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Unsupervised Categorization in a sample of children with autism spectrum disorders

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ABSTRACT

Studies of supervised Categorization have demonstrated limited Categorization performance in participants with autism spectrum disorders (ASD), however little research has been conducted regarding unsupervised Categorization in this population. This study explored unsupervised Categorization using two stimulus sets that differed in their difficulty of Categorization according to the simplicity model. ASD participants displayed a greater tendency to categorise according to one dimension as compared with mental-aged matched participants in the easily categorised sets, but both ASD and Control groups became more prone to one-dimensional sorting as the difficulty of the Categorization task increased. These results are discussed in terms of the processes underlying over-selective responding.

The ability to categorise items can be regarded as fundamental to many aspects of functioning, and disruptions to this ability may have profound impacts on a person's ability to understand their environment (e.g., Bott, Brock, Brockdorff, Boucher, & Lamberts, 2006; Demetras, Post, & Snow, 1986). Thus, it is important to investigate Categorization abilities across a variety of populations, including in individuals with autism spectrum disorders (ASD). There are many forms of Categorization behaviour, which can be based on quite different mechanisms and principles, and it is important to explore each of these in the context of ASD. For example, some Categorization may be achieved on the basis of learning which items belong to which categories (supervised Categorization), and some categories are the result of intuitive groupings of items (unsupervised Categorization). To date, there have been no investigations of the latter form of Categorization for individuals with ASD, and the primary aim the current report is to document these abilities in individuals with ASD over a variety of circumstances. To make clear, it is important to study Categorisation in this context (i.e., with an ASD population) because there are several quite different explanations which try to explain the cognitive deficits behind ASD (e.g., such as Dube et al., 1999, for attentional deficits or Leader, Loughnane, Mc Moreland, & Reed, 2009, for retrieval deficits). For this reason, Categorization offers a useful means to experimentally assess the ability of this population to perform decisions which have not previously been explored (i.e., unsupervised decisions), thus this has real world applications. To this end, these methods could further our understanding of these cognitive deficits, and potentially lead to more refined screening methods.

Supervised Categorization concerns learning pre-specified categories, where the experimenter determines which items belong to particular categories, and the participant must then learn to which category a new item belongs. In most cases, this is done by trial and error learning, with the participant receiving corrective feedback (e.g., Demetras, Post, & Snow, 1986). Reduced supervised Categorization ability has been noted in children with ASD (e.g., Klinger & Dawson, 2001). This is the difficulty in developing categories when feedback is given (i.e., supervised). In such a case, participants are given corrective

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feedback in terms of the item and its associated category label, which refers to the category to which it belongs. In this study, autistic people had greater difficultly (i.e., it took longer to learn the category labels) as compared with a control population. The study concluded by suggesting that greater over-selectivity in autism was responsible for the reduced ability to learn the category labels associations with the item structures. This over-selectivity was attributed to the cognitive deficits in the ability to learn the category structures, which supported the learning deficits theories.

Similarly, Bott et al. (2006) reported reduced Categorization ability in adults with ASD, even when they ensured that the participants attended to multiple dimensions when learning the category structure. In this study, adults with high-functioning ASD required more time to learn the category structures, and did not display high performance during generalisation. It could be noted that this process of trial and error Categorization learning is rather akin to the simple discrimination learning procedures used in over-selectivity procedures, in which individuals with ASD also display reduced ability to correctly identify all members of a reinforced complex stimulus (e.g., Leader et al., 2009).

In contrast to the work directed at exploring supervised Categorization, little research has been conducted into unsupervised Categorization in individuals with ASD. Unsupervised Categorization refers to the spontaneous Categorization of stimuli where no corrective feedback is given. Participants are given a range of stimuli, and then simply categorise them on the basis of what they feel to be most intuitive; thus, unsupervised Categorization deals with unlearned category coherence (Murphy & Medin, 1985). Thus, an unsupervised Categorization task directly explores intuitive Categorization of items comprising a number of dimensions to which attention must be paid (e.g., Pothos & Chater, 2002; Pothos et al., 2008). The simplicity model (e.g., Pothos & Chater, 2002), is one model of unsupervised Categorization, and assumes that a Categorization can simplify the description (via encoding information, in the simplest of ways) of the objects to be categorised. The prediction is that the greater the simplification, the more intuitive the category structure. In brief, a definition is provided for the information content of the uncategorised items, and for how a Categorization can reduce this information content. The model has been validated in terms of presenting groups of items to naïve participants (in control and dyslexic participants; Nikolopoulos & Pothos, 2009), and asking them to divide the items in a way that seems intuitive (Pothos, Perlman, et al., 2011; Pothos et al., 2008). Also, it is interesting to note that both supervised and unsupervised learning have shared properties, such as, it has been demonstrated that the most intuitive category structures in an unsupervised task are also the most easy to learn in a supervised learning task (Pothos, Edwards, & Perlman, 2011).

However, there have been no investigations of unsupervised Categorization in individuals with ASD, and exploration of these abilities would increase understanding of Categorization abilities for this population as well as the underlying deficits in the cognitive mechanisms of over-selectivity. Most theoretical views of ASD would predict (e.g., the attentional deficit theory, Dube et al., 1999; or encoding, Boucher & Warrington, 1976) that there would be a deficit in unsupervised Categorization. Such an assumption would lead to the hypothesis that, if attention (Dube et al., 1999; Lovaas, Schreibman, & Koegel, 1971), and encoding (Boucher & Warrington, 1976; Reed & Gibson, 2005), deficit views of ASD are correct, then those with ASD would not be able to attend or encode the multiple stimulus dimensions, and, therefore, would perform worse on a two-dimensional unsupervised Categorization task (i.e., there would be a greater number of one-dimensional sorts), compared to a Control group who could attend to both dimensions. Additionally, work from the over-selectivity field has also suggested that, as the task becomes harder, greater levels of over-selectivity would be noted (e.g., Reed & Gibson, 2005). Given this, more one-dimensional sorts would be expected for harder tasks than for easier tasks, and this would be expected to be seen in a more pronounced form in individuals with ASD.

1. Method

1.1. Participants

Twenty-two children (11 with ASD and 11 mental-aged matched typically developing children) were employed. All of these participants had verbal ability. The group with ASD was all diagnosed as having childhood autism by a paediatrician who was independent from the study. The diagnosis was made using a combination of DSM-IV criteria for these disorders and clinical judgment.

The participants with ASD were recruited through specialist educational provisions for young people with ASD, which were attached to mainstream provision, and from those mainstream educational settings for the Control group. Consent for participation was sought from the parents of the children, who completed an ABC questionnaire and returned it if they consented for their child to participate. Participants were not rewarded in monetary terms for participating in the research, and the study was fully approved by the Universities ethical board.

To gauge the approximate severity of the ASD in the sample, the ABC (Autism Behaviour Checklist) was employed (parent-rated). This was conducted for the ASD group only. The ABC measure showed that the mean (standard deviation) of the overall ABC score for this sample was 81.91 (33.33), indicating that this sample was of a higher than average autistic severity (the ABC has a cut off of 67 for probably autism).

The mental age of the group with ASD was matched to the chronological age of the Control group by use of the British Picture Vocabulary Scale (BPVS). The mean chronological age for ASD group was 10.71 (±1.6; range = 8.1–13.6) years, but the mean verbal mental age of the group with ASD, measured by the BPVS, was 10.0 (±2.23; range 7.4–13.8) years. The chronological age of the Control group was 9.92 (±2.03, range = 7.3–13.2) years, with a mean verbal mental age of 10.1 (±2.33, range = 8.2–13.1) years representing a good match on both variables to the group with ASD.

1.2. Defining one vs. two dimensional sorting

For this study, a novel approach to assess over-selectivity in an unsupervised Categorization task was used. This was because, to date, no existing measures have been used in an unsupervised Categorization task with an ASD population. To do this, a simple approach was used to determine a one and two dimensional sort. Any category that used only one of the dimensions of the stimuli was called a one-dimensional category (sort). For example, if a stimulus 'A' had 10 CM legs and 11 CM body, stimulus 'B' had 10 CM legs and 11 CM body, stimulus 'C' had 10 CM legs and 1 CM body, and Stimulus 'D' had 10 CM legs and 1 CM body, and the category made by a participant was 'ABC' in one category and 'D' in a separate category, then the category decision for 'C' would be recorded as a one-dimensional sort. This is because, as the body was very different to the items in its category (only the one dimension of legs was similar), it was more similar to the category D if both dimensions were used. Also, the 'A' and 'B' items would be recorded as a two-dimensional sort as these had very similar dimensions of both body and legs (identical in this example). To make this point more specific, the preferred two dimensional classifications were used as suggested by the simplicity model to compare the participant's categories against (see Fig. 2). If items were categorised in the same way as the model suggested then they were recorded as two dimensional sorts, if they were categorised in a similar way to the example above, which did not match the predictions made by the model, then they were recorded as one dimensional sorts. There was also a third type of sort that was recorded, 'other'. 'Other' sorts were recorded when items were placed by themselves and were clearly neither one nor two dimensional sorts, and were then discarded.

2. Materials

2.1. Categorization stimuli

For this study, the stimuli and procedure were identical to those employed by Pothos et al. (2008), and Pothos, Edwards, et al. (2011) and Pothos, Perlman, et al. (2011). A summary of the materials is given here (see Pothos, Edwards, et al. 2011; Pothos, Perlman, et al., 2011, for full details of computational details of the simplicity model used). The stimuli were created which resembled spiders, and had two relevant features, the body and the legs. The sizes of the legs and body were altered, between 40 mm and 80 mm (using a Webber fraction of 8%), so that the stimuli sets were presented in terms of different levels of how intuitive these were (i.e., low intuitiveness and high intuitiveness). The stimuli were presented on individual cards. See Fig. 1 for an example of the stimuli that was used.

In Pothos et al. (2008), Pothos, Edwards, et al. (2011) and Pothos, Perlman, et al. (2011) they used the simplicity model to predict category intuitiveness in unsupervised Categorization, and how easy it would be to categories each stimulus set. Intuitive refers to how easy the categories are to Categorize, i.e., the ability to place these into groups without any learning of the possible category structures. When given a set of stimuli based on two dimensions (legs and body), the model predicts how best the categories (or clusters) should be organized. This organization by the model (codelength) is a complex term,

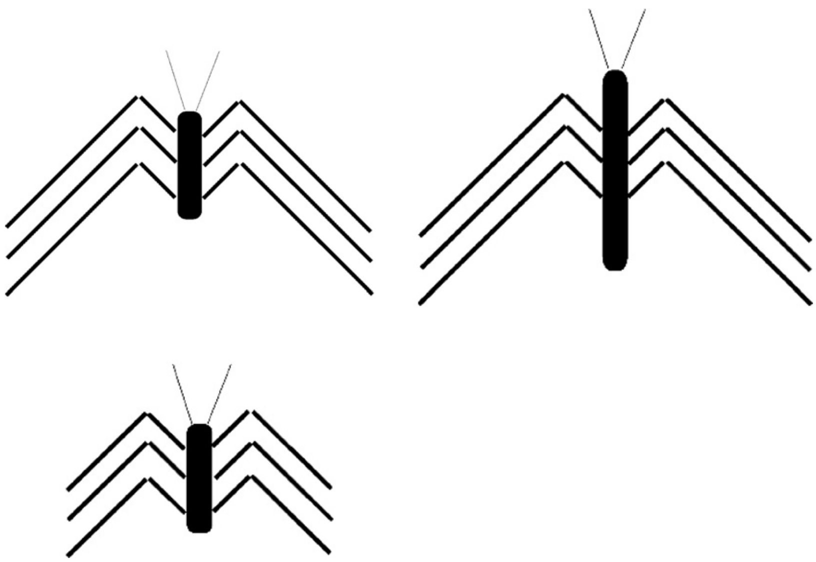

Fig. 1. A representation of the stimuli used in all experiments, where the body and legs of the items change between items.

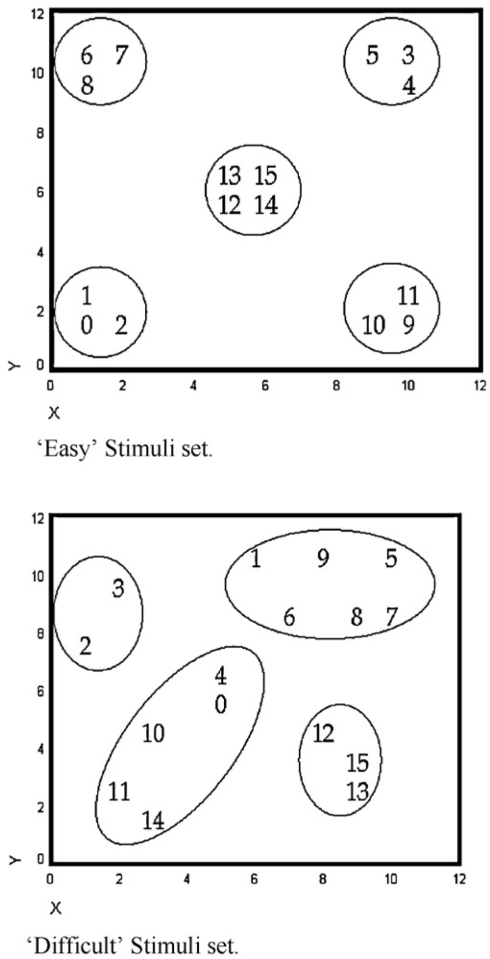

Fig. 2. Stimuli spread, *x*-axis refers to the body and the *y*-axis refers to the height of the items in CM. These are the classifications predicted as most intuitive by the simplicity model (Pothos & Chater, 2002). The top image refers to the Five Cluster, 5347, 'Easy' stimuli set and the lower one the Random Cluster, 5150, 'Difficult' stimuli set.

referring to computational complexity, and the reduction of codelength, where maximum within group similarity and minimum between group similarity is sought (see Pothos et al., 2008). The suggested categories by the model correspond to how participants without cognitive deficits, categories these items. For the present paper, the only concern should be these suggested categories (see Fig. 2) produced by the simplicity model on the basis of two dimensions, and not how the computational term is produced.

Crucially, Pothos et al. (2008), Pothos, Edwards, et al. (2011) and Pothos, Perlman, et al. (2011) demonstrated that, of the two suggested categories that were used in this study, 'Five Clusters' (see Fig. 2) was the easiest. It had the highest frequency of preferred classifications, where most participants selected the categories for this stimulus set as predicted by the model, and 'Random Cluster' was more difficult as there were less frequency of preferred Categorization as predicted by the model. Note, that in Pothos et al. (2008), Pothos, Edwards, et al. (2011) and Pothos, Perlman, et al. (2011), the DV for ease of Categorization was the frequency of preferred. For this present paper, the only concern is that the easier category, 'Five Clusters', should show fewer one-dimensional sorting for both Control and ASD groups, as compared with 'Random Cluster', but for both sets, ASD participants should demonstrate more one-dimensional sorting. This is because 'Five Clusters' is predicted to be more intuitive by the model, and thus easier to categorize, and the ASD group should over-select due to attentional deficits, and more so than a Control group.

2.2. Autism Behaviour Checklist

Autism Behaviour Checklist (ABC) is a 57-item checklist, where a total score of 67 or more is taken by to suggest *probable* autism. Reports on reliability have been high, although the convergence between the ABC and other instruments has not been good. Thus, it is important to note that the measure may not give a similar picture of the child's autism as other instruments, although it was still considered useful as: (1) no special training in administration or scoring is required, and, in the current study, it was to be completed by parents; and (2) it was to be used as a research tool gauging the relative effects of autistic symptomatology across the participants, rather than to make absolute judgements regarding the impact of symptoms.

2.3. British Picture Vocabulary Scale

British Picture Vocabulary Scale (BPVS) is derived from the Peabody Picture Vocabulary Scale, and measures receptive language ability. The BPVS is standardized for use on children in the UK between 3- and 17-year-old, and gives an age equivalent score for this ability. It has an internal reliability of 0.93 (Cronbach's alpha), and has a 0.59 correlation with the Reynell Comprehension Scale.

3. Procedure

Testing occurred in a quiet room containing a table and two chairs in the child's school. The participant and the experimenter sat opposite each other across the table. A particular stimuli set was spread out on a table in front of the participant. The participant was then given instructions to classify the items into groups using both the dimensions of body and legs, in the way that they felt was the most intuitive. They had as much time as they wanted to complete the task. Once this set had been categorised, the participant was given the second set immediately (there were, in total, two sets with 16 items each). The sets were presented in a random order across the participants. Participants with ASD and the Control group were then given the BPVS.

4. Results

Table 1 shows the number of classifications that were made by the two groups that were classified as either one or two dimensional across the two tasks (easy and hard). Inspection of these data shows that for the easy set, both groups produced more two dimensional classifications than one dimensional sets, but that this tendency was more pronounced for the matched Control group than the group with ASD, thus the ASD group made more one-dimensional sorts. For the difficult set, there were fewer two dimensional sorts for both groups, but this tendency was more pronounced for the group with ASD, who demonstrated more one-dimensional sorts than the Control group.

A mixed two-factor analysis of variance (ANOVA) was used with participant group (ASD or Control) as the between factor and the Categorization task difficulty (easy or difficult) as the within level, with one-dimensional sorts as the DV. The results $F(1) = 22.15$, $P < 0.01$ for the main effect, task difficulty, showed a significant increase in one-dimensional sorts, when task difficulty was increased. However, when comparing the interaction between difficulty and participant group (ASD or Control), then the results were $F(1) = 0.15$, $P = 0.69$, and were not significant, suggesting less of a difference between the ASD and Control groups. The main effect for groups ASD and Control was $F(1) = 1.992$, $P = 0.087$, which is a boarder significance.

To further understand the specific differences, a series of t-tests were used to identify the specific interactions. As with all multiple-post hoc tests, a Bonferroni correction should be assumed as a conservative estimate for alpha (in this case 0.01). For ASD vs. Control in the easy task difficulty, $t(20) = 1.78$, $P = 0.045$, which indicated that for the easy set the ASD group were making significantly more one-dimensional sorts (marginally greater than the conservative correction). However, for the ASD vs. Control in the difficult task, $t(20) = 0.958$, $P = 0.18$,which demonstrated no significant difference between the ASD and Control group for one-dimensional sorts, in this more difficult task.

When comparing Easy vs. Difficult task difficulty in the ASD group, $t(20) = 2.12$, $P = 0.024$, demonstrated the task difficulty significantly increased one-dimensional sorts for the ASD group (again, marginally greater than the conservative correction). This was also found for the Easy vs. Difficult task difficulty in the Control group, $t(20) = 2.466$, $P = 0.01$, so task difficulty also significantly increased one-dimensional sorts in the Control group. These additional t-tests are important to demonstrate that for both ASD and Control groups, the task difficulty (difficult stimuli set) significantly increased one-dimensional sorts.

5. Discussion

The present study explored the conditions under which over-selectivity in an unsupervised Categorization task was made when comparing between an ASD and Control population. Further to this, task difficulty in this unsupervised task was also explored for over-selectivity.

Table 1
Categorizations of stimuli sets by both groups.

	ASD		Control	
	One dimensional	Two dimensional	One dimensional	Two dimensional
Easy	13	33	5	51
Difficult	24	25	18	42

The main findings of the study show, through the ANOVA, that there was an overall increase in over-selectivity (one-dimensional sorting) when task difficulty was increased but no significant difference when comparing with the ASD and Control groups. However, the post hoc *t*-tests showed that there was a significant difference (marginal after the Bonferroni correction) between the ASD vs. Control groups for the easy condition but not for the difficult condition. This latter finding demonstrates that when task difficulty increases so does one-dimensional sorting, even in the Control group, and supports Reed and Gibson (2005). This is also supported by the other main finding that when comparing the Easy vs. Difficult conditions using *t*-tests it was shown that for both groups, ASD and Control, over-selectivity (one-dimensional sorting), significantly increased.

These findings demonstrate that there is, generally, greater over-selectivity for the ASD group as compared to the Control group for easy unsupervised Categorization tasks, but when the difficulty of these tasks increase, then this is not the case, as there is also over-selectivity in the Control group.

The findings generally support the work of Bott et al. (2006), who found over-selectivity in supervised Categorization tasks, where both supervised and unsupervised learning use the ability to represent similarity, and category coherence (Pothos, Edwards, et al. 2011). The interesting novel finding here is that, unlike supervised learning, unsupervised tasks have no learning in these tasks, so over-selectivity due to learning and memory can be excluded in this study as possible reasons for the over-selectivity. The possible explanations here are the mechanisms of attention and encoding. These findings, thus provide, further evidence in support of attentional and encoding mechanisms of over-selectivity such as attention deficits (e.g., Dube et al., 1999) and or encoding problems (e.g., Boucher & Warrington, 1976).

The obvious limitations to such an experiment are that in terms of Categorization, unsupervised Categorization represents only one area of a much larger research area. There are several other areas which can be explored in the future, which makes this research interesting.

Further to this, the idea of category coherence can be further investigated with additional studies exploring background information, and how concepts are learned in ASD populations. For example, by identifying that autistic children have deficits in how they learn concepts may help identify new learning strategies for these populations, where more emphasis could be made towards category learning as well as the traditional methods used. These could be identifying and training more thoroughly the dimensions of colour, size, function etc., of concepts, where little work has been carried out in these domains.

This work has the potential to further help the understanding of the basic mechanisms behind over-selectivity. It could also allow for future investigations to explore ways in which the tailor-making of better screening methods for the early detection of autism in young people could be possible. For example, there may be many causes of over-selectivity and many cognitive mechanisms defective in an ASD individual. There may also be differences from one ASD person to another, in that for one ASD individual there may be more defects in attention as opposed to learning or memory, in another ASD individual it may be that learning or memory are the causes for their over-selectivity. It is only through a broad range of tailor-made screening methods that this could be assessed, and only through a broad range of investigations, exploring all aspects of cognition, can such methods be identified.

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