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Category induction in autism: Slower, perhaps different, but certainly possible

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Available studies on categorization in autism indicate possibly intact category formation, performed through atypical processes. Category learning was investigated in 16 high-functioning autistic and 16 IQ-matched nonautistic participants, using a category structure that could generate a conflict between the application of a rule and exemplar memory. Same–different and matching-to-sample tasks allowed us to verify discrimination abilities for the stimuli to be used in category learning. Participants were then trained to distinguish between two categories of imaginary animals, using categorization tests early in the training and at the end (160 trials). A recognition test followed, in order to evaluate explicit exemplar memory. Similar discrimination performance was found in control tasks for both groups. For the categorization task, autistic participants did not use any identifiable strategy early in the training, but used strategies similar to those of the nonautistic participants by the end, with the same level of accuracy. Memory for the exemplars was poor in both groups. Our findings confirm that categorization may be successfully performed by autistics, but may necessitate longer exposure to material, as the top-down use of rules may be only secondary to a guessing strategy in autistics.

Keywords: Autism; Categorization; Discrimination; Perception; Learning; Rules.

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Categorization consists in grouping together several entities, thereby contributing to the organization of our knowledge about these entities. Several theories have been proposed to explain categorization on the basis of *rules*, exemplar *memory*, or similarity to a *prototype*. First, "rule" models propose that when forming a new category, we extract a rule that defines category membership (Martin & Caramazza, 1980). Second, according to "exemplar" models, categorization relies on the memorization of the encountered members of a category. A new instance would be compared to stored exemplars and classified in the category where similarity to these exemplars is maximal (Medin & Schaffer, 1978; Nosofsky, 1986). Third, we could build a prototype from the central tendency of the different members of a category (Rosch & Mervis, 1975; Smith & Minda, 1998, 2002). These three mechanisms may be combined, for example by memorizing instances that constitute exceptions to the categorization rule (Nosofsky, Palmeri, & McKinley, 1994), or may be competing in different contexts and with different types of material (Allen & Brooks, 1991; Ashby, Alfonso-Resse, Turken, & Waldron, 1998; Erickson & Kruschke, 1998).

Atypicalities in categorization processes can be expected in autism, a neurodevelopmental condition in which the development of communication, social interactions, behaviour patterns, and interests differs from that of other individuals. For instance, elementary processes possibly involved in category formation, such as discrimination and feature detection, are generally enhanced in autistic individuals (Bertone, Mottron, Jelenic, & Faubert, 2005; Bonnel et al., 2003; Plaisted, O'Riordan, & Baron-Cohen 1998a, 1998b). A greater ability to perceive differences among entities may hinder the tendency to group entities together in the same category (Plaisted, 2001).

In an early series of studies, Tager-Flusberg (1985a, 1995b) and Ungerer and Sigman (1987) investigated autistic semantic categorization in quasi-natural situations, by testing the influence of a category on the grouping of pictured items. They concluded that semantic categories are organized normally in children with autism. This conclusion was recently refined by Gastgeb, Strauss, and Minshew (2006), who studied the influence of typicality on the categorization of common objects (couches, chairs, cats, and dogs). In both control and autistic participants, response times increased for atypical exemplars relative to typical exemplars. However, autistic children, adolescents, and adults showed slower response times for atypical items than did control participants. The categorization of atypical items would require additional perceptual processing, in terms of considering quantitative spatial information, comparing the item to stored exemplars, and comparing multiple features, because these items are more likely to differ from the prototypical structure of the category (Jolicoeur, Gluck, & Kosslyn, 1984). Gastgeb et al. argued that this additional perceptual processing may be less efficient in autistic individuals, although accuracy was similar in autistic and control participants.[1]

Slower categorization processes in the presence of average performance may indicate atypical strategies rather than mere deficits. Perceptual category learning tasks allow for the manipulation of stimulus properties and of the extent to which the participants are exposed to the stimuli, in order to investigate learning rates and strategies. Klinger and Dawson (2001) studied category learning in autistic children with measured intelligence below the normal range matched with children showing mental retardation, as well as typically developing children (control participants). In a familiarization task, participants had to categorize imaginary animals. Participants were then asked which one of two new animals was a member of the previously learned category. When a simple rule distinguished members from nonmembers, there was no difference between the three groups. However, when participants had to

[1] Note that this finding seems contradictory to that of Dunn, Gomes, and Sebastian (1996) in a categorical verbal fluency task, where autistics performed as well as nonautistics in providing examples of categories, but chose less typical examples.

choose between two animals differing in typicality (one typical and one atypical), only control participants reliably chose the typical one. The authors suggested that autistic children, as well as those with mental retardation, despite a similar ability to infer category-defining perceptual rules, may be less likely to use prototypical information.

The different behaviour exhibited by both the autism and the mental retardation groups may, however, be related to their shared lower intelligence. This indeed seems likely to be the case, given some recent results from autistic individuals with normal measured intelligence. Using categories similar to that of Klinger and Dawson's (2001) study, Molesworth, Bowler, and Hampton (2005) presented participants with a recognition task using previously seen animals and new animals varying from high to low typicality. Both autistic and nonautistic groups showed a classic prototype effect: The more typical the stimuli, the higher the proportion of recognition answers. Therefore, autistic participants performed as though they had built categories similar to those built by nonautistic participants during their training with the stimuli.

Two other recent studies suggest that categorization mechanisms would not greatly differ in autistic individuals, but some indices point to category-learning strategies that might differ in some respect between autistic and nonautistic individuals. In a previous study, we investigated categorical perception for a continuum of ellipses to which participants had not previously been exposed (Soulières, Mottron, Saumier, & Larochelle, 2007). As their performance in a thin/large categorization task suggested, autistic and nonautistic participants created similar categories in terms of boundary location and sharpness. In a same/different discrimination task, nonautistic participants showed better performance when the two stimuli to discriminate belonged to opposite categories than when the two stimuli were in the same category. On the other hand, the performance of autistic participants did not vary whether or not the two stimuli belonged to the same category. The abstracted categories therefore had less influence on stimulus discrimination in autistic participants.

In another study, Bott, Brock, Brockdorff, Boucher, and Lamberts (2006) had participants learn to classify rectangles varying in height and width into two different categories. Autistic participants took significantly longer to learn the categories and, as a group, seemed to make their categorical decisions based on fewer dimensions than did nonautistic participants, as suggested in a similarity judgement task with the stimuli. The earlier suggestion that a superior discrimination ability could facilitate the learning of individual exemplars and hinder or slow down the formation of categories (Plaisted, 2001) was partly confirmed. Bott et al. indeed found slower category acquisition in autism, but no evidence for increased memory of exemplars.

The present experiment was designed to evaluate autistic individuals' category-learning process, as well as the respective influences of competing categorization mechanisms, an aspect that was not explored in previous studies. To achieve this, we used a category structure, cleverly designed by Allen and Brooks (1991), which could generate a conflict between the application of a rule and exemplar memory. Their paradigm provides a way to establish whether a different category acquisition rate results from superior reliance on exemplar memory or rules during categorization. More generally, it allows characterization of learning and categorization strategies via careful analysis of individual response patterns.

The stimuli were composed of five binary attributes, three of which were included in a rule defining membership in one of two categories. During the training phase, participants had to learn to categorize the stimuli. In Allen and Brooks's (1991) original study, some participants were told the categorization rule; others were not. Feedback concerning response accuracy was provided following each trial. For a subsequent test phase, new stimuli were created by inverting the value of one of the three rule attributes, which resulted in a change of category according to the rule, for half of the new stimuli. Although these stimuli, called negative transfer items, belonged to a given category according to the rule, they were more similar to learned items belonging to the opposite category. Categorizing these negative transfer items according to the rule results in their being classified in the category opposite to their most similar training item. Conversely, classifying these negative items according to similarity to the items used in the training phase results in their being placed in the same category as their most similar learned item, therefore violating the rule. Allen and Brooks's results showed increased response times and error rates for negative transfer items,[2] which suggests that categorization performance was influenced by exemplar memory, even when a rule was provided.

Our goal was to determine whether autistic individuals would rely on similar categorization mechanisms when they must use their own strategies to learn the categories (rule not given). Two control tasks, a same–different task (Task 1) and matching-to-sample task (Task 2), were added before category training to verify whether perceptual or working memory differences between the two groups could influence the learning of categories. Both control tasks allowed verification of the ability to consider multiple dimensions when processing the stimuli (particularly given the results from Bott et al., 2006) and to discriminate between stimuli on the dimensions relevant to the experiment. The matching-to-sample task required finding, among a pair of stimuli, the one that was identical to a sample stimulus. This task additionally ensured that participants were able to maintain stimulus information in short-term memory (seeing as there was a delay between the stimulus pair and the sample stimulus). During the categorization task, extensive training with feedback was provided, with test phases at two different levels of training (Tasks 3a and 3b). The pattern of answers allowed for performance comparisons at the group level, and in terms of individual strategies. Finally, a recognition task (Task 4) was performed to test the prediction of a better exemplar memory in autism.

We did not expect to find between-group differences in the control tasks, as autistic individuals generally perform as well as, or even better than, nonautistic individuals on discrimination tasks (see Mottron, Dawson, Soulières, Hubert, & Burack, 2006a; or Plaisted, 2001). However, consistent with Bott et al.'s (2006) results and Plaisted's prediction, we hypothesized that autistic participants would need more training to reach their optimal performance in the categorization task. This slower acquisition was hypothesized to be accompanied by a different combination of learning and categorization strategies

Method

Participants

A total of 16 high-functioning autistic participants (with a mean IQ of 108) were recruited from the Rivière-des-Prairies Hospital (Montréal, Canada) Pervasive Developmental Disorders Specialized Clinic database. All participants met criteria for autism according to the Autism Diagnostic Interview–Revised (ADI-R; Lord, Rutter, & Le Couteur, 1994) and the Autism Diagnosis Observation Schedule (ADOS-G; Lord et al., 2000). A comparison group of 16 typically developing participants was recruited from the same database. A questionnaire screened for any history of neurological or major psychiatric disorders in the nonautistic participants as well as in their first-degree relatives. Autistic and nonautistic participants were individually matched according to their full scale IQ (FSIQ) measured by one of the Wechsler Intelligence scales, with a maximum difference of 5 points in each pair of participants (except for one pair with a difference of 7). No significant difference was found between the two groups on FSIQ, $t(30) = 0.54$, $p = .59$, Verbal IQ, $t(30) = 0.04$, $p = .97$,

[2] For the rule group (where the rule was explicitly given), there was an increase in error rates and response time for negative transfer items. For the no-rule group, there was only an increase in error rates, but this increase was greater (>60%) than that of the rule group (±15%).

Performance IQ, $t(30) = 1.09$, $p = .29$, or age, $t(30) = 0.56$, $p = .58$. Table 1 summarizes the participants' characteristics. A power analysis confirmed that minimum sample sizes of 13 participants per group were sufficient to detect a between-group difference, assuming an effect size similar to that extrapolated from Bott et al.'s (2006) categorization training data ($d = 1.18$) with a power of 0.80 and an alpha level of .05.

All participants, or their parents in the case of minors, gave informed consent and received a monetary compensation for participating in the study, which was formally approved by Rivière-des-Prairies Hospital's ethical committee.

Materials

The stimuli were taken from Lacroix, Giguère, and Larochelle (2005) and conformed to the structure designed by Allen and Brooks (1991). The stimuli set consisted of a set of 16 imaginary animals varying on five binary attributes: head shape (oval or D-shaped), back pattern (striped or spotted), tail type (cane or staircase shaped), body shape (round or angular), and colour (yellow or green). A rule involving three attributes (head shape, back pattern, and tail type) divided the stimuli in two categories, the "Tremblay" and the "Beaulieu". Table 2 shows the categorical structure of the stimuli. If a stimulus possessed two or three out of the three attribute values specified in the rule (symbolized by a 1 in Table 2), it was considered a "Tremblay". Otherwise it was a "Beaulieu". This rule is a disjunction of conjunctions: In order to be a Tremblay, an item must have attributes (A and B) or (B and C) or (A and C). Note that none of the three rule attributes was by itself perfectly predictive of the category; each had only a .75 cue validity. Two attributes were not included in the rule (body shape and colour) and were nondiagnostic of category membership, each of their values appearing equally often in each category (.5 cue validity).

Eight stimuli were used as training exemplars. The eight "transfer" exemplars were obtained by inverting the value for the back pattern (the second attribute in Table 2) on each training exemplar (a stimulus that had stripes now had spots and vice versa). For half of the "transfer" exemplars, this inversion changed the category membership according to the rule. Four types of stimuli were therefore created: positive training items (training stimuli whose corresponding transfer stimuli are still in the same category), negative training items (training stimuli whose corresponding transfer stimuli are in the opposite category), positive transfer items (transfer items whose corresponding training items are in the same category), and negative transfer items (transfer items whose corresponding training items are in the opposite category). Examples of stimuli are given in Figure 1.

Careful counterbalancing was achieved in order to avoid any possibility of a particular combination of attributes being easier to remember. Accordingly, there were four different rules depending on which value (for example, oval or D-shaped head) of the three critical attributes was specified in the rule. Moreover, for each rule, the two sets of eight stimuli could be used either as training or as transfer exemplars. Therefore, the four rules and the two sets of stimuli yielded eight different combinations of stimuli making up the two categories. Two participants per group were tested using each of these eight combinations.

For the recognition task, 16 new stimuli were added to the training and transfer items. The training and transfer stimuli represented only 16 of 32 possible combinations of five binary attributes. The new stimuli resulted from the 16 remaining combinations. Lastly, a mask

Table 1. *Participant characteristics for the autistic and nonautistic groups*

	Autistic group M (range)	*Nonautistic group M (range)*
Full-scale IQ	108.3 (89–129)	110.5 (88–128)
Verbal IQ	109.4 (81–132)	109.2 (91–128)
Performance IQ	105.1 (77–126)	109.8 (87–128)
Chronological age	17.8 (11–29)	16.7 (11–27)
Gender	12 M, 4 F	12 M, 4 F

Note: M = male; F = female.

Table 2. *Category structure used in the first three tasks*

	Training items						*Transfer items*					
Items	*Category*	*Head*	*Back Pattern*	*Tail*	*Body shape*	*Colour*	*Category*	*Head*	*Back Pattern*	*Tail*	*Body shape*	*Colour*
Positive	Tremblay	1	1	1	0	0	Tremblay	1	0	1	0	0
	Tremblay	1	0	1	1	1	Tremblay	1	1	1	1	1
	Beaulieu	0	1	0	1	1	Beaulieu	0	0	0	1	1
	Beaulieu	0	0	0	0	0	Beaulieu	0	1	0	0	0
Negative	Tremblay	0	1	1	0	1	Beaulieu	0	0	1	0	1
	Tremblay	1	1	0	1	0	Beaulieu	1	0	0	1	0
	Beaulieu	1	0	0	0	1	Tremblay	1	1	0	0	1
	Beaulieu	0	0	1	1	0	Tremblay	0	1	1	1	0

Note: Table 2 presents the structure of the eight training items and the eight transfer items. All items vary on five binary attributes (head, back pattern, tail, body shape, and colour). Three attributes (head, back pattern, and tail) are diagnostic, which means that one of their values is found more often in one category than the other. The last two attributes (body shape and colour) are nondiagnostic because their values appear equally often in each category. On the left are training items (each row represents an item) and on the right are the transfer items, obtained by changing the value of the attribute "back pattern" (stripes vs. spots). The positive training items have corresponding transfer items that are in the same category. The negative training items have corresponding transfer items that belong to the opposite category.

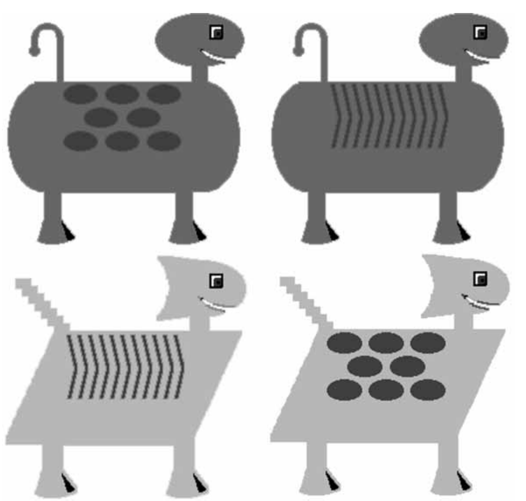

Figure 1. *Examples of stimuli used in the four tasks. On the left side are examples of training stimuli, with their corresponding transfer stimuli on the right side.*

combining the two possible values for each attribute was used in the matching-to-sample task.

Procedure

Each participant sat in an entirely black booth and looked through a window at a computer monitor displaying the stimuli. Viewing distance was approximately 50 cm. Stimuli were presented on a black background on the computer monitor. Lighting and noise conditions were maintained to a minimum. The experiment involved four tasks, which were done in the same order by all participants. It was designed with and controlled by MEL Professional v.2.01 (Schneider, 1989). The entire experiment lasted approximately 40 minutes, including pauses at the decision of the participant.

Task 1: Same–different discrimination. This control task involved same–different judgements on two stimuli presented simultaneously on each side of the screen. The eight training stimuli were used equally often in a random sequence of 104 trials. Every combination of two different stimuli was presented twice, for a total of 56 "different" trials. Pairs containing the same stimulus were presented six times each, for a total of 48 "same" trials. The stimuli remained visible until the participant responded by pressing one of two keys on the keyboard. A fixation cross was displayed in the centre of the screen during 1,500 ms before the stimuli were presented. There was a 1,000-ms intertrial interval during which a blank screen was presented.

Task 2: Matching-to-sample. The second control task used a matching-to-sample paradigm, in which participants had to decide which stimulus of a pair was identical to a target stimulus presented before. The 28 combinations of the eight training stimuli were presented four times, with each stimulus of a pair presented twice as a target, for a total of 112 randomized trials. Each trial began by a fixation cross presented for 1,500 ms, followed by the target stimulus presented in the centre of the screen for 300 ms. The stimulus was replaced by a mask presented in the exact same location for 100 ms. Then the stimulus pair was presented and remained visible until the participant answered. Again, the intertrial interval was 1,000 ms.

Task 3: Categorization. This task involved categorizing the stimuli as belonging to the "Tremblay" or the "Beaulieu" category. On each trial of the two training phases, participants saw one stimulus at a time and were instructed to categorize it as a "Tremblay" or as a "Beaulieu" by pressing one of two keys. Feedback about the correct category was given after every trial. The feedback consisted of either the phrase "bonne réponse" ("correct answer") accompanied by the name of the correct category on the screen, or the phrase "mauvaise réponse" ("wrong answer") accompanied by a short buzzing sound and the name of the correct category. The first training phase was composed of 5 blocks of 8 randomized trials (1 per training stimulus), for a total of 40 trials. The second training phase contained 15 blocks of 8 randomized trials, for a total of 120 trials. A test phase occurred after each of the two training phases. In each of the two test phases, the eight training stimuli were mixed with the eight transfer stimuli, for a total of 16 trials presented in a random order. Participants were instructed that the task was identical to that of the previous training phase, but that there would be no feedback during this part of the experiment. Trials began by a 1,500-ms fixation cross, followed by the stimulus that remained visible until the participant pressed a key. Feedback (provided only in the training phases) was presented for 2,000 ms. Intertrial interval was 1,000 ms.

Task 4: Recognition. This recognition task required stimuli to be classified as either "old" or "new". The "old" stimuli were those seen in Tasks 1 to 3. They consisted of the eight training and eight transfer stimuli. The "new" stimuli comprised the 16 remaining stimuli, which had never been seen in the experiment. To maximize the possibility of revealing differences in familiarity between seen and unseen items, participants gave their answers on a six-button response box. The buttons 1 to 3 corresponded to "old" answers and 4 to 6 to "new" answers with increasing levels of confidence in their answers (e.g., 1 = "old, absolutely sure", 6 = "new, absolutely sure"). The stimuli were presented one at a time and remained visible until the participant pressed a button. Participants received no feedback pertaining to the accuracy of their answers. Each stimulus was presented once, for a total of 32 trials. The presentation of a fixation cross and the intertrial interval were similar to those in previous tasks.

Results

Data preparation

Trials yielding response times (RTs) larger than 3 standard deviations (*SD*s) from the individual participant's mean were removed (in both RT and accuracy data). This procedure resulted in a loss of less than 5% of the trials in each task and yielded no empty cell. Note that following Allen and Brooks (1991), error trials were included in RT analyses. Paired samples statistical analyses were done using an alpha level of .05. A Greenhouse–Geisser correction was applied to all analyses of variance (ANOVAs), and partial eta-squared (η_p^2) values were reported as estimates of effect size.

Task 1: Same–different discrimination

Accuracy. Similar accuracy levels were observed in the two groups (autistic group: $M = 98.2\%$, *SD*

= 2.4%; nonautistic group: $M = 96.1\%$, $SD = 3.6\%$). The data were subjected to a repeated measures, two-way ANOVA involving the factors differing attributes (0, 2, 3, or 4 attributes differing) and group (autistic vs. nonautistic group). This analysis revealed no main effect of differing attributes, $F(2.06, 30.86) = 1.78$, $p = .19$, $\eta_p^2 = .11$, or group, $F(1, 15) = 2.72$, $p = .12$, $\eta_p^2 = .15$, and no interaction between the two factors, $F < 1$.

RT. The RT data were submitted to the same analysis as the accuracy data. This analysis revealed only a main effect of differing attributes, $F(1.66, 24.94) = 12.91$, $p = .00$, $\eta_p^2 = .46$. Both groups of participants answered more rapidly as the number of differing attributes increased (respectively, 1,434, 1,277, 1,117, and 1,029 ms for 0, 2, 3, and 4 differing attributes). The effect of group and the interaction between the two factors were not significant, both Fs < 1.

Task 2: Matching-to-sample

Accuracy. A repeated measures, two-way ANOVA was performed on the percentage of correct responses, with the factors differing attributes (2, 3, or 4 attributes) and group (autistic vs. nonautistic). This analysis revealed only a main effect of differing attributes, $F(1.44, 21.62) = 9.47$, $p = .00$, $\eta_p^2 = .39$, with performance increasing from 93.4% to 97.4% as the number of differing attributes increased. There was no significant effect of group, $F < 1$, or interaction between the two factors, $F(1.88, 28.19) = 1.86$, $p = .18$, $\eta_p^2 = .11$.

RT. The same ANOVA as that for accuracy data was done on the RTs. This analysis revealed a main effect of differing attributes, $F(1.68, 25.22) = 21.55$, $p = .00$, $\eta_p^2 = .59$. There was no effect of group, $F < 1$, and no significant interaction between group and differing attributes, $F(1.43, 21.44) = 2.44$, $p = .12$, $\eta_p^2 = .14$. The average response time decreased, from 661 to 579 ms, as the number of differing attributes increased.

Accuracy was almost perfect for both groups on both control tasks (1 and 2). Moreover, RT analyses revealed that participants from both groups did not differ significantly in their sensitivity to the number of differing attributes. Clearly, all participants were comfortable in considering and comparing the different attributes making up the animals. Therefore, any differences in categorization are not likely to be accounted for by differences in discrimination or sensitivity to the number of differing attributes.

Task 3a: Categorization test after 5 blocks of training

Accuracy. Note that accuracy was computed as the percentage of answers that conformed to the three-attribute rule, both for training and for transfer items. Hence, the accuracy for transfer items was relative to the rule. A repeated measures, three-way ANOVA was conducted on the data, with the factors group (autistic vs. nonautistic), item type (training vs. transfer items), and rule conflict (positive vs. negative items). This analysis revealed only a main effect of group, $F(1, 15) = 9.23$, $p = .01$, $\eta_p^2 = .38$. As can be seen in the top part of Figure 2, autistic participants were significantly less accurate (57.6%) than nonautistic participants (69.8%) at this stage of training. There was no significant effect of item type, $F < 1$, or rule conflict, $F(1, 15) = 3.31$, $p = .09$, $\eta_p^2 = .18$, and no significant interaction between these factors, all ps $> .18$.

RT. The mean RT was 1,338 ms in the autistic group and 1,488 ms in the nonautistic group. The same analysis as that for accuracy was conducted on RT data and revealed no significant main effect of group, $F < 1$, item type, $F < 1$, or rule conflict, $F(1, 15) = 2.09$, $p = .17$, $\eta_p^2 = .12$, and no interactions between these factors (all ps $> .23$).

Task 3b: Categorization test after 20 blocks of training

Accuracy. The bottom part of Figure 2 presents the results for the second categorization test. The same ANOVA as that done after 5 blocks of training was conducted. Again, there was no significant effect of item type, $F(1, 15) = 2.59$, $p = .13$, $\eta_p^2 = .15$, or rule conflict, $F < 1$. But contrary to the results

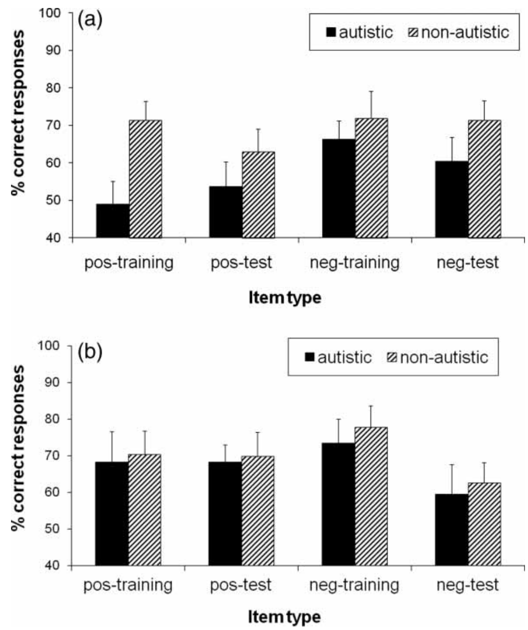

Figure 2. *Percentage of correct responses in the first categorization test (top panel) and in the second categorization test (bottom panel), for both groups. Training and transfer items that belong to the same category are labelled "pos" (positive). Training and transfer items that belong to opposite categories are labelled "neg" (negative). Error bars show the standard error from the mean.*

after 5 blocks of training, there was no main effect of group, $F < 1$, after 20 blocks of training. The analysis also showed an interaction between item type and rule conflict, $F(1, 15) = 4.91$, $p = .04$, $\eta_p^2 = .25$. For positive items (both training and transfer exemplars are in the same category), there was no difference between training and transfer items, $p = .92$. In contrast, for negative items (training and transfer exemplars are in opposite categories), accuracy was significantly higher for training items than for transfer items, $p = .02$. This corresponds to the hypothesized conflict effect, between the application of a rule and memory of exemplars. The effect was of similar magnitude for both groups (interaction group by item type by rule conflict: $F < 1$). There was no other significant interaction, all Fs < 1.

RT. Response times were similar in the autistic group (1,304 ms) and nonautistic group (1,375 ms). The same analysis as that for accuracy was conducted on the RT data and revealed no main effect (all Fs < 1) and no interactions between the factors (all $p > .19$).

Comparison between Tasks 3a and 3b. Accuracy results from the two tests (after 5 blocks and after 20 blocks of training) were included in a single analysis to compare performance across tests. A repeated measures, four-way ANOVA was performed, with the factors test (5 vs. 20 blocks), group (autistic vs. nonautistic), item type (training vs. transfer items), and value (positive vs. negative items). There was no main effect of test, $F(1, 15) = 2.22$, $p = .16$, $\eta_p^2 = .13$, item type, $F(1, 15) = 1.80$, $p = .20$, $\eta_p^2 = .11$, or value, $F < 1$. There was a main effect of group, $F(1, 15) = 4.64$, $p = .05$, $\eta_p^2 = .24$, with a significant group by test interaction, $F(1, 15) = 5.95$, $p = .03$, $\eta_p^2 = .28$. In the autistic group, there was a significant increase in accuracy at the second test, $p = .03$ (mean accuracy for the first and second tests: respectively, 57.6% and 67.1%). No such improvement was found in the comparison group, $p = 1$ (mean accuracy 69.8% at both tests). None of the other interactions was significant.

Correlation with age and IQ. In order to verify whether age was related to the observed results, correlations with performance for the two categorization tests were computed separately for autistic and nonautistic participants. In the autistic group, age was not correlated with performance, either at the first categorization test, $r = .26$, $p = .34$, or at the second one, $r = .01$, $p = .97$. The same pattern was observed in the nonautistic group. Age did not correlate with performance at either of the two categorization tests: respectively, $r = -.26$, $p = .33$, and $r = -.13$, $p = .63$.

The potential effect of IQ on accuracy was addressed by individual pairing of autistic and nonautistic participants on FSIQ. Nevertheless, a correlation analysis was conducted for IQ as well, as categorization difficulties have been reported in autistic individuals with IQ below the normal (Klinger & Dawson, 2001). In our autistic group, FSIQ did not correlate significantly with performance at either of the two categorization tests: respectively, $r = .42$, $p = .11$, and $r = .19$, $p = .48$. Similarly, FSIQ did not correlate with performance, $r = .21$ and $.19$, $p > .40$, in the nonautistic group. The same correlations were repeated with Verbal and Performance IQ versus accuracy. The only $p < .20$ was for a nonsignificant correlation between Verbal IQ and accuracy at 5 blocks of training in autistic participants, $r = .41$, $p = .12$. To ensure that IQ was not significantly contributing to the effect of group observed at 5 blocks of training, an exploratory analysis of covariance was conducted with group as a between-subjects factor and FSIQ as a covariate. It revealed the same significant group difference in accuracy at 5 blocks of training, $F(1, 29) = 6.18$, $p = .02$. The same was true whether Verbal IQ or Performance IQ was used as a covariate.

Individual response patterns. Considering that it was extremely difficult to memorize complete exemplars during the categorization task (because an exemplar was only individualized by the specific combination of its five attributes), is the poor performance on negative transfer items really dependent on similarity to trained exemplars belonging to the opposite category? In order to answer to this question, analyses were done on the performance of each individual participant at each test—that is, after 5 blocks and after 20 blocks of training. Taking into consideration the pattern of responses given by each participant to various subsets of items, it was possible to determine whether the participant used a one-attribute rule (e.g., all the red ones are in the Tremblay category), a two-attribute rule (e.g., the oval head with spots are Tremblay, whereas the D-shaped head with stripes are Beaulieu), the three-attribute rule that was used to build the categories (e.g., if it has two out of three of spots, cane tail, and oval head, it is a Tremblay, otherwise it is a Beaulieu), or no rule at all. These analyses, as well as the decision criteria involved, are described in the Appendix. Table 3 presents the number of participants who used each strategy at each categorization test. After 5 blocks of training, the answers for 8 autistic participants revealed no consistent pattern. The same was true of only 2 nonautistic participants. There was a significant difference in the distribution of autistic and nonautistic participants using a consistent rule versus no identifiable rule, using a McNemar test, $p = .03$. This explains the difference found between the autistic and nonautistic groups in average performance on the first test, since using rules based on one or two diagnostic attributes yields 75% accuracy.

Table 3. *Individual strategies used for each categorization test*

	5 blocks		*20 blocks*	
Rule	*Autistic*	*Nonautistic*	*Autistic*	*Nonautistic*
1 attribute	2	5	2	1
2 attributes	6	8	10	11
3 attributes	0	1	1	1
No rule	8	2	3	3

Note: Individual response patterns were analysed separately for the first (left side) and second (right side) categorization tests. The number of participants from autistic and nonautistic groups who used a one-attribute, two-attribute, or three-attribute rule is shown. The number of participants who used none of these rules is entered under the label "no rule".

After 20 blocks, the distribution of participants was equivalent in the two groups, $p = 1$, as was average performance. Analyses performed separately for participants using a two-attribute rule and for those using either a one-attribute rule or no rule revealed different patterns of performance regarding negative items (see Figure 3). Participants who used a two-attribute strategy showed worse performance for negative transfer items (compared to training items), $F(1, 20) = 7.84$, $p = .01$, $\eta_p^2 = .28$, whereas participants who used a one-attribute rule or no rule had equivalent performance for negative training and transfer items, $F < 1$. Participants using a two-attribute rule are therefore responsible for the worse performance for transfer items whose most similar training exemplar belongs to the alternate category. As is discussed later, this result, which has been attributed in the past to a conflict between the application of a rule and exemplar memory, can

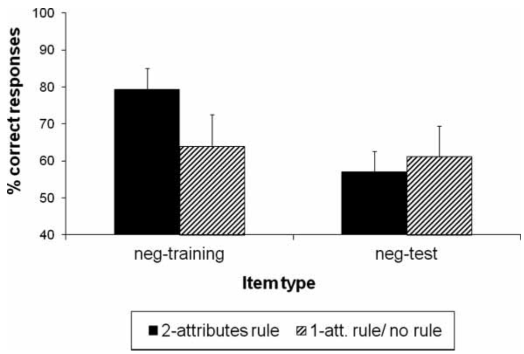

Figure 3. *Percentage of correct responses in the second categorization test (Task 3b), according to the strategy chosen by participants: a two-attribute rule (in black) or either a one-attribute rule or no identifiable strategy (in black and white). neg = negative. Error bars show the standard error from the mean.*

be explained by the application of a two-attribute rule without invoking any exemplar memory.

In order to test directly whether the exemplar strategy proposed by Allen and Brooks (1991) accounted for the performance of the individual participants, we predicted the response pattern that would have been obtained had participants categorized new items by comparing them to the most similar training item (see Appendix for detailed explanation).

After 5 blocks, individual results showed that no participant classified according to exemplar memory. After 20 blocks of training, results from all the nonautistic participants and from 14 out of 16 autistic participants showed no indication of classification according to exemplar memory. The performance of 2 autistic participants was ambiguous, being compatible with the exemplar strategy and with the use of a two-attribute rule (which is where they were classified in Table 3). Given that 1 of these 2 participants obtained only 47% correct answers in the recognition test (data from the other participant being unavailable), the use of exemplar memory is highly unlikely. But, whatever may be the case with these 2 participants, it is clear that exemplar memory cannot be responsible for the negative transfer effect observed at the group level.

Task 4: Recognition

Due to experimenter error, data from 6 autistic and 6 nonautistic participants were lost.[3] Accuracy data were computed for the remaining 10 participants in each group, which remains a group size sufficient to observe relevant differences. Dichotomizing the response scale (i.e., old = 1 to 3 vs. new = 4 to 6) showed recognition performance to be at chance level in both groups: 45% of correct responses in the autistic group (SD = 7%) and 48% in the nonautistic group (SD = 6%). In order to verify the possibility that mixing the transfer stimuli (seen only twice before the recognition task) with the training stimuli (seen more than 20 times) could have masked the learning of the training exemplars, the three types of stimulus (training, transfer, and new) were entered in an analysis using the 6-point response scale as dependent variable. The use of the more sensitive 6-point scale as a dependent variable (instead of accuracy computed as 0 or 1) maximizes the possibility of detecting a memory trace for the trained exemplars. A two-way analysis of variance was conducted with group (autistic vs. nonautistic) as a between-subjects factor and item type (training, transfer, and new) as a within-subjects factor. This analysis revealed no main effect of group, $F < 1$, or item type, $F(1.87, 33.67) = 2.11$, $p = .14$, $\eta_p^2 = .11$, and no interaction between the two factors, $F(1.87, 33.67) = 1.37$, $p = .27$, $\eta_p^2 = .07$. No explicit memory for "complete exemplars" was found in either of the two groups.

Discussion

Data summary

This study investigated category learning in 16 autistic participants of normal intelligence,

[3] There was no significant difference in IQ (Full Scale, Verbal, and Performance IQ), age, and accuracy in categorization (at the first and second tests) between the subsets of participants for which data were available or lost. The same was true when comparing participants with and without recognition data within each group, and across groups (autistic versus nonautistic) for participants with recognition data.

compared with 16 typically developing participants, individually matched on IQ. After controlling for discrimination abilities using a same–different task and a matching-to-sample task, participants were trained to distinguish two categories of imaginary animals. Categorization ability was measured at two stages of training. Memory of exemplars was then assessed through a recognition task. Autistic participants were slower to reach their maximum level of categorization accuracy, which was, however, identical to that of comparison participants. Discrimination and recognition performance were similar in both groups.

Categorization abilities and strategies

The first finding of this study is that autistic individuals of normal measured intelligence were able to perform at a normal level in a categorization task involving relatively complex, multidimensional information. Taken together, the results from Molesworth et al. (2005), Bott et al. (2006), Soulières et al. (2007), and the present results do not support overall inferior categorization in autistic persons of normal measured intelligence, at least for visual stimuli. Interestingly, autistic individuals took longer to learn the categories, but in the end categorized the same way as nonautistic participants. This result is similar to the result obtained in the study from Bott et al., where autistic participants took more training blocks to reach the category learning criterion (46 blocks vs. 30 blocks for control participants). It is also consistent with Plaisted's (2001) prediction that better discrimination abilities would hinder the grouping of entities on the basis of their similarities, but category learning up to an optimal level is nevertheless possible in autistic individuals.

Apart from determining the overall categorization level achieved by autistic individuals, the present study aimed at determining whether there are differences in the categorization processes used by autistic and typical individuals. How did participants proceed to learn the categories? Had the majority of participants succeeded in inferring the complex three-attribute rule defining the categories, performance would have been at ceiling. There is considerable evidence that typical individuals would usually not infer such a complex rule, often relying instead on simpler rules (see for example Ahn & Medin, 1992). It was therefore surprising to notice that 1 participant in each group inferred the complex rule allowing them to perfectly categorize the stimuli (no other strategy could yield a perfect accuracy given the category structure). Obviously, the majority of participants did not infer that rule and had to resort to a good enough rule to classify the stimuli. Individual analyses provided a way to distinguish between different possible strategies. For the first categorization test (after 5 blocks of training), a different distribution of strategies was observed in each group. Control participants used either a one- or a two-attribute rule, with only 2 participants using no identifiable strategy. By contrast, half the autistic participants used no identifiable strategy, which means that they were guessing, changing strategy over test trials, or gathering information.

After 20 training blocks, the picture is quite different. Similar proportions of participants in each group used a definite strategy, the most frequent being a two-attribute rule (10 autistic and 11 nonautistic participants). Only 3 participants in each group used no identifiable strategy. Taken together, results from the two categorization tests suggest that nonautistic participants used the same categorization strategies throughout the experiment. Autistic participants used no identifiable strategy early in the training, but used strategies similar to that of the nonautistic participants at the end of training. This pattern corresponds to the increase in accuracy from the first to the second categorization test in the autistic group, up to the level obtained by the nonautistic group.

How autistics learn. Why do autistics take longer to adopt a classification strategy? Difficulties in executive functions have been explored by Bott et al. (2006) as a potential explanation for slower category acquisition. As problems in attention shifting have been reported in autism, a difficulty in changing the focus of attention from one dimension to multiple dimensions in order to successfully learn the categories could explain why autistic participants took longer to learn the categories in their experiment. Other executive deficits such as processing feedback (which is seen after surgical lesions of dorsolateral prefrontal and orbitofrontal cortex; Hornak et al., 2004) would also slow down or alter learning of new categories. Difficulties in the Wisconsin Card Sorting Test (WCST)—a test in which one needs to rely on experimenter feedback to learn how to classify the cards—have indeed been reported in autism (Pennington & Ozonoff, 1996), though inconsistently. It is, however, unlikely that an executive deficit or a more specific difficulty in processing feedback could explain the slower category acquisition in our autistic participants, based on their clinical files and their response patterns in the categorization tests.[4]

Another alternative is that autistic participants may classify at random until a pattern emerges from the feedback they receive—a form of implicit learning—whereas nonautistic participants may consciously try explicit rules. In a review of learning processes in autism, Dawson, Mottron, and Gernsbacher (2008) conclude that implicit learning may be important in autistic cognition, but that "implicit learning" in autism may not have exactly the same form or role as that in nonautistic cognition. The learning processes favoured by autistics may include a first stage of implicit extraction of regularities from apparently passively viewed (and/or heard) material, this learning then being augmented by explicit rule extraction (Baron-Cohen, 2003; Heaton & Wallace, 2004; Hermelin & O'Connor, 1986; Miller, 1999; Mottron, Lemmens, Gagnon, & Seron, 2006b). Furthermore, an extensive exposure to the material may precede the actual manifestation of learning in the behaviour of autistic individuals. Such a form of learning could explain why autistic participants in our study seemed to classify at random early in the training but nevertheless reached the same level of accuracy as nonautistic participants later in the training. Note that with a different kind of training (e.g., passive exposure), autistics might perform differently.

Finally, one may wonder whether the pattern of results in the autistic group is related to the use of dichotomic attributes. The study from Bott and colleagues (2006), in which continuous dimensions were used with similar results, suggests that the pattern of results that we obtained is not related to the particular use of dichotomic attributes.

Significance of the conflict effect. After 20 blocks of training, both groups showed an increase in error rates for untrained items that were very similar to a member of one category but belonged to the other category. According to Allen and Brooks (1991), this conflict effect comes from putting some items in the same category as the most similar training item, which supposes a memory for items (exemplar memory). However, both groups performed at chance level in the recognition task (Task 4), which tested exemplar memory. Most importantly, how is the "exemplar memory" effect to be reconciled with the individual response patterns showing no evidence of categorization according to comparison to the most similar training items? We propose that the categorization performance observed could be fully accounted for on the basis of rule application. A thorough analysis of the stimulus structure shows that applying a two-attribute rule is sufficient to produce the so-called "conflict effect" without referring to an exemplar memory (see Appendix). In short, our results show no evidence of either explicit or implicit exemplar memory.

As for when a three-attribute rule is given to the participants (as Allen & Brooks, 1991, did in some of their experiments), Lacroix and colleagues

[4] Going back to the clinical files of the autistic participants from our study, no executive dysfunction was noted among the 13 participants who received a neuropsychological evaluation. Seven had taken the WCST (clinical version, not computerized) and achieved results within the average range, while 6 had taken the Tower of London, also with results within the average range. Also, no evidence of repetitive responding was found in the two categorization tests: A comparable number of participants in both groups provide four or more consecutive answers from the same category (6 autistic vs. 9 nonautistic participants).

(2005) offered an alternative explanation to the conflict effect. They concluded that it could be explained by the idiosyncratic rule attributes and by the context attributes on which attention was brought to bear in Allen and Brooks's experiments. An important finding of the present study is that the poor performance obtained with negative transfer items in a category induction task does not prove exemplar memory either. There is little doubt that exemplar memory effects are a component of categorization mechanisms, but may not be as strong as originally claimed.

Conclusions

This study indicates that perceptual categorization of relatively complex visual information can be successfully performed by autistics of normal intelligence, although not as quickly as in nonautistics. The slower access to the optimum level of categorization is linked to autistic participants taking more time to adopt a definite strategy during the training. This could potentially result from a larger reliance on implicit learning as discussed recently (Dawson et al., 2008). Above all, whatever learning process takes place in autistics, this process ends up being as efficient as that in nonautistics.

Additional studies are needed to pinpoint the specific learning strategies favoured by autistics and the learning contexts that would optimally fit these strategies. In doing so, the present study has highlighted the importance of careful individual analyses in order to reveal these strategies.

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APPENDIX

Decision criteria for individual strategies

For the individual response pattern analysis, data were analysed separately for the two categorization tests. In a first step, the percentage of correct answers was screened to see whether any participant showed perfect or near-perfect (1 error out of 16, i.e., 94%) performance. In those cases, the strategy used by the participant could only be the correct three-attribute rule (remember that using a single diagnostic attribute, a two-attribute rule or eventually memory of exemplars would have yielded an overall accuracy of about 75%). Perfect or near-perfect performance occurred in two cases, 1 nonautistic participant showing an accuracy level of 100% on both tests and 1 autistic participant scoring 94% on the second test.

In a second step, the easiest strategy—that is, classifying on the basis of a single attribute (a one-attribute rule)—was assessed. The five possible one-attribute rules were tested for each participant. A one-attribute rule was hypothesized to be used when the participant's responses matched those predicted by the one-attribute rule for 15 or 16 out of the 16 items (still allowing for at most one error in the application of the rule).

In a third step, all possible two-attribute rules were assessed, except for the rule combining the two nondiagnostic attributes. A rule based on the two nondiagnostic attributes would have been totally uninformative about category membership since all pairs of binary attribute values occurred equally often in both categories in both training and transfer items. Therefore, this combination could not subserve a classification rule. Predictions could be derived from the other possible two-attribute combinations by analysing how the various pairs of values were distributed over categories during training. For example, if one considers head and colour, items with the values 1 and 0 on the two attributes (labelled items 1−0 hereafter) systematically belonged to the Tremblay category during training, whereas items 0−0 belonged to the Beaulieu category (see training items from Table 2). Items 0−1 and 1−1 could belong either to the Tremblay or to the Beaulieu category during training, so that no reliable decisions could be made for these items on the basis of head and colour. Analysis of each participant's responses was therefore limited to those made on the 8 items with consistent values (e.g., 1−0 and 0−0 for the combination head−colour), 4 of which were used during training and the other 4 as transfer items. A two-attribute rule was hypothesized when the participant's answers matched the predictions derived from the rule for 7 or 8 items out of the 8 items selected (allowing for at most one error as for the other strategies; but note that allowing the same percentage of errors, i.e., 1 out of 8 predictions and 2 out of 16 predictions, would have yielded the same patterns of results). The predictions and analyses were of course adjusted to take into account factors counterbalanced between participants (e.g., which of the four rules was used to define category membership and which items were used during training versus test). Finally, participants for which no strategy could be identified after these three steps were considered to have used either no strategy or an unidentified strategy.

If one analyses the response pattern obtained on the basis of each of the two-attribute rules considered (as a function of the category structure illustrated in Table 2), then one realizes that reliance on some two-attribute rules would produce an increase in error rates for negative transfer items. The interested reader may verify in Table 2 that considering head and colour will lead to wrongly classifying some negative transfer items. As previously mentioned, considering head and colour during training will lead to classifying items with values 1−0 as Tremblay and items 0−0 as Beaulieu. It can be seen in the table that some transfer items in the bottom right quadrant will be misclassified. According to the correct answer determined by the three-attribute rule, the negative transfer item 1−0 is a Beaulieu and the item 0−0 a Tremblay. Our analyses revealed that such a conflict effect would occur with four out of the nine possible two-attribute rules considered. Three other two-attribute rules lead to equal performance on positive and negative transfer items, whereas the remaining two rules lead to worse performance on positive transfer items. Unfortunately, by being based on only seven or eight responses, our analyses of the individual participants' strategies were not sufficiently constrained to be able to tell exactly which two-attribute rule was followed by a given participant. Sometimes, a participant's responses matched the predictions of different two-attribute rules. Nonetheless, if one considers the results obtained with participants classified as using a two-attribute rule, then one should find worse performance overall on negative transfer items than on negative old items because this is the result predicted by the largest number of two-attribute rules (four out of nine). Indeed, Figure 3 confirms that for participants using a two-attribute rule, a conflict effect was found—that is, negative transfer items were less adequately classified than training items. This was not true of participants using a one-attribute rule or no rule. In short, reliance on a two-attribute rule leads to the type of conflict effect attributed by Allen and Brooks (1991) to exemplar memory, but, of course, two-attribute rules do not involve or require any memory of the other three attribute values making up each exemplar.

Finally, we tested directly whether exemplar memory could account for the results obtained by the participants. According to the exemplar strategy proposed by Allen and Brooks (1991), participants would first memorize to which category each training item belonged. Having memorized the training exemplars, the participants would then have wrongly classified negative transfer items because they closely resembled learned exemplars belonging to the alternative category. On the other hand, positive transfer items would be correctly categorized because each closely resembled a training exemplar that belonged to the same category. This rationale allowed prediction of the response to all 16 items. These predictions were matched with the response pattern of each individual participant, again allowing at most one error on the part of the participant. At the first categorization test, no participant exhibited exemplar memory (the highest score being 12 predictions correct out of 16). At the second categorization test, the vast majority of participants—30 out of 32—exhibited no exemplar memory; 2 autistic participants, however, could have used exemplar memory. The rule-based analyses previously described revealed the response pattern of each of these 2 participants to match with the application of a two-attribute rule. The category structure and the response patterns do not allow determining unambiguously which of the two strategies was used. However, the use of a two-attribute rule is a more likely and more economical explanation as the majority of participants clearly used a two-attribute rule. Moreover, the data from the recognition task showed results at chance level for 1 participant.