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Understanding individual differences in representational abstraction: The role of working memory capacity☆

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ABSTRACT

Several studies have reported differences in categorization strategies among participants: some learn a category by making abstraction across the category members while others use a memorization strategy. Despite the prevalence of these differences, little attention has been paid to investigating what influences some to use an abstraction strategy and others a memorization strategy. The current study had two goals: in a first experiment we investigated whether these differences were stable across time, using the parallel form method often used in psychometric research, and in a second experiment we investigated whether the individual differences in categorization strategy were related to working memory capacity. We used a modelling strategy, in which we not only focused on full abstraction and memorization strategies, but also on intermediate strategies in which some category members are abstracted and others are not. The first study revealed that the individual abstraction strategy of individual participants in two different experiments, performed at different times, correlate significantly, and second study showed that these individual differences were related to the working memory capacity of the participants.

It is well known that there are differences in the strategies people rely on when learning categories from labelled exemplars. As early as 1984, Medin, Altom, and Murphy (1984) asked participants to report the strategy they used when learning a category. These self- reported strategies could be classified in five different types, including a prototype and memorization strategy, and the relative frequencies of the types indicated that they were fairly equally used. A similar questionnaire approach was used by Little and McDaniel (2015a), showing that 37% of their participants classified themselves as exemplar-learners, while 51% classified themselves as rule-learners. Transfer performance confirmed the validity of the self-reported strategies. Opting for a different methodology, Craig and Lewandowsky (2012) used the response patterns on transfer items to identify the strategy of individual participants. The two most popular strategies used in their study were a rule-based and an exemplar strategy. The same transfer method was employed by McDaniel, Cahill, Robbins, and Wiener (2014) to discriminate between individuals using a rule-based approach or an exemplar strategy. Using a combined analysis of the response patterns and a modelling perspective, Johansen and Palmeri (2002) reported interindividual differences in addition to intraindividual differences in learning ill-defined categories: by the end of training, participants differed in the strategy they used. They furthermore found evidence that strategies shifted over the course of learning. These results were later confirmed by Raijmakers, Schmittmann, and Visser (2014) using a latent Markov analysis. Others used a modelling perspective to find differences in the extent to which participants used a prototype versus an exemplar strategy. Smith, Murray, and Minda (1997), for example, contrasted an exemplar model and a prototype model using the data of individual participants. Their results indicated that a large subgroup of their participants (40% of the participants across the two experiments) learned the categories by abstracting a prototype while the others used an exemplar strategy (though see, Nosofsky & Zaki, 2002).

Given the strong evidence for the presence of differences in categorization strategy, surprisingly little attention has been paid to understanding these differences. One of the first and most important steps that has to be taken when investigating these differences is to establish whether they are meaningful and represent vast individual differences in categorization strategy. It is therefore worthwhile to first of all demonstrate that these differences are stable over time. A recent study of McDaniel et al. (2014) showed that individuals diverge in the type of strategy they use in a function-learning task and that the preferred strategy generalized to an abstract coherent categorization task. Thus, individual differences in the function-learning task were quite stable across tasks. In Study 1, we further investigated whether individual differences in categorization

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strategies can be reliably assessed, using a parallel testing perspective (Lord & Novick, 1968). If the differences in categorization strategy represent vast individual differences, we would expect these differences to be stable over time.

Secondly, the stability of these differences over time would allow us to investigate what makes people different with respect to their categorization strategy. One factor that has been linked to categorization strategy is working memory capacity. Since categorization requires the active processing and manipulation of category information, working memory can be expected to play a role in category learning (see e.g., Craig & Lewandowsky, 2012). Furthermore, Sewell and Lewandowsky (2012) found a relationship between working memory capacity and the extent to which people are able to coordinate different types of partial-knowledge structures, in this case two different types of rules. They showed that participants with higher working memory capacity were better able to coordinate these two types of rules and to adjust their categorization judgment to each of these rules when expected. However, Craig and Lewandowsky (2012) and Little and McDaniel (2015a) found no such relation at all.

In the present study, we further investigate whether the individual differences in categorization strategy were related to working memory capacity. More specifically, following Sewell and Lewandowsky (2012), we expect that the higher one's working memory capacity, the easier it is to actively retain different types of information, and thus the lower the individuals' tendency to make abstraction across the category members. The lower one's working memory capacity, on the other hand, the more need to summarize information and thus the more need to make abstraction across the category members. In sum, we hypothesize that participants with lower working memory capacity will make more abstraction across category members than participants with a higher working memory capacity.

In the next section, we will outline the modelling framework that we used to determine the level of abstraction employed by the participants in their categorization strategies. Then, we discuss two experiments, one in which the stability of individual differences in abstraction was investigated and one in which we related these individual differences to working memory capacity. In the discussion, we relate our findings to previous studies.

1. Assessing representational abstraction

There is a long-standing tradition in the categorization literature to rely on formal models to determine the underlying categorization strategy that participants use. Some models assume a single type of category representation, like the Generalized Context Model (GCM; Nosofsky, 1984) and ALCOVE (Kruschke, 1992), which assume an exemplar strategy; the Multiplicative Prototype Model (Reed, 1972; Nosofsky, 1987; Smith & Minda, 2000), which is based on a prototype representation, or the decision-bound theory (Ashby & Gott, 1988; Ashby & Maddox, 1993) which is built around a rule strategy. Other, so called hybrid models combine several (mostly two) strategies. Examples of hybrid models are RULEX (Nosofsky, Palmeri, & Mckinley, 1994), SUSTAIN (Love, Medin, & Gureckis, 2004), the rational model (Anderson, 1991), COVIS (Ashby, Alfonso-Resse, Turken, & Waldron, 1998) and ATRIUM (Erickson & Kruschke, 1998). Within the RULEX framework it is, for example, assumed that during category learning subjects start by extracting a rule while storing exceptions to this rules separately. The rational model interpolates between an exemplar and prototype representation by assuming that groups of category members are clustered together. Whenever a new stimulus is encountered, it can be added to an existing cluster or it can form a new cluster (see also SUSTAIN, for comparable ideas). In the present study, we rely on a similar hybrid model, the Varying Abstraction Model (VAM; Vanpaemel & Storms, 2008), to determine the degree to which individual participants make abstraction across category members.

The VAM defines category representations that lie on a continuum from minimal (separate exemplars) to maximal abstraction (a single prototype). A category representation is formed by dividing the points in the Multidimensional scaling (MDS) space that make up a category into clusters and by averaging the coordinates of the points that were clustered together. The resulting coordinates define a set of subprototypes that make up the category representation. For example, if a cluster Q_j contains n_j stimuli, the coordinate value μ_{jk} for subprototype j on dimension k is calculated by averaging the coordinate value of all n_j stimuli on dimension k:

$$\mu_{jk} = \frac{1}{n_j} \sum_{x_i \in Q_j} x_{ik},$$

where x_{ik} is the coordinate value of stimulus i on dimension k.

The number of different possible representations depends on the number of category members to be learned. A category with four members, for example, can lead to 15 different representations according to the VAM (see Fig. 1). A category with six members can be represented by 203 different representations.

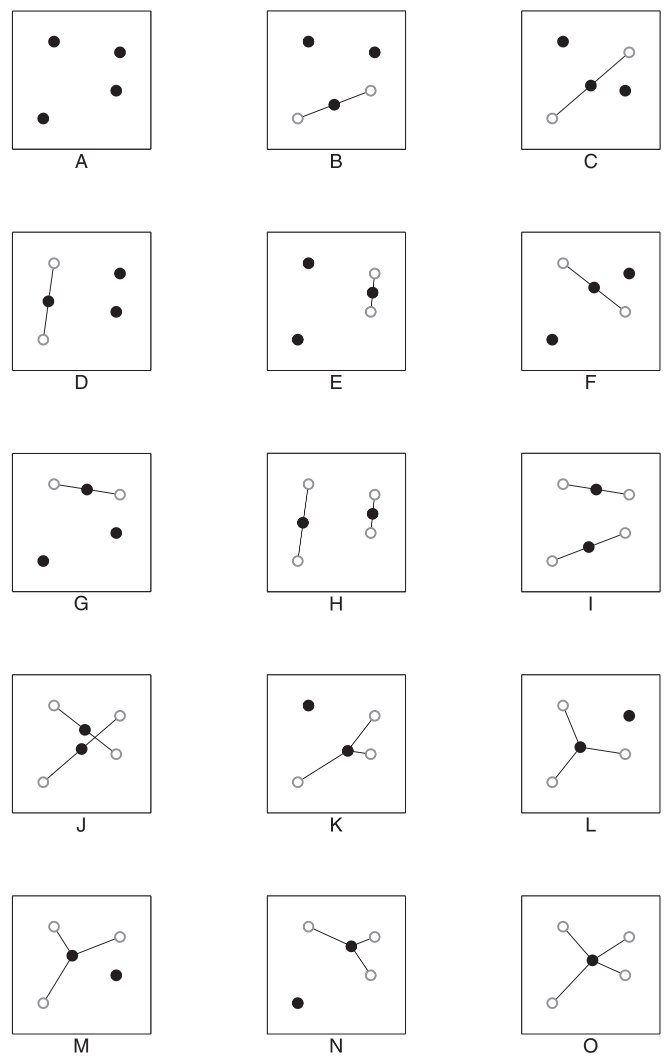

Fig. 1. The 15 possible representations for a category with four members. The subprototypes are represented by the black circles and are connected by lines to the original category members (the white circles). Panel A shows the exemplar representation (no members are merged); Panel O shows the prototype representations (all members are merged together into a single subprototype); Panels B–G show intermediate representations with three subprototypes; and Panels H–N show intermediate representations with two subprototypes. Figure with approval taken from Vanpaemel and Storms (2008).