research papers

The Role of Different Types of Labels in Learning Statistically Dense and Statistically Sparse Categories

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Abstract. Four experiments were conducted to assess the influence of label type (Experiments 1a and 1b) and the interference from articulation (Experiments 2a and 2b) on the learning of dense vs. sparse categories in classic category formation tasks with feedback. It was found that using pictorial labels improves dense category learning, but for sparse category learning it has no effect. Sparse category formation was more effective in conditions with easily verbalized labels (familiar color names, no verbal interference). Additionally, it was shown that verbal interference (the additional task to verbalize the labels) worsens sparse category formation, but for dense category formation it has no effect. The results of our experiments are discussed in accordance with the Competition Between Verbal and Implicit Systems (COVIS) model of multiple systems of categorization.

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Introduction

Category learning is one of the basic cognitive functions of human beings. Categories help people to organize their knowledge about the world and to predict the properties of new objects. The ability to form new categories and to use them in cognitive processing is based on the implicit assumption that some objects share some common properties. The category rules people use in everyday actions are not homogeneous in their structure. For example, we distinguish dragonflies from butterflies on the basis of separate features that are easily verbalized, such as big eyes or transparent wings. At the same time, our memory stores many examples of dragonflies and butterflies and allows us to classify a new object without the involvement of language but rather through the comparison of this object with stored examples, using all the features at once.

Traditional psychological theories of category learning usually choose one organizational principle to explain learning and categorization, whether it is the memorizing of all category examples (Medin & Shaffer, 1978), finding the most predictive features (Bruner, Goodnow, & Austin, 1986), or computing the most frequent feature values (Rosch & Mervis, 1975).

A different class of theories supposes that multiple category systems (MCS) are involved in category learning. The most well known example of MCS theory is Gregory Ashby's Competition Between Verbal and Implicit Systems (COVIS) theory. In one early study, Ashby and colleagues (Ashby, Alfonso-Reese, Turken, & Waldron, 1998) found two relatively independent systems of building categorization rules: the implicit system (categorization rules are built on a principle similar to prototype formation, i. e., on the basis of the summation of a large number of features) and the explicit, or verbal, system (categorization rules are built on the basis of the extraction of a few relevant features). The launch of each system can be initiated by using objects with different frequency distributions of feature values. Category examples can be very similar to each other in many features. This similarity automatically launches the implicit system, and such categories can be called *dense categories*. Other categories are called *sparse categories*, which are produced by the explicit system, and their exemplars have only a few features in common. For example, prototype formation in the natural environment is a version of dense category learning because none of the object's features is the only relevant one. Well-defined scientific concepts are examples of sparse categories. In his subsequent research, Ashby found that the functioning of these category systems is impaired independently under different neurological disorders (Ashby, Noble, Filoteo, Waldron, & Ell, 2003). Also, it is evident from COVIS that the implicit system evolved first and appears to be basic in animals, and the verbal system developed later and is limited to adult humans.

The COVIS theory was used in the experimental psychological research of Sloutsky (2010), who suggested that those two systems begin functioning at different ages. He named the systems: "compression-based" (implicit) and "selection-based" (explicit or verbal). The compression-based system develops from birth and leads to dense category formation. The selection-based system appears much later (after the age of 5) and undergoes several qualitative changes during its development. These changes are connected, first of all, with language, which demands not only an advanced ability for the cross-modal processing of information, but later the ability to use some object features (such as labels) but not the others (such as perceptual features) as indicators of category resemblance. Second, as categorical information for the selection-based system is localized in some special features of objects, category learning by this system demands a supervised attention shift. Therefore, it cannot operate properly without advanced executive function. Furthermore, as it results from such a description of MCS ontogenesis, the work of the category systems depends on feedback to a variable degree. It was shown in Kloos and Sloutsky's (2008) experiment that five year old children and adults both performed better in concept formation with feedback when categories were sparse (and, respectively, the selection-based system was used) and performed better without feedback when categories were dense (the compression-based system was used).

The Role of Language in Category Learning

The MCS theory has many supporters because it offers a convenient way of describing categorization: any of the multiple systems can be presented as an independent module specializing in a certain type of task (Yamauchi, Love, & Markman, 2002; Hoffman & Rehder, 2010), category structure (Miles & Minda, 2011), or the availability of feedback (Maddox, Ashby, & Bohil, 2003). However other researchers claim that the MCS theory is only good at demonstrating the differences between categorization systems that can be easily corresponded to specific brain areas (Love, 2013). For instance, the visual similarity of category examples indeed activates the visual cortex and the absence of such similarity forces us to deliberately shift our attention between features which requires a mature prefrontal cortex. Will the differences between categorization systems remain under other circumstances, not connected only to the difference between a superficial similarity of category examples?

The most interesting question, from our point of view, is how these two categorization systems deal with language signs. Lupyan and colleagues showed that words used as feedback during category learning can also strengthen the visual differences between objects (Lupyan, Rakison, & McClelland, 2007). Words also prepare our perception for categorical tasks by evoking our expectations to see similar objects even before these tasks are given (Kotov, Kotova, Vlasova, & Agrba, 2012).

How important is a verbal label for different systems of categorization? The answer to this question lies partly in the MCS theory: verbal feedback is not needed for the implicit system but it is useful for the explicit system. From our point of view, this answer is not complete because there is no simple correspondence between the type of category and the presence of verbal labels in real-life, non-experimental conditions. For instance, examples from natural categories, which usually come from the work of the implicit system (such as *a dog*) can be marked by names in some communicative situations but not in others. Moreover, a child's lexicon develops most intensively from 2 years of age (Bloom, 2000) until 5–6 years, the period when, according to MCS theory, the system of explicit learning has not yet begun functioning. Thus, to understand the role of verbal labels in explicit and implicit systems, one should ask which properties of the language signs are crucial for the successful learning of each type of category. Considering that words contain both perceptive (acoustic, or visual in written form) and non-perceptive (semantic, conventional) characteristics, we hypothesize that different characteristics will be important for different categorization systems in category formation.

Experiment 1a

We used a classical category formation task with feedback in all four experiments in our study. We activated the implicit learning system by using a dense distribution of feature values; for the explicit system, we used a sparse distribution. The types of category labels shown to participants as feedback after each trial varied between the four experiments. This allowed us to explore which type leads to more successful category formation in each of the two learning systems.

In Experiment 1, we tested the hypothesis that the learning of dense categories is more efficient if the labels for different categories are based on a perceptive distinction, such as color (pictorial labels), compared to verbal labels (two different words as category names). On the contrary, we expected that the performance in the sparse categories condition would be higher if verbal labels are used.

Method

Participants. A total of 59 (41 female) undergraduate students from the Russian State University for the Humanities, Moscow, participated in the experiment to satisfy credit requirements for psychology courses. They ranged in age from 19 to 34 years ($M = 21.2$, $SD = 2.45$). Participants were assigned to experimental conditions in random order. 18 of them learned dense categories with pictorial labels as feedback; 12 learned sparse categories with pictorial labels; 18 learned dense categories with verbal labels; and 11 learned sparse categories with verbal labels.

Stimuli. We made two sets of images with different feature distributions, one for the dense categories and one for the sparse (Table 1). Features were characteristics of the body parts of an artificial insect, resembling a dragonfly in shape (Figure 1). Each of the five features could be either long or short: legs (*f1:* 1 — long, 0 — short), forewings (*f2:* 0 — long, 1 — short), hindwings (*f3:* 1 — long, 0 — short), thorax (*f4:* 1 — long, 0 — short) and abdomen (*f5:* 0 — long, 1 — short).

Each of the five features varied in the dense categories so that objects from one category had exactly four features with certain values, either 0 or 1, while the remaining feature had a different value, 1 or 0, respectively (upper half of Table 1). For instance, in one of the categories with the dense distribution, one exemplar would have long legs ($f1 = 1$), long forewings ($f2 = 0$), short hindwings ($f3 = 0$), short thorax ($f4 = 0$) and long abdomen ($f5 = 0$). Another example from the same category would have short legs ($f1 = 0$), short forewings ($f2 = 1$), short hindwings ($f3 = 0$), short thorax ($f4 = 0$) and long abdomen ($f5 = 0$); etc. Examples with all values from a single category ("00000" or "11111") were not presented.

The sparse categories were defined by a single feature value that was common for all category examples (lower half of Table 1); that is, short/long length of the legs (examples in Table 1) or short/long length of the hindwings. All other feature value occurrence was counterbalanced. Thus, the generalization that participants had to form was based on four out of five features in the dense categories and on only one key feature in the sparse categories.

The size of the images was 744 × 524 pixels.

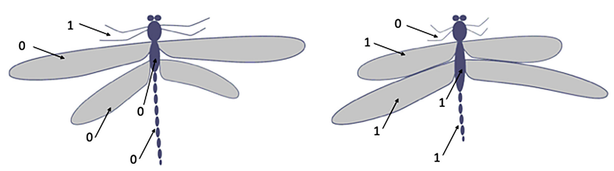

Figure 1. Examples of category members (category A on the left panel, category B on the right panel, dense category structure). Feature values are the body parts, either long or short: legs (0 — short, 1 — long), forewings (0 — long, 1 — short), hindwings (0 — short, 1 — long), thorax (0 — short, 1 — long) and abdomen (0 — long, 1 — short).

Table 1. Distribution of Feature Values in Different Types of Categories

	Category A					Category B				
	f1	*f2*	*f3*	*f4*	*f5*	*f1*	*f2*	*f3*	*f4*	*f5*
Dense category structure	1	0	0	0	0	0	1	1	1	1
	0	1	0	0	0	1	0	1	1	1
	0	0	1	0	0	1	1	0	1	1
	0	0	0	1	0	1	1	1	0	1
	0	0	0	0	1	1	1	1	1	0
Sparse category structure	**0**	0	1	1	0	**1**	0	1	1	0
	0	1	0	0	1	**1**	1	0	0	1
	0	0	0	1	1	**1**	0	0	1	1
	0	1	1	0	0	**1**	1	1	0	0
	0	0	1	0	1	**1**	0	1	0	1

Note. Bold numbers in the sparse category rows are the values of the relevant feature.

The type of label varied in each type of category (dense or sparse). In the verbal label condition, one of the two words, corresponding to one of the two categories, was presented to the participants after each trial as feedback. We told our participants that these words — *imperator* (the emperor) and *krasavitsa* (the beauty) — were the biological names for the two types of dragonflies. Those words had meanings in natural language (as is typical for biological names), and participants could read them, verbalizing these labels by themselves. For the other condition, the labels were two dragonfly silhouettes of the same shape but different colors (red and green). This label type was pictorial, and although participants could associate the colors with the words "red" and "green", they could not read the labels explicitly, as they could do with the printed words in the verbal condition. The size of the labels (words and images) was approximately the same.

Procedure. Each participant was randomly assigned to one of the four conditions defined by the combination of category type (dense or sparse) and label type (verbal or pictorial). The participants performed the standard classification task with feedback. They were told that they would see images of dragonflies and that they should decide whether each belonged to Category <label of category> or <label of other category>. They were told that they would have to guess at first, but that they should be able to learn how to respond correctly as they went along. The training series consisted of six blocks, with ten objects in each block (five from each of the two categories, see Table 1). The order of the examples inside each block was randomized. The images were viewed on a 15-inch screen with 1024 × 768 pixel resolution from a distance of about 60 cm. Responses were collected with PsychoPy 1.83. Each trial started with a white background presented for 1 second. Then the image of the category example appeared at the center of the screen for 1.5 seconds. The image then disappeared, followed by the white background again, and the participant had up to 5 seconds to decide which one of the two categories that example belonged to. The participant responded by pressing one of two keys. After the key press, the participant was given feedback (the correct label for that category was shown) for 0.5 seconds.

To estimate learning efficiency, we averaged the responses within a block (0 for incorrect response; 1 for correct). Thus, the performance at chance level corresponded to 0.5. The data were analyzed separately for each category type (dense and sparse categories). We used a 2×6 repeated measures ANOVA, with label type (verbal or pictorial labels) as a between-subject factor and training block (six blocks) as a within-subject factor. We did not compare the performance in the learning of the dense categories with the sparse categories as the former would require participants to remember and pay attention to all features, while the latter would require attention shifting from one feature to another. These difference in the structure and the content of cognitive operations did not allow us to compare the efficiency of the two systems of categorization. Thus we only assessed and discussed the performance changes in each system separately, depending on the labels involved.

Results and Discussion

Descriptive statistics are shown in Appendices A and B. We used analysis of variance with repeated measures (ANOVA) without corrections on multiple comparisons (dense categories condition: Mauchly's $W = .706$, $p = .674$; sparse categories condition: Mauchly's $W = .633$, $p = .850$). The ANOVA did not reveal any interaction between block number and label type in learning dense categories, $F(5, 170) = 0.722$, $p = .607$, $\eta^2_p = .021$. However, we found a main effect of the training block factor, $F(5, 170) = 9.220$, $p < .001$, $\eta^2_p = .213$. The categorization performance depended on label type for the dense categories. The performance was much higher with the pictorial label than with the verbal label, $F(1, 34) = 6.217$, $p = .018$, $\eta^2_p = .155$ (see Figure 2, left graph).

The ANOVA also did not reveal any interaction between blocks and label type in learning sparse categories, $F(5, 105) = 0.432$, $p = .825$, $\eta^2_p = .02$. The effect of block was significant, $F(5, 105) = 12.525$, $p < .001$, $\eta^2_p = .374$. There were no significant differences in performance in the sparse categories depending on label type, $F(1\ 21) = .059$, $p = .810$, $\eta^2_p = .003$ (see Figure 2, right graph).

Our hypothesis, which suggested that the label type would have an opposite impact on the learning of different types of categories, was partly confirmed. Indeed, the participants were much better at forming dense categories with the pictorial label than with the verbal label. The color difference between labels probably provided an additional link with the object's visual features and all those features were processed by the implicit categorization system as a whole. But the word as a label probably demanded additional processing because of its semantic load.

We did not find significant differences in the performance of sparse category formation depending on label type. This result does not agree with our hypothesis, as we suggested that verbal labels but not pictorial ones should be relevant for the explicit, or verbal, system. A possible explanation could be the naming, which participants could perform by themselves inwardly during the sparse category learning (some participants talked about this spontaneously). According to the spontaneous reports of study participants, we suggest that in the sparse category condition they verbalized the image label as "red" or "green", while the participants who were forming the dense categories verbalized it very rarely. But these observations were occasional and we can not test it directly. We suppose that the objective form of the pictorial label was substituted with a subjective one, which was more convenient for the participant, and so the label became verbal. To test this, we conducted an additional experiment with a new pictorial label, the appearance of which was as symbolical as the verbal one, but which was inconvenient for spontaneous verbalization.

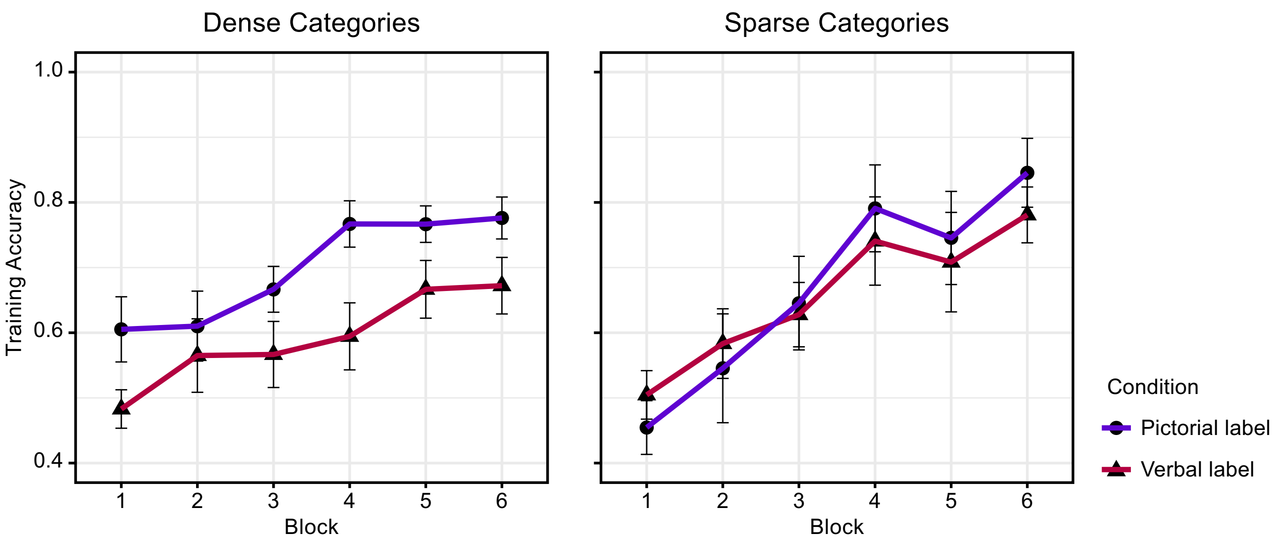

Figure 2. Average performance at each block for each category type and each label type.

Experiment 1b

To choose labels with a new shape, we used a set of old Cyrillic and Latin fonts. We selected two labels which were the hardest to verbalize (according to the report of three experts), since they least resembled the letters of modern Cyrillic or Latin alphabets and were unknown to the participants. According to our hypothesis, this difficulty in spontaneous internal verbalization of the label should reduce the performance, but only for the sparse category learning.

Method

Participants. A new group of 38 (18 female) undergraduate students at the Russian State University for the Humanities, Moscow, participated in the experiment to satisfy credit requirements for psychology courses. 20 of them participated in dense category learning and 18 underwent sparse category learning. They ranged in age from 17 to 28 years ($M = 18.34$, $SD = 3.65$). We compared the data of this group with the data from the previous experiment.

Material. The material for category formation was the same as before; only the form of the feedback was changed. We used two symbols from rare alphabets, which were confirmed to be unknown to the participants (Ѭ and Њ). We further refer to these labels and condition as unverbalized.

Procedure. The category forming procedure was exactly the same as in Experiment 1a, except we added four additional blocks of learning. We extended the procedure to ten training blocks because the performance on the first three blocks had almost no difference for any conditions in previous experiments, and does not exceed the chance level.

We analyzed only the first six blocks, as in Experiment 1a, but used the last four for Experiment 2a. After the category formation stage (i.e., after the first six blocks), we asked the participants to draw those unverbalized labels (from memory) and to answer a few questions such as whether they wanted to name those labels, and if so how, and also whether it was difficult for them to use those labels (as feedback). Those participants who could not remember the labels were excluded from further data analysis ($n = 5$; 3 from the dense category learning condition). We used the unverbalized labels both for the sparse category and the dense category. The dense category condition allowed us to test our hypothesis that processing the features by the implicit system of learning is only possible when all of the features have visual but not semantic differences. The use of the unverbalized label should, nevertheless, induce adults to treat them as speech components and not as simply visual images.

Results and Discussion

Descriptive statistics are shown in Appendices A and B. We combined the data from Experiments 1a and 1b together in one ANOVA. We used analysis of variance (ANOVA) with repeated measures, without corrections on multiple comparisons (dense categories condition: Mauchly's $W = .825$, $p = .773$; sparse categories condition: Mauchly's $W = .569$, $p=.120$), with label type (verbal, pictorial and unverbalized labels) as a between-subject factor and number block (ten blocks) as a within-subject factor. The ANOVA did not reveal any interaction between blocks and label type in learning dense categories, $F(10, 265) = 0.712$, $p = .713$, $\eta^2_p = .026$. But we found a significant impact of the training block in all conditions together, $F(5, 265) = 11.362$, $p < .001$, $\eta^2_p = .177$. The label type factor was significant, $F(2, 53) = 5.331$, $p = .008$, $\eta^2_p = .167$ (see Figure 3, left graph). We used Bonferrroni's post-hoc test to compare differences between the new condition (unverbalized label) and the conditions from the previous experiment (verbal label and pictorial label). In the dense category learning, a difference in performance was found only between the unverbalized label condition and the pictorial label condition, $t = 3.016$, $p = .012$ (see Figure 3, left graph). Performance was lower in the unverbalized label condition. We did not find any difference between the unverbalized label condition and the verbal label condition, $t = -3.326$, $p = 1.0$ (see Figure 3, left graph).

In the case of learning sparse categories, the ANOVA did not reveal any interaction between blocks and label type, $F(10, 190) = 1.875$, $p = .051$, $\eta^2_p = .09$. We found a significant impact of the training block factor in all conditions together, $F(5, 190) = 14.951$, $p < .001$, $\eta^2_p = .282$. The condition factor was significant, $F(2, 38) = 2.395$, $p = .044$, $\eta^2_p = .152$ (see Figure 3, right graph). We compared used Bonferrroni's post-hoc test to compare differences between the new

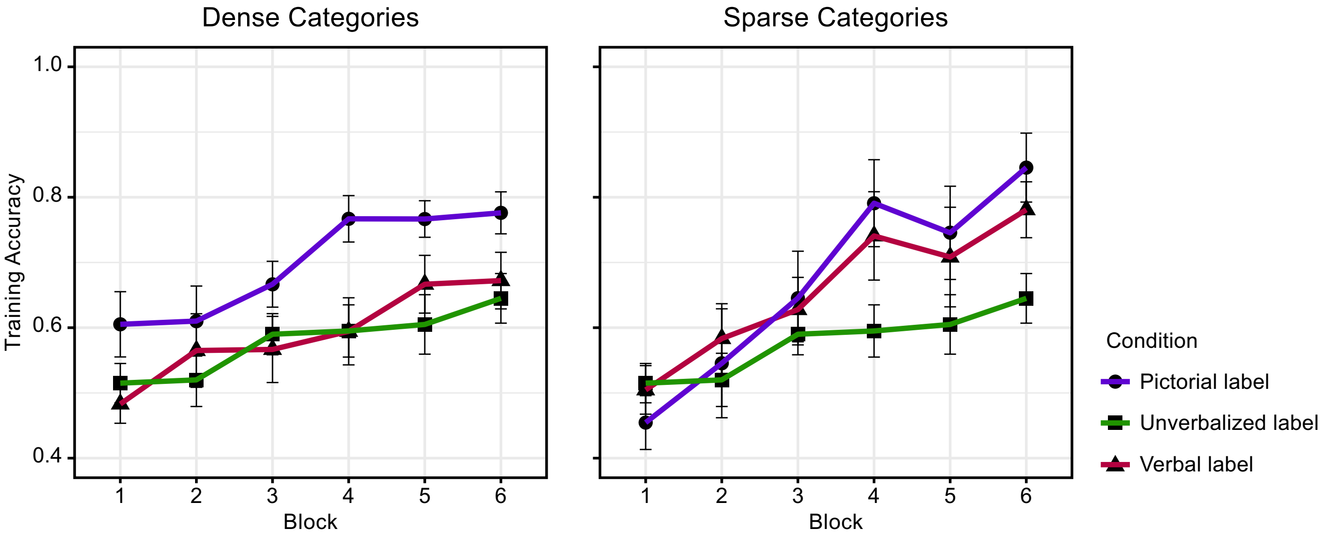

Figure 3. Average performance at each block for each category type and each label type (with unverbalized label condition).

condition (unverbalized label) and conditions from the previous experiment (verbal label and pictorial label) for the last three blocks of learning (4–6).

We found significant differences in performance in the sparse category learning between the unverbalized label condition and the verbal label condition, $t = -2.618$, $p = .038$ (see Figure 3, right graph). Also we found significant differences between the unverbalized label condition and the pictorial label condition, $t = 3.407$, $p = .005$ (see Figure 2, right graph). Performance was lower in the unverbalized label condition than in the verbal and pictorial label conditions.

We therefore obtained evidence in favor of our hypothesis that there is an additional internal verbalization of the label, necessary for its use in the explicit system of learning (i. e., in the sparse category learning). The results of Experiment 1b show that the use of an unverbalized label reduces the sparse category learning performance.

Considering the work of the implicit system of learning (i. e., dense categories), we can see that the use of unverbalized labels also led to a lower learning performance compared to the use of pictorial labels. The performance of learning with unverbalized labels was the same as with the verbal labels. According to participant reports, most of them saw the new labels as letters of some alphabet, even if they had never seen them before. In other words, they treated them as features of a symbolic nature and that complicated the association of those perceptive features with the others.

Why does the symbolic character of the unverbalized labels not help in the formation of sparse categories and the explicit system of learning as a whole? We hypothesize that the functioning of the explicit system is not just regulated or launched by an object's feature frequency, but also requires some means of attention control that is separate from the features and serves to single them out. Words can work as a means of control, as they are perceived as something that indicates the purpose of learning and draws attention to the difference between generalizations.

Language, however, as a learning tool that is evolutionarily newer than categorization, also has newer constraints on categorization functioning. One such constraint is its physical nature — articulation. The main function of language is communication, and this function demands the possibility for (sub)vocal articulation, which is why, we suppose, that demand should be partly reserved for categorical learning: only those words that can be articulated in the case of an increasing load on attention are convenient for the explicit system.

The word's form, convenient for articulation, is more important for the explicit system than for the implicit one. The implicit system picks out common features among the objects with a strong external resemblance. Meanwhile, the explicit system picks out common features among objects with great variability in their appearance. This is why it is better tuned to rapid attention shifts towards new information than the implicit system. If the word has a new and unused articular form, then some of the attention resources will be spent on it instead of searching for relevant features.

For example, if the participants wanted to name the unverbalized labels marking two categories, it would be an additional task for the explicit learning system, competing with the categorization task. This is true only for those cases of articulation when the chosen name is unknown and the verbalization is not automatic. The study by Miles and Minda (2011, Experiment 1b) showed that the concurrent task of demanding verbalization (for example remembering a set of numbers appearing before each category example, to define later whether the target number was in the set) challenges category formation when the explicit system is working. But this does not happen with the implicit system. We, in turn, suppose that such results should be observed even in simpler cases, such as when we give participants a new label for the category and ask them to say its name aloud every time a new category example appears. Such vocalization, although not related to the other task (as in Miles & Minda's 2011 experiment), nevertheless will interfere with category learning. This interference should take place only with the explicit learning system, not the implicit one. The implicit system does not require any means of attention control and additionally verbalizing a new label should not interfere with category learning.

Experiment 2a

In Experiment 2a, we asked participants to additionally verbalize a new label (from the unverbalized label condition in Experiment 1b) to themselves during the entire learning procedure. This verbalization was like an interference task. We hypothesized that it would lower the performance on sparse category formation and have no impact on dense category formation.

Method

Participants. A new group of 36 (21 female) undergraduate students at the Russian State University for the Humanities, Moscow, participated in the experiment to satisfy credit requirements for psychology courses. 18 of them participated in dense category learning and 18 performed sparse category learning. They ranged in age from 17 to 30 years. We compared the data of this group with the data from Experiment 1b.

Material. The material was the same as in Experiment 1b.

Procedure. In addition to the category learning procedure, we asked our participants to say to themselves the "name" of the category labels (ѢЖ or Ѣ) as soon as the label appeared on the screen. We chose the names based on some outward resemblance to letters of the Russian alphabet: [zhi] and [yur]. The label (ѢЖ or Ѣ) appeared on the screen as feedback after the participants chose the category for the current example. To make sure that participants did not forget to say the label's name to themselves, we conducted a practice session before the experiment: the participants had to say the names aloud and as fast as they could when the labels appeared on the screen one by one. We also continued to remind them to say the label's names to themselves at each trial after each training block.

Results and Discussion

Descriptive statistics are shown in Appendices A and B. We combined the data from Experiments 1b and 2a together in one ANOVA. We used analysis of variance with repeated measures without corrections on multiple comparisons for the dense categories condition (Mauchly's $W = .309$, $p = .710$) and with Greenhouse–Geisser correction for the sparse categories condition (Mauchly's $W = .052$, $p < .001$), with instruction (with and without an additional verbalization task) as a between-subject factor and number block (ten blocks) as a within-subject factor. The ANOVA did not reveal any interaction between blocks and instruction to verbalize the labels in learning dense categories, $F(9, 324) = 0.345$, $p = .959$, $\eta^2_p = .009$. Again we found a significant impact of the training block, $F(9, 324) = 8.083$, $p < .001$, $\eta^2_p = .183$. But the performance was the same in the unverbalized label condition (data from Experiment 1b) and the condition with the verbalization instruction, $F(1, 36) = 2.445$, $p = .127$, $\eta^2_p = .064$ (see Figure 4, left graph).

The ANOVA did not reveal any interaction between blocks and label type in learning sparse categories, $F(5.24, 178.1) = 1.166$, $p = .328$, $\eta^2_p = .033$. We found a significant impact of the training block, $F(5.24, 178.1) = 4.335$, $p < .001$, $\eta^2_p = .114$. Performance was significantly lower in the condition with the verbalization task than in the unverbalized label condition, $F(1, 34) = 5.951$, $p = .020$, $\eta^2_p = .149$ (see Figure 4, right graph). Although not very pronounced, this difference shows that participants almost did not form the category in the condition with the instruction to verbalize the labels (see Figure 4, right graph); the learning curve only rises to the .56 level by the tenth training block — practically the level of chance.

Thus we showed that the use of verbal labels in sparse category formation and explicit learning differs considerably from the use of the label for dense category formation and implicit learning. If the non-automatic articulation of the new labels did not lead to a decrease in the performance of dense category formation, the verbal labels in explicit learning only allow for the successful definition of the categorization rule when they have a convenient verbal shape which does not distract from the task.

An alternative explanation of these results, however, could be the vulnerability of the sparse category formation process to any interfering tasks, not necessarily verbal ones. In order to control for this, we carried out a fourth experiment that included the interfering task with a label but the task itself was nonverbal.

Experiment 2b

For this experiment, we swapped the label's outward appearance and its verbal form. The participants saw on the screen the syllables [Zhi] and [Yur] (in Russian letters) as the labels, and should have imagined their iconic shapes (those used in Experiment 2a: Ѭ and Њ). Thus they still were given an additional task, but, from our point of view, this nonverbal task should reduce the performance in neither sparse nor dense category formation. Since the participants were given a convenient verbal form as the main label (syllables they could read automatically), the label in its turn should be able to perform its function and any additional manipulation with the label (such as imagining the visual forms) will be structurally irrelevant to the main task and so will not lead to a drop in performance.

Method

Participants. A new group of 38 (15 female) undergraduate students at the Russian State University for the Humanities, Moscow, participated in the experiment to satisfy credit requirements for psychology courses (19 for dense category learning and 19 for sparse category learning). They ranged in age from 18 to 27 years. We compared the data of this group with the data from Experiment 2a.

Material. The difference from the task in previous experiments was the feedback: this time, it was a notation of the syllables [Zhi] and [Yur] to mark each of the two categories. The notation of the syllables was of the same size and appeared on the screen for the same time as the previous feedback images.

Procedure. Before the main session, participants were trained to imagine the iconic shapes (Ѭ and Њ) in response to the syllables' appearance ([Zhi] and [Yur]) on the screen (the imagination task condition). They could only start the main session when they drew such shapes correctly (from memory) after ten practice trials. We also continued to remind them to visualize those labels during the main session. Nonetheless, it was still difficult to control whether they really performed the visualization, and therefore we unexpectedly asked them to draw the labels again after the tenth training block in the main session. The participants who formed categories successfully but were unable to

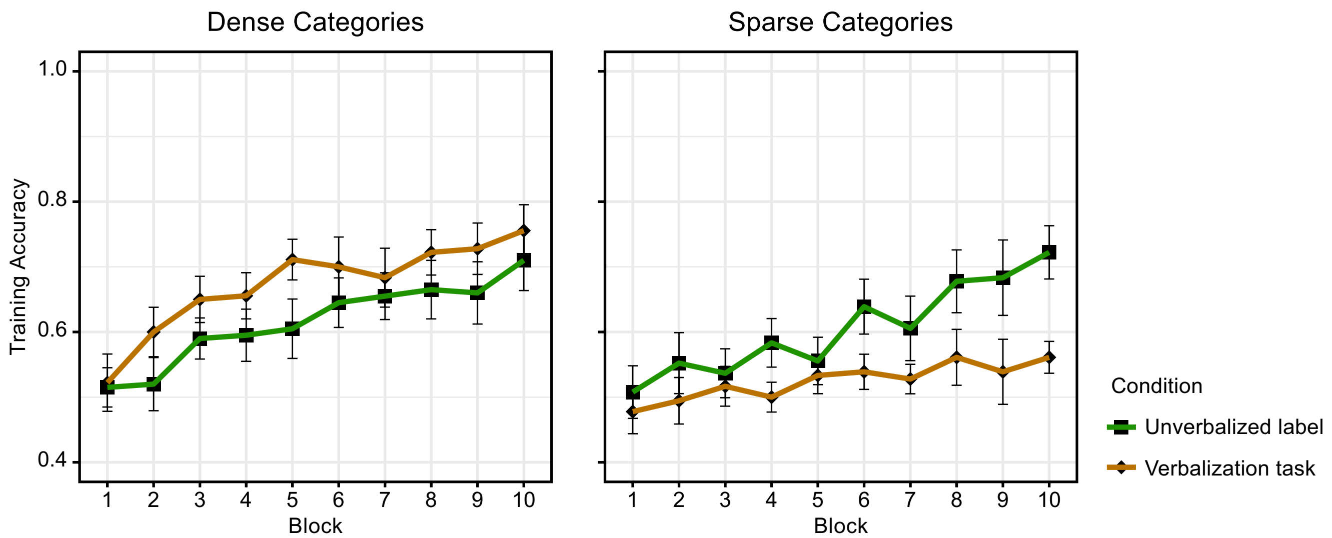

Figure 4. The performance of the dense and sparse category formation with an additional loading on label control.

draw the labels correctly were excluded from further data processing ($n = 2$).

Results and Discussion

Descriptive statistics are shown in Appendices A and B. We combined the data from Experiments 1b and 2a together in one ANOVA. We used analysis of variance (ANOVA) with repeated measures with Greenhouse-Geisser correction for the dense categories condition (Mauchly's $W = .076, p < .001$) and sparse categories condition (Mauchly's $W = .110$, $p = .008$), with type of additional task (verbalization or imagination task) as a between-subject factor and number block (ten blocks) as a within-subject factor. The ANOVA did not reveal any interaction between number block and task type in learning dense categories, $F(6.56, 229.5) = 0.412$, $p = .884$, $\eta^2_p = .012$. We found a significant impact of the training block factor, $F(6.56, 229.5) = 7.839$, $p < .001$, $\eta^2_p = .183$. Performance was the same in the conditions with verbalization and imagination tasks, $F(1, 35) = 0.110$, $p = .742$, $\eta^2_p = .003$ (see Figure 5, left graph).

The ANOVA did not reveal any interaction between blocks and task type in learning sparse categories, $F(6.05, 211.7) = 0.326$, $p = .924$, $\eta^2_p = .009$. We found a significant impact of the training block factor, $F(6.05, 211.7) = 2.699$, $p = .015$, $\eta^2_p = .078$. Performance was much better in learning categories in the imagination task condition than in the verbalization one, $F(1, 35) = 12.27$, $p = .001$, $\eta^2_p = .260$ (see Figure 5, right graph).

Thus, we showed that the lower performance in the conditions with additional verbalization could not be explained just by the general mechanism of interference to which the explicit system of learning is so vulnerable.

General Discussion

By changing various properties of the verbal labels and different actions with the labels through the series of four experiments, we demonstrated the different functions that labels can have in the learning of different types of categories. We found that visual characteristic distinctions of the labels (colors) were more convenient for dense category learning, whereas the verbal form (the possibility of verbalization) was more important for sparse category learning. At first glance, these results correspond well to the main statements of the MCS theory and other experimental results in the MCS context. For example, one experiment with pre-schoolers showed that they, unlike adults, could not separate a word from the object's other features and perceived it as an equivalent feature (Deng & Sloutsky, 2013). In an induction task, the category label was pitted against a highly salient feature, such that the reliance on the label and the reliance on the salient feature would result in different patterns of responses. The results indicate that children rely on the salient feature, but not the category label, when performing induction. That is, if the implicit system of learning is the only one available for children of this age, verbal labels will be included in the generalization along with the object's other features.

However, we obtained additional data that could not be reconciled with the MCS theory. For example, when given nonverbal labels during sparse category formation, participants spontaneously verbalized them (according to participant reports following Experiment 1a). In the case of dense category formation, however, performance in the condition with unverbalized labels differing notably from the object's other features was nonetheless lower than in the condition with labels differing in color (Experiment 1b). These results taken together pose a question that the MCS theory cannot answer: what property of an object or a label will or will not be a feature? This question does not concern the involvement of attention — whether the participants will notice this property or not — but rather a different relation and different actions with these features during the formation of the two types of categories.

In the second experiment (2a), we showed that when actualization of the correspondence of the label (symbol) with its artificial name (syllable) is low, the performance of sparse category formation declines, in contrast to dense category formation. The power of interference from the articulation of a new name during sparse category formation was even stronger than in the experiment by Miles and Minda (2011), because our participants were unable to form the category even in the last training block. This fact is especially notable since the interference in our experiment (i.e., the destructive effect of syllable articulation) only

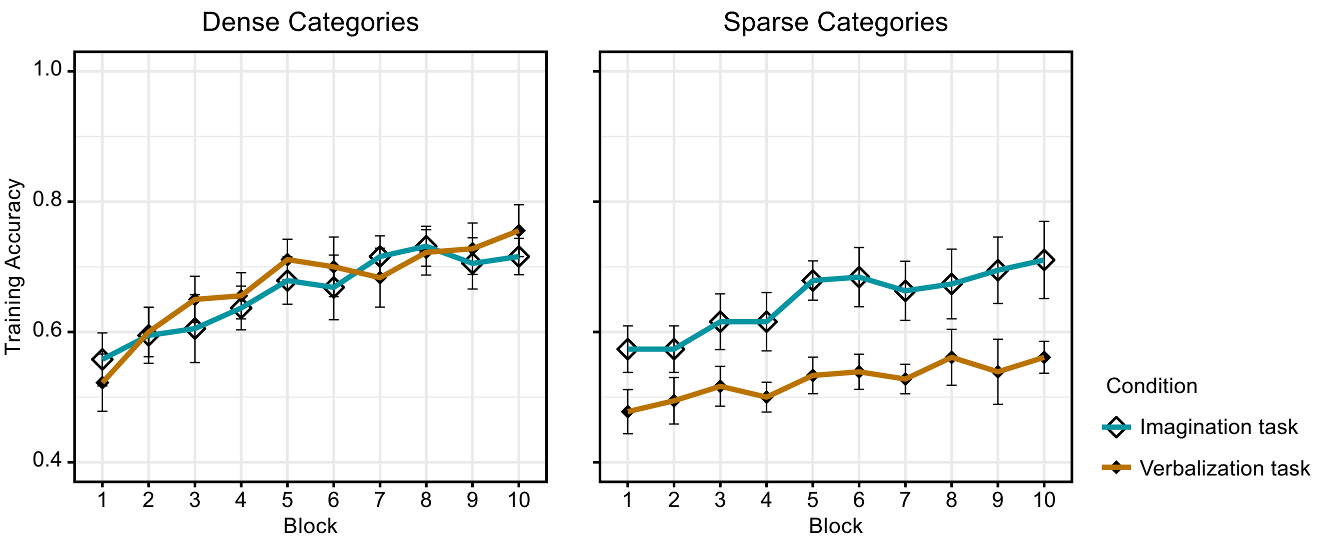

Figure 5. The performance of dense and sparse category formation in the verbalization and imagination task conditions.

began to work at the end of the trial when the feedback appeared, unlike in Miles and Minda's experiment where the interference lasted from the perception of an example to the end of the appearance of feedback. Miles and Minda used a traditional paradigm with an interference task, where the interference task accompanies the entire process of the main task performance. Performing category formation includes different phases, such as the creation and testing of hypotheses. In this study, the interference task was presented during the last phase but the effect was similar. In future studies, the interference task can be presented in an early phase, before getting feedback. It is expected that this can be crucial for learning dense categories. It is also interesting that in the experiment by Miles and Minda, the interfering task demanded not saying numbers to oneself but imagining a geometrical pattern, which led to a symmetrical worsening of dense category formation, but that did not happen in our experiment (2b). We suggest that a key factor here is not just the dependence of category formation on label properties, but the stage of the learning process when this dependence is established. In the case of dense categories and implicit learning, the initial stages where information about the visual features is collected are more important than the results of the hypotheses testing after feedback. That is why interference from the tasks demanding the imagining of additional spacial-visual patterns will only work when it accompanies these initial stages.

Conclusions

Category learning is a difficult task for the human cognitive system. Signs and labels help to solve this problem, but with different types of categories the help manifests in different ways. Why is it that the visual discrimination between an object's features and a label's features is so important for dense category formation, and the opportunity for easy verbalization is important for sparse category formation? Apparently, it is related to the different structure of cognitive operations involved in the category formation process. This suggestion underlies MCS theories, such as COVIS. However, at present there are not enough data considering what exactly makes these operations different from each other. Our research is the first to show this distinction via the relation of the category with the properties of different labels and actions with those labels. Further research is needed for a deeper investigation into this relation. Many more questions concern dense category learning. It is yet to be explained why participants prefer not to verbalize category names in the dense category formation process. Is there interference related to the perception of a label in dense categories, and if so, what could be its nature? It is also necessary to investigate at what stage of category perception and decision making about category membership the interference works in dense category formation.

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Appendix A. Descriptive Statistics for Dense Category Learning

Block	Pictorial Label (Experiment 1a)		Verbal Label (Experiment 1a)		Unverbalized Label (Experiment 1b)		Verbalization Task (Experiment 2a)		Imagination Task (Experiment 2b)	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	.605	.212	.483	.125	.515	.135	.522	.187	.558	.177
2	.610	.228	.565	.239	.520	.182	.600	.161	.595	.187
3	.667	.149	.567	.215	.590	.141	.650	.151	.605	.227
4	.767	.151	.594	.218	.595	.179	.656	.15	.637	.146
5	.767	.119	.667	.188	.605	.204	.711	.132	.679	.158
6	.776	.137	.672	.184	.645	.170	.700	.194	.668	.216
7	—	—	—	—	.655	.161	.683	.192	.716	.139
8	—	—	—	—	.665	.201	.722	.148	.732	.134
9	—	—	—	—	.66	.214	.728	.167	.705	.172
10	—	—	—	—	.710	.208	.756	.169	.716	.121

Appendix B. Descriptive Statistics for Sparse Category Learning

Block	Pictorial Label (Experiment 1a)		Verbal Label (Experiment 1a)		Unverbalized Label (Experiment 1b)		Verbalization Task (Experiment 2a)		Imagination Task (Experiment 2b)	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	.455	.137	.505	.129	.508	.171	.478	.144	.574	.156
2	.546	.277	.583	.185	.552	.199	.494	.051	.574	.156
3	.646	.238	.628	.171	.537	.159	.517	.130	.616	.186
4	.791	.221	.741	.235	.583	.158	.500	.097	.616	.195
5	.746	.237	.708	.264	.556	.154	.533	.119	.679	.132
6	.846	.175	.781	.149	.639	.179	.539	.115	.684	.198
7	—	—	—	—	.606	.210	.528	.096	.663	.198
8	—	—	—	—	.678	.205	.561	.182	.674	.233
9	—	—	—	—	.683	.246	.539	.212	.695	.222
10	—	—	—	—	.722	.173	.561	.104	.711	.258

экспериментальные сообщения

Роль знаков разного типа в научении статистически плотным и неплотным категориям

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Аннотация. Испытуемым предъявляли классическую задачу на категориальное научение с обратной связью. Мы использовали два типа категорий — статистически плотные и статистически неплотные. Было проведено четыре эксперимента для оценки роли типа знаков (эксперимент 1) и интерференции со стороны действий со знаком (эксперимент 2) на научение разным типам категорий. Мы обнаружили, что при научении статистически плотным категориям было важнее визуальное сходство знака с другими перцептивными признаками объекта, а при научении статистически неплотным категориям важнее была легкость вербализации знака. Дополнительно было показано, что вербальная интерференция в отношении знака категории ухудшала формирование неплотных категорий, но не ухудшала формирование плотных категорий. Результаты исследования обсуждаются в связи с теорией множественных систем категоризации (COVIS).

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Ключевые слова: категоризация, категориальное научение, знак, структура категории, научение

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