults recruited from MTurk who were compensated at a rate of $8 per hour. An additional 17 participants (11 in the dense condition, six in the baseline condition) were tested but removed because of failure to reach a criterion of more than 70% accuracy on the exposure-phase cover task used in these conditions. This criterion was imposed because the removal of RT limits rendered the cover task extremely simple, and poor accuracy should result only from inattention.

Materials.

Category exemplars. Category exemplars in this experiment were identical to the dense-category exemplars from Experiments 1 and 2 (Table 1).

Baseline stimuli. Baseline stimuli were 80 creatures composed of the same binary-valued features as category exemplars. As in category exemplars, all feature values occurred with equal frequency. However, these stimuli were created by randomly combining the values of the features so that they had no category structure.

Design and procedure. As in Experiment 2, this experiment used a between-subjects design in which each participant was randomly assigned to one of two exposure conditions: category (n = 44) or baseline (n = 43).

Exposure phase. The exposure-phase procedure was similar to the procedure in Experiments 1 and 2, with the following exceptions: (a) The RT allowance limits were eliminated, and (b) because the elimination of the RT allowance limits rendered the task much easier than in Experiments 1 and 2, the practice task was also eliminated.

Explicit phase. As in the preceding experiments, the purpose of the explicit phase was to test the effects of exposure condition on the accuracy with which participants learned to categorize the category exemplars given explicit supervision with feedback. However, in this experiment, the explicit phase served as a check that the same ready-to-learn effect observed in preceding experiments would transpire with the methodological refinements to the exposure phase. Therefore, to keep the study short (see Note 1), we limited the explicit phase to a single block of 12 trials. To generate 12 trials, we pseudorandomly selected six of the category exemplars from each of the categories to appear in this phase; these exemplars preserved the category structure in which one feature was deterministic, five were probabilistic, and one was irrelevant.

Results

Exposure phase. Change in RT over the exposure phase is shown in Figure 4. Prior to the analyses, trials with inaccurate responses and trials with extremely long RTs (> 2,000 ms) were removed, resulting in the removal of 2.28% of trials. Analyses of the exposure phase in Experiment 3 were similar to analyses in Experiments 1 and 2, with the exception that the hierarchical Bayesian model predicted change in RT as a nonlinear function of trial number. This change was made because, in the absence of the reduction in RT allowance in Experiment 3, participants showed a typical pattern of an initial steep decrease followed by shallower decreases in RT. Following evidence that individual participants' RT across trials of a task decreases as an exponential function of trial (Heathcote et al., 2000), we used the following nonlinear function:

$$\text{RT} = \text{asymptote} + (\text{intercept} + \text{asymptote}) \times 2^{(1-\text{trial})/\text{rate}}$$

This function includes three parameters: (a) an intercept, (b) a rate parameter that captures how quickly the asymptote is reached, and (c) a parameter for the asymptote that RT approaches. Similar to analyses of change in RT in Experiments 1 and 2, we used a hierarchical Bayesian model to jointly estimate these parameters for participants and conditions. However, all three parameters were needed to describe the change in RT across trials, and no single parameter unambiguously captured speedup. To capture speedup, following Steyvers and Benjamin (2019), we used these parameters to calculate slopes. To calculate slopes for each sample from the posterior, we (a) took the curve defined by the three parameter values, (b) calculated the slope on each trial as the derivative of the curve on that trial, and (c) calculated speedup as the average slope across trials. Because there is no a priori expectation about how much incidental exposure to category exemplars may be needed to foster implicit learning, we calculated the average slope across all trials, the first half of trials, and the second half of trials. We then calculated condition differences in slopes following the same approach as in the analyses for Experiments 1 and 2. As in the preceding experiments, this model revealed that participants in the category-exposure condition did not decrease more in RTs than participants in the baseline-exposure condition (89% HDI for slope differences included 0 for the average across trials [–1.48, 1.91], the first half of trials [–2.13, 2.64], and the second half of trials [–1.12, 0.98]).

Explicit phase. Category learning in the explicit phase is depicted in Figure 5. Analyses of the explicit phase in this experiment used the same approach as the analyses in Experiments 1 and 2. In this experiment, the model that best fitted the data in the explicit phase was one in which intercepts but not slopes for accuracy were drawn from different distributions on the basis of exposure condition. This is likely due to the shortened length of the exposure phase; accuracy did not change sufficiently over trials in this condition to detect differences in learning slopes. Therefore, following the same approach as in previous experiments, we tested whether category-learning intercepts were larger in the category- than the baseline-exposure condition. As shown in Figure 6, this was indeed the case (i.e., the 89% HDI for differences between intercept distributions was [0.18, 0.95]). These results replicated those of Experiments 1 and 2, which suggested that incidental exposure to dense categories facilitated category learning during brief access to explicit teaching.

As in Experiments 1 and 2, incidental exposure to dense categories in Experiment 3 facilitated subsequent explicit category learning, even when participants showed no evidence of robust category learning during exposure. Additionally, Experiment 3 provided evidence that the ready-to-learn effect is not due to mere familiarity with category features.

In the experiments thus far, we assessed implicit category learning during incidental exposure by having incidental exposure to categories occur in a cover task in which category membership was perfectly (although implicitly) correlated with correct responses. Thus, it is possible that incidental exposure fostered readiness to learn only because participants spontaneously treated the exposure phase cover task as a supervised category-learning task, in which they attempted to learn a relationship between the stimuli and events in the cover task. This possibility is countered by evidence from a supplemental experiment that revealed different results when participants were prompted to treat the cover task as a supervised category-learning task (see the Supplemental Material). Experiment 4 further investigated this possibility by testing whether incidental exposure to dense categories would produce the ready-to-learn effect even when it occurred in a different cover task, in which category membership was unrelated to task responses. Participants saw the same regularities in Experiment 4 as in previous experiments, but in the context of a one-back task in which responses were unrelated to category membership.

Experiment 4

Method

Participants. Participants were 62 adults recruited from MTurk who were compensated at a rate of $12 per hour. It is important to note that this experiment took place during the first months of the COVID-19 pandemic lockdowns, when members of the population from which participants were recruited (e.g., gig workers) were likely under greater than normal levels of stress. Because of this consideration, we increased the rate of compensation and shortened the exposure phase of the experiment (see below; note that this change did not bias this experiment toward replicating the previous results because any effect of shortening the exposure phase should *decrease* the chances of replicating the ready-to-learn effect). In addition, although most participants performed well on the new one-back exposure phase cover task, an additional 11 participants were recruited but removed because of inattentive performance (i.e., having a lower hit rate vs. false-alarm rate for detecting repeated stimuli in the one-back task).

Materials.

Category exemplars. Category exemplars in this experiment were identical to the dense-category exemplars in the preceding experiments (Table 1).

Baseline stimuli. Baseline stimuli were identical to the baseline stimuli used in Experiment 3, which were composed of the same binary-valued features as the category exemplars. Because the exposure phase was shortened (see below), only 40 baseline stimuli were used.

Design and procedure. This experiment used a between-subjects design in which each participant was randomly assigned to one of two exposure conditions: category (n = 28) or baseline (n = 34).

Exposure phase. The exposure phase differed from Experiments 1 to 3 in that it used a new cover task, which was a one-back task. Participants first received instructions that they would complete a task in which they would see sequentially presented creatures and that their job would be to indicate whether the currently presented creature was the same as the one they saw on the previous trial. On each trial, participants saw either a category stimulus (category-exposure condition) or baseline stimulus (baseline-exposure condition) on either a left or a right panel. In contrast with the preceding experiments, stimuli did not jump to the panel; instead, the appearance of the stimulus on a panel was static. In only the category-exposure condition, the category membership of the category exemplar was perfectly correlated with the panel on which it appeared (thus preserving the correlation with context shown in Table 1).

For each trial, participants were instructed to remember the stimulus, which appeared for a minimum of 2 s before participants could proceed. With the exception of the first trial in a block, participants were prompted to indicate whether the stimulus (i.e., the “creature”) was the same as the stimulus that appeared on the preceding trial. There were two repeated stimuli in each block, one from each category. For nonrepetitions of category exemplars, the category exemplars that appeared on consecutive trials always came from different categories to reduce conflict between visual similarity (which is higher for same- than for different-category exemplars) and the one-back task.

Participants received corrective feedback following each response and completed a total of 40 trials, divided across four blocks. The exposure phase was shortened to four blocks, in comparison with the eight blocks in the preceding experiments, out of consideration for the possibility that the stress of the COVID-19 pandemic might make it challenging for participants to attend to a repetitive task for a long period of time.

Explicit phase. The explicit phase in this experiment used the same three-block explicit phase procedure as in Experiments 1 and 2.

Results

Exposure phase. There was no assessment of implicit category learning in the exposure phase of this experiment because there was no correlation between category membership and responses in the cover task. Therefore, we used data from the exposure phase only to check that participants attended to the one-back task. We assessed attentive performance by comparing hit rates for detecting repetitions (i.e., proportion of hits out of hits + misses) with false-alarm rates for misidentifying nonrepetitions as repetitions (i.e., proportion of false alarms out of false alarms + correct rejections). As noted above, 11 participants were excluded because of inattentive performance (lower rate of hits than false alarms). Attentive performance in the remaining sample was high (hit rate – false-alarm rate: $M = .73$, $SD = .24$) and significantly above the chance level of 0, $t(61) = 23.71$, $p < .0001$.

Explicit phase. Category learning is depicted in Figure 5, and the results of the statistical analyses are presented in Figure 6. As in Experiments 1 and 2, the model that best fitted the data in the explicit phase was one in which slopes but not intercepts for accuracy were drawn from different distributions on the basis of exposure condition. Therefore, we used the same approach as in Experiments 1 and 2 to compare category-learning slopes in the category-exposure and baseline-exposure conditions. As shown in Figure 6, category-learning slopes were steeper for participants in the category-exposure than the baseline-exposure condition (i.e., the 89% HDI for differences between slope distributions was [0.01, 0.06]).

These results replicated and extended the results of Experiments 1 to 3, indicating that incidental exposure to dense categories improved category learning from brief access to explicit teaching. Moreover, the ready-to-learn effect transpired in spite of the fact that, unlike in the preceding experiments, category membership in the exposure phase was not correlated with responses that participants made during the cover task.

Experiment 5 investigated the robustness of the ready-to-learn effect by further weakening the link between the to-be-learned categories and the conditions in which participants were incidentally exposed to them. Recall that in Experiments 1 to 4, category membership was correlated with both visual features and the context in which exemplars appeared. This characteristic mirrors correlations in real-world categories (e.g., membership in the category of dogs is correlated with both visual features and contexts such as homes and parks; Eckstein et al., 2006; Henderson et al., 1999; Mack & Eckstein, 2011). However, to investigate whether incidental exposure to categories fosters readiness to learn without any correlation with context, we removed context from the exposure phase in Experiment 5 and replaced it with a new visual feature that was added to both category exemplars and baseline stimuli (Fig. 1c). In category exemplars, the new visual feature had the same correlation with category membership as context in Experiments 1 to 4. This replacement was necessary to maintain the level of category density present in the preceding experiments. For the same reason, like context, the new visual feature was not available to participants during subsequent explicit category learning.

Additionally, incidental exposure in all the preceding experiments occurred while participants completed a task that involved looking at and responding to the category exemplars or baseline stimuli. To render exposure even more incidental, we ensured that incidental exposure in Experiment 5 occurred while participants completed a task unrelated to these stimuli (i.e., a one-back task with sounds).

Experiment 5

Method

Participants. Participants were 78 adults recruited from both MTurk (who were compensated at a rate of $12 per hour) and the undergraduate population at The Ohio State University (who were compensated with course credit). All participated via the same online platform. An additional three participants were recruited but removed because of inattentive performance (i.e., having a lower hit rate than false-alarm rate for detecting repeated stimuli in the one-back task).

Materials.

Category exemplars. Category exemplars in this experiment were similar to the dense-category exemplars in the preceding experiments, with the exception that context was eliminated and replaced with a new visual feature (Fig. 1c). To keep category density the same as in the preceding experiments (Table 1), we made the new visual feature, like context, visible only during the exposure phase, and it was removed from the stimuli in the explicit phase.

Baseline stimuli. Baseline stimuli were similar to the baseline stimuli used in Experiments 3 and 4, with the exception that these stimuli also included the new visual feature that was added to category exemplars when they appeared in the exposure phase.

Sounds. This experiment included two sounds for use in a one-back task. The sounds were two distinct computer-generated sound effects downloaded from online sound-effects libraries and edited to be 2 s in duration.

Design and procedure. This experiment used a between-subjects design in which each participant was randomly assigned to one of two exposure conditions: category (n = 40) or baseline (n = 38).

Exposure phase. The exposure phase used a one-back cover task with sounds. Participants were first informed that they would complete a task in which they would hear sequentially presented sounds and that their job would be to indicate whether the currently presented sound was the same as the one they heard on the previous trial. On each trial, participants heard one of the two sound stimuli and simultaneously saw either a category exemplar (category-exposure condition) or a baseline stimulus (baseline-exposure condition) in the center of the screen. For each trial, participants were instructed to remember the sound. With the exception of the first trial in a block, participants were prompted to indicate whether the sound was or was not the same as the sound they heard on the preceding trial. The two sounds were presented equally often during a block, and each sound was repeated across consecutive trials once during a block (for a total of two repeated sounds per block). Importantly, sounds and sound repetitions within blocks were pseudorandomized to ensure that they were unrelated to the category exemplar or baseline stimuli. In the category-exposure condition, (a) each sound occurred equally often with members of each category, (b) repetitions and nonrepetitions occurred equally often with members of each category, and (c) repetitions occurred equally often for consecutive trials in which members of the same category appeared, and consecutive trials in which members of different categories appeared. In the baseline-exposure condition, sound repetitions and nonrepetitions occurred on the same trials within blocks as in the category-exposure condition and were necessarily unrelated to the baseline stimuli because baseline stimuli had no category structure. Participants received corrective feedback following each response and completed a total of 80 trials, divided across eight blocks.

Explicit phase. The explicit phase in this experiment used the same three-block explicit-phase procedure as in Experiments 1, 2, and 4.

Results

Exposure phase. As in Experiment 4, there was no assessment of implicit category learning in the exposure phase of this experiment, so we used data from the exposure phase only to check that participants attended to the one-back task. We used the same approach as in Experiment 4 to assess attentive performance on the basis of hit and false-alarm rates. As noted above, three participants were excluded because of inattentive performance (lower hit rate than false-alarm rate detecting repetitions). Attentive performance in the remaining sample was high (hit rate – false-alarm rate: M = .87, SD = .22) and significantly above the chance level of 0, $t(77) = 34.66$, $p < .0001$.

Explicit phase. Category learning is depicted in Figure 5. As in Experiments 1, 2, and 4, the model that best fitted the data in the explicit phase was one in which slopes but not intercepts for accuracy were drawn from different distributions on the basis of exposure condition. Therefore, we used the same approach as in these preceding experiments to compare category-learning slopes in the distributions for the category-exposure and baseline-exposure conditions. As shown in Figure 6, category-learning slopes were steeper for participants in the category-exposure than the baseline-exposure condition (i.e., the 89% HDI for differences between slope distributions was [0.01, 0.10]).

These results replicated the ready-to-learn effect observed in the preceding experiments. Moreover, readiness to learn transpired even when incidental exposure occurred while participants completed a task with unrelated sound stimuli and when there were no contexts correlated with category membership. It is also worth noting that although the magnitude of the ready-to-learn effect overlapped with the effect observed in Experiments 1 to 4 (Fig. 6), the overall difference in category learning appeared smaller (Fig. 5). One candidate explanation for this difference is that participants in the preceding experiments treated context as a form of explicit feedback and thus the exposure phase as a supervised category-learning task. However, as noted above, this explanation is countered by evidence from a supplemental experiment (see the Supplemental Material) in which treating the exposure phase as a supervised category-learning task led to a very different pattern of results from the results of Experiments 1 to 4. Therefore, an alternative explanation is that participants encoded the exemplars to a lesser degree in the exposure phase because the cover task required participants to attend only to sounds. According to this explanation, attention to category exemplars during incidental exposure influences the effect of such exposure on subsequent readiness to learn.

General Discussion

Across five experiments, incidental exposure to exemplars of categories rendered participants ready to learn: that is, fostered better category learning from explicit teaching than exposure to baseline stimuli. This novel finding highlights an important synergy between incidental exposure and explicit information about category membership that may explain how people learn so many real-life categories with minimal access to explicit teaching.

Category structure

Incidental exposure produced the ready-to-learn effect only for dense categories in which many features were correlated with membership and not sparse categories with few category-relevant features. This incidental-exposure advantage for dense categories contrasts with learning from explicit teaching alone (in the baseline-exposure condition), in which sparse categories were, if anything, slightly easier to learn. Therefore, learning sparse categories may require a goal to learn categories that prompts participants to search for and attend to category-relevant features (Kloos & Sloutsky, 2008; Rehder & Hoffman, 2005). Given that real-world experience is dominated by incidental exposure, these findings may explain why dense categories are preponderant in real-world category knowledge (Malt, 1995; Malt & Smith, 1984; Rosch et al., 1976).

Learning during incidental exposure

The ready-to-learn effect transpired even though learners showed no evidence of robust implicit category learning during incidental exposure. Specifically, in Experiments 1 to 3, category membership was perfectly but implicitly correlated with responses in the incidental-exposure cover task. Extensive evidence attests that similar correlations can speed improvements in RT (Chun & Jiang, 1998; Goujon et al., 2015; Nissen & Bullemer, 1987; Schwarb & Schumacher, 2012). Thus, learning the categories during incidental exposure could speed responses but did not.

This pattern of undetected initial learning that influences subsequent learning is similar to effects referred to in the animal-learning literature as latent learning. For example, in sensory preconditioning and second-order conditioning phenomena, learning associations between stimuli A and B can be too weak to be detected, but when B becomes associated with C, so does A (for a review, see Spear et al., 1990). Thus, effects on subsequent learning can transpire even when initial learning does not influence behavior. By the same token, even incidental exposure in prior studies that did not yield evidence of category learning (Clapper, 2006; Clapper & Bower, 1994, 2002) may have rendered participants ready to learn.

Internal supervision?

Just as category membership is correlated with category labels in supervised category learning, during exposure, category membership in Experiments 1 to 3 was correlated with events in the cover task to which participants responded. This raises the possibility that the ready-to-learn effect transpired because participants treated the cover task as a supervised-classification task. Evidence against this possibility comes from (a) the ready-to-learn effect in Experiments 4 and 5, in which category membership was unrelated to cover task responses, and (b) a supplemental experiment (see the Supplemental Material) that yielded strikingly different results when participants were prompted to treat the cover task as supervised classification. Specifically, participants exposed to categories both sped up more rapidly during the exposure phase and showed evidence of already knowing the categories from the start of the explicit phase. These findings strongly suggest that the ready-to-learn effect did not transpire because participants treated incidental exposure as supervision.

Future directions

The ready-to-learn effect represents a new approach to studying the contributions of incidental exposure to category learning. One open question is *how* incidental exposure renders people ready to learn. For example, learners might store in memory the exemplars they experience during incidental exposure (Nosofsky, 2011). For dense categories, representations of stored exemplars in memory may be more similar for exemplars from the same categories than from different categories. These stored exemplars might thus help learners generalize category labels that they begin to learn from explicit teaching to other members of the same category (Fig. 7). We simulated this possibility using the SUSTAIN model of category learning (Love et al., 2004) and found that passive storage of exemplars prior to the simulated explicit phase did indeed improve category learning (see the Supplemental Material).

Another important question is how incidental exposure influences category representations. Explicit teaching often leads to impoverished ("rule-based") representations of even dense categories (Deng & Sloutsky, 2015, 2016; Ward et al., 1990; Ward & Scott, 1987; Yamauchi & Markman, 1998) because learners focus on the fewest number of features needed to classify exemplars (Rehder & Hoffman, 2005). This narrow focus is challenging to reconcile with findings that representations of real-world categories capture many

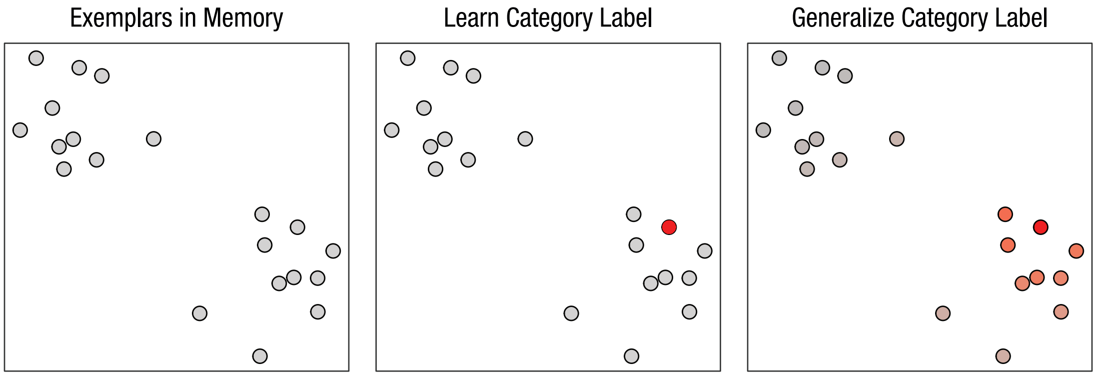

Fig. 7. Schematic of a candidate ready-to-learn mechanism. These panels depict exemplars from dense categories with high within-category and low between-category similarity, as in the dense-category-structure condition. For visualization purposes, exemplars vary along two continuous dimensions rather than the seven binary-valued features used in the experiments. According to the mechanism, similarity between exemplars passively stored in memory allows learned category labels to generalize to members of the same category.

correlated features (Malt, 1995; Malt & Smith, 1984; McRae et al., 2005; Rosch, 1975; Rosch et al., 1976). Our findings suggest that incidental exposure may avoid this narrow focus: Whereas sparse categories with few category-relevant features were, if anything, slightly easier to learn from explicit teaching alone, incidental exposure fostered learning only for dense categories with many category-relevant features. Therefore, incidental exposure may help people form richer category representations (Kloos & Sloutsky, 2008).

Finally, given that this research was motivated by how categories are learned under real-world conditions, it will be valuable to investigate whether the ready-to-learn effect generalizes beyond the present study of adults learning artificial categories. For example, because much of category learning takes place during development, it would be particularly illuminating to study the contributions of incidental exposure in infants and children. Similarly, although the dense categories used in the present experiments were designed to capture the feature correlations of real-world categories, they deviate from real-world categories in other ways. For example, categories were constructed from binary-valued features, whereas the features of real-world categories may be more accurately characterized as distributions of values along continuous dimensions, such as size or color (e.g., French et al., 2004). Therefore, future work could illuminate whether the ready-to-learn effect transpires for more realistic or real-world but unfamiliar categories.

Conclusion

Much of our exposure to entities that we represent as members of categories is likely both incidental and unsupervised, and provides us with only limited access to explicit information about category membership. Here, we present evidence for the ready-to-learn-effect, in which incidental exposure and limited access to explicit teaching combine synergistically to build human category knowledge.

Transparency

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L. Unger developed the study concept. L. Unger and V. M. Sloutsky designed the study. L. Unger analyzed the data, and both authors interpreted the results. L. Unger drafted the manuscript. Both authors revised the manuscript and approved the final version for submission.
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Supplemental Material

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Notes

1. Experiments 1, 3, 4, and 5 were conducted with participants recruited from MTurk. Conducting studies with online samples offers the advantage of recruiting a more diverse, representative sample than the commonly used approach of recruiting samples from populations of university students (Casler et al., 2013). At the same time, additional differences between online and in-lab samples are important to note. First, in the lab, participants complete studies without distractions and with the knowledge that their performance is being monitored by an experimenter. These characteristics may foster attentiveness and compliance but are absent in online studies. Second, the majority of MTurk participants take part in studies to earn income as a part- or full-time job rather than as paid leisure (Hitlin, 2016), which may motivate some participants to complete studies quickly rather than attentively. For these reasons, the present experiments were designed to be as short as possible while addressing the questions of interest. In addition, failure to meet simple criteria for attentiveness may exclude more participants from online samples than is typical when conducting research with university students in the lab.
2. Note that Experiments 3 to 5 used baseline stimuli generated from unstructured combinations of the same features as category exemplars.
3. In Experiment 3, these reductions were eliminated, and analyses predicted RT as a nonlinear function of trial number.

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