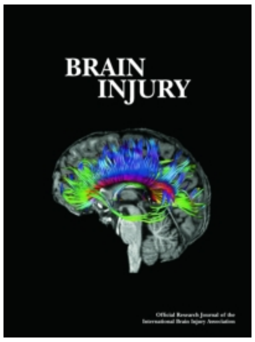

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ORIGINAL ARTICLE

Unsupervised categorization with individuals diagnosed as having moderate traumatic brain injury: Over-selective responding

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Abstract

Primary objective: This study explored over-selectivity (executive dysfunction) using a standard unsupervised categorization task. Over-selectivity has been demonstrated using supervised categorization procedures (where training is given); however, little has been done in the way of unsupervised categorization (without training).
Methods and procedure: A standard unsupervised categorization task was used to assess levels of over-selectivity in a traumatic brain injury (TBI) population. Individuals with TBI were selected from the Tertiary Traumatic Brain Injury Clinic at Swansea University and were asked to categorize two-dimensional items (pictures on cards), into groups that they felt were most intuitive, and without any learning (feedback from experimenter). This was compared against categories made by a control group for the same task.
Outcomes and results: The findings of this study demonstrate that individuals with TBI had deficits for both easy and difficult categorization sets, as indicated by a larger amount of one-dimensional sorting compared to control participants. Deficits were significantly greater for the easy condition.
Conclusions: The implications of these findings are discussed in the context of over-selectivity, and the processes that underlie this deficit. Also, the implications for using this procedure as a screening measure for over-selectivity in TBI are discussed.

Keywords

Unsupervised categorization, traumatic brain injury, over-selectivity, cognition, simplicity model

History

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Introduction

Category learning is an essential part of making sense of the world around us, by organizing information most efficiently through an information minimization approach. Disruption in the ability to form categories has been shown to translate into difficulties with learning language and perceptual discriminations [1,2]. It is, therefore, important to study categorization abilities in several different populations, including people with TBI, because this is a condition which predominantly implicates the prefrontal cortex, often without serious impairment of measurable aspects of memory or intellectual ability [3,4]. Instead, and more frequently, deficits in decision-making and planning daily activities are present [5], as well as the flexibility of rule use as part of executive function [6,7]. In experimental settings, the prefrontal cortex has been shown to be important when completing complex tasks which require explicit rules, such as those found in categorization tasks [8]. In addition to this, individuals with TBI have demonstrated a lack of ability in making categorical discriminations between the different features of objects [9].

There are many types of categorization paradigms and each relies upon different aspects of cognition. For example, supervised categorization [2], which uses feedback from the experimenter to learn which items belong to which existing categories. In experiments, the participant is given several items and receives corrective feedback when an item is placed in the wrong category. Categorization attempts to identify how individuals build knowledge about the world, by understanding how information about items around them is used (e.g. dimensions, colour, semantics, etc.) to form categories. A real world example of this could be learning the category of 'table' or 'chair' for the first time. A table can have several shapes (long, short), colours, functions (to eat, to work), possible labels (table, desk), etc. When learning this for the first time, corrective feedback is given from the environment (maybe a parent or a teacher in this case), allowing the individual to learn and eventually form a complete category concept for 'table'. Experiments using supervised categorization procedures have demonstrated that, after TBI, individuals have difficulty abstracting from a prototype. Prototype abstraction is a form of supervised categorization (where corrective feedback is given) that helps individuals learn the pre-specified category structure of a set of items when given feedback about whether their decisions are correct (i.e. using the average representation of a learned category and applying it to other situations) [10].

Research in autism spectrum disorders [2] has indicated that over-selectivity (the inability to process all the dimensions of items) is responsible for an inability to abstract prototypes.

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Although autism is quite different from TBI, both populations have demonstrated over-selective responding (attentional/category coherence problems) with categorization tasks. Over-selectivity (the dependent measure in the present study) is where an individual uses some parts of the environment at the expense of others (e.g. placing too much attention on one property of the items and ignoring or failing to process others) [2]. Various cognitive deficits lead to over-selectivity and there are the interventions used to remediate them [11]. Over-selectivity in an autistic population has been attributed to attentional deficits [12], learning deficits [2] and retrieval deficits [13]. Also, over-selectivity in supervised categorization tasks has been identified in other clinical conditions, such as TBI [10,14].

The current study uses an unsupervised categorization procedure [11] which involves no learning on the part of the participant. It is based, instead, on the intuitive similarity of items [15]. For example, the participant is given a range of items and must categorize these on the basis of what they feel is most intuitive, based on category coherence [16]. Unsupervised categorization is, therefore, based on attentional and coherence aspects of cognition, as there is no pre-defined rule from which to learn how to categorize. For example, when you see items which you have never encountered before, you could group them into categories which you feel best discriminates the items, maybe based on size or colour, etc., but there will be no, or very little, semantic information upon which to base the category decision. This type of task is designed to explore categorizing without prior learning, based on more attentional/category coherence mechanisms and not learning mechanisms. The identification of specific cognitive deficits (i.e. over-selectivity) during unsupervised categorization in TBI could have important implications for the types of interventions used and developed in clinical practice, for example, assessing attentional/coherence based over-selectivity (through unsupervised categorization procedures) as well as more learning based over-selectivity (as found with supervised categorization procedures).

Up to this present time, there has been no research examining the abilities of a TBI population using the unsupervised categorization paradigm, which is the primary aim of this study. The over-selectivity in a TBI population when using a supervised task makes it reasonable to assume that over-selectivity will be found in an unsupervised task because, although these tasks use different cognitive processes, TBI patients tend to have short-term decision and planning-based problems [5], which is consistent with the type of cognition the unsupervised categorization task demands. Therefore, it is likely that the TBI population will display greater over-selectivity compared to the control group.

Method

Participants

The TBI population was selected from a cohort referred to the Head Injury Clinic at Swansea University (n = 44). Patients were referred because they exhibited long-term executive deficits which affected their everyday activities and imposed constraints on community independence. In all cases, the presumption of executive deficits was based on reports made by the patient's relatives, then confirmed through a semi-structured clinical interview.

TBI severity was determined by Glasgow Coma Scores at the time of hospital admission (GCS = 9.54, SD = 1.2), indicating moderate brain injury. The mean time between injury and participation was 3.2 years (SD = 1.1). The control group were 44 members of the general public that were matched for age (TBI = 34.7, SD = 12.2; control = 36.2, SD = 13.5) and intelligence (TBI mean IQ = 98.3, SD = 12.6; control IQ = 99.4, SD = 14.7) as measured by the WAIS III [17].

The categorization task

A standard approach for measuring one vs two dimensional sorting was employed as in previous studies [11,18–20] (see Figure 1). Stimuli were based on two dimensions (body and legs) and the experimenter counted how many categorization sorts used both the leg and body dimensions. If the participant categorized all big leg items with other big leg items and all small leg items with other small leg items, but ignored the body size for any of the items, then this would be classified as a one-dimensional (over-selective) sort. A simple example is of four items with different dimensions, e.g. Item A, legs at 10 cm, body at 11 cm; Item B, 10 cm for legs and 11 cm for body; Item C, 10 cm for legs, 1 cm for body; and Item D, 10 cm for legs and 1 cm for body. If the category 'ABC' was made and 'D' was categorized as separate then 'C' would be counted as a one dimensional sort (one count of over-selectivity), as only the one dimension of legs was used and not body. If both dimensions had been use, then two categories of 'AB' and 'CD' would have been produced. This would, therefore, have been counted as two, two-dimensional sorts and no counts of over-selectivity.

Figure 2 illustrates this point with a more specific example for an Easy Categorization task. A category formation of {0, 1, 2} {6, 7, 8} {5, 3, 4} {11, 9,10} {12, 13, 14, 15} is suggested by the simplicity model [11,18–20], which optimizes items within categories based on the number of dimensions used when categorizing items using two dimensions. If a classifica-

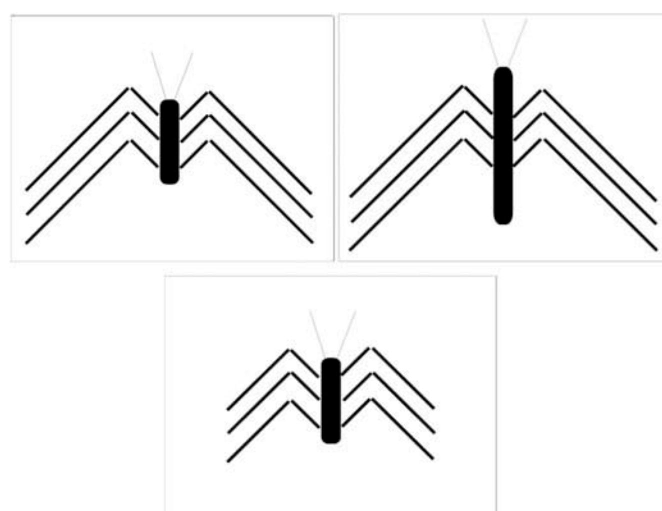

Figure 1. A representation of the stimuli used in all experiments, where the body and legs of the items change in size between items.

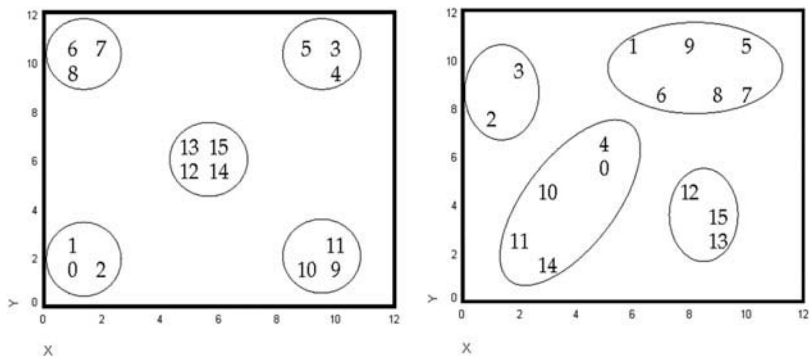

Figure 2. Stimuli spread, x-axis refers to the body and the y-axis refers to the height of the items in CM. These are the classifications predicted as most intuitive by the simplicity model [15]. The top image refers to the Five cluster, 'Easy' stimuli set and the lower one the Random cluster, 'Difficult' stimuli set.

tion is made whereby 10 is categorized with {0, 1, 2} instead of {11, 9} then that would be recorded as one count of over-selectivity (one dimensional sorting), as one of the dimensions of 10 is identical in size to that of the items (0 and 2) in the category {0, 1, 2}, whilst the other dimension is completely different in size. This would suggest that the participant was not using both dimensions, which would produce a category {11, 9, 10}, where both dimensions are similar in size, as suggested by the simplicity model [11,21–23]. If the outcome category {0, 1, 2, 10} was created then this would demonstrate that the participant would only be using a single dimension in categorizing the item and, therefore, an example of over-selectivity (one dimensional sorting).

For this study (see Figure 1) the stimuli used resembled simple two dimensional schematic representations (spiders) with two dimensions that were altered between stimuli, the legs and the body, which were between 40–80 mm (using a Weber fraction of 8%; see Pothos et al. [22] for a full explanation of the computational principles). The stimuli were presented on individual cards and each set (two sets in total) had 16 items, each differing in how intuitive (how easy) they were to categorize. The simplicity model was used [21–23] to develop the category structure in terms of how easy or difficult (how intuitive) they were to categorize. When given several items in a set of stimuli using two dimensions, the simplicity model uses the spatial distances between the items dimensions, by attempting to reduce the spatial distance and the number of comparisons needed, using categories. The organization of the model is complex and uses a computation term of code-length to identify maximum within-group similarity and minimum between-group similarity [21–23]. What is important in terms of the present study is not the complex way the model computes the categories, but that the outputted categories of the simplicity model are those which are optimal for using two dimensions when given particularly noisy stimuli sets, a finding validated with large participant numbers [21–23]. Again, this model was used just to develop the category structures (i.e. to give sizes for the legs and bodies for each item) in terms of easy and difficult. It is not used in any analysis for this present study. The two categories used in this study, based on the simplicity model (see Figure 2) were 'Five Clusters', which is the easiest, and the 'Random Clusters', which is the more difficult to categorize.

Procedure

Participants were assessed individually. Stimuli were shuffled and taken out of a folder in random order then spread out on a large table. Instructions were provided (in scripted form) which asked the participant to categorize the items in a way they felt was most intuitive based on perceptions of similarity. They were also instructed that similar objects should end up in the same categories and that any number of categories were allowed. There was no time limit on this task; however, the task typically lasted just a few minutes. Participants were not influenced in how they made the categories and, if they asked any questions during the task, they were redirected to the instructions. The stimuli sets were shuffled after each participant. The sets were also counterbalanced between participants so that there were no order effects.

Results

Table I shows the number of one-dimensional classifications that were made by the TBI and the control group for the conditions Easy and Difficult. On inspecting the data, both TBI and control groups produced more one-dimensional (over-selective) sorts for the Difficult condition, as compared with the Easy condition. The TBI population had a greater number of one-dimensional sorts for both the Easy and Difficult conditions compared to the control group.

A mixed two-factor Analysis of Variance (ANOVA) was used with participant group (TBI or control) as the between factor and the categorization task difficulty (Easy or Difficult) as the within level, with the number of one-dimensional sorts (over-selectivity) as the DV. The results showed a significant increase in the number of one dimensional sorts for both groups when task difficulty increased ($F(1, 86) = 113.628$,

Table I. The mean and standard deviations of one dimensional sorting between the control and TBI conditions as well as within the category difficulty conditions.

	Control	TBI
Easy	0.3 (0.59)	1.05 (0.65)
Difficult	1.7 (1.07)	2.05 (0.68)

$p < 0.001$, for the main effect, task difficulty). When comparing the interaction between task difficulty and participant group (TBI or control), the results indicated that the number of one-dimensional sorts made by TBI and control groups were significantly different ($F(1, 86) = 3.277$, $p < 0.05$) which suggests (along with the descriptive statistics) that the TBI had significantly more one-dimensional sorts, compared to the control, across both conditions. Crucially, the interaction shows that the data for both groups were ordinal, allowing the main effect to be supported. The other main effect, the number of one dimensional sorts between groups, was significant ($F(1, 86) = 22.599$, $p < 0.001$), indicating that the TBI group had a greater number of one-dimensional sorts compared to the control group.

To analyse this further, a series of *t*-tests were used to compare post-hoc interactions and a Bonferroni correction was used as a conservative estimate for alpha (0.01). For TBI vs control in the Easy condition the results (which along with the descriptive statistics) show that the TBI group were making more one-dimensional sorts as compared with the control group for the Easy condition (where $t(86) = 6.051$, $p < 0.001$). In the Difficult condition the results again indicated that the TBI group made more one-dimensional sorts as compared to the control ($t(86) = 1.784$, $p = 0.04$), although this was above the conservative Bonferroni corrected alpha of 0.01. For the TBI group, Easy vs Difficult categorizing was significantly different ($t(43) = 7.46$, $p < 0.001$), indicating there were more one-dimensional sorts for the difficult condition. Finally, for the control group, Easy vs Difficult, categorizing revealed more one-dimensional sorts for the more difficult condition as compared to the Easy condition ($t(54) = 8.518$, $p < 0.001$).

Discussion

The present study explored whether there would be greater levels of one-dimensional sorts in a TBI population as compared to a control using a standard unsupervised categorization task with two levels of task difficulty. One-dimensional sorts were used as an indicator of over-selectivity in both the TBI and control populations.

The main findings were that there were more one-dimensional sorts when the task difficulty increased for both groups and that the TBI group displayed more one-dimensional sorts than the control group in both the Easy condition and the Difficult conditions (in the Difficult condition it was marginally non-significant when using a conservative Bonferroni correction).

The findings demonstrate that the TBI population were over-selecting when using an unsupervised categorization task. This means they have difficulty with tasks involving attention and category coherence, which is consistent with other work [24]. They also demonstrated that, by increasing task difficulty, over-selectivity increases, both in control and clinical populations. These findings are also largely consistent with work conducted in the area of autism, when using the same task [11]. Although autism and TBI are very different clinical disorders, there may be some commonality in the types of cognitive processes being deficient (under-developed or damaged); therefore, some of the interventions and protocols for treatment and diagnosis (especially in relation to diagnostics for over-selectivity) may be useful for both populations. However, this is entirely speculative at this stage and would need much further work to verify.

In terms of the present results, evidence is given which seems to support the case for attentional/coherence-based deficits, as unsupervised categorization does not involve aspects of learning (whereas supervised categorization does). This does not mean that learning-based deficits are not present in TBI when using categorization tasks. The results are also complimentary to previous work [2] and help provide a bigger picture of cognitive deficits in a TBI population in relation to over-selectivity and categorization.

In terms of potential applications, these findings have important implications for possible methods for screening over-selectivity in a TBI population and identifying the most appropriate forms of interventions to reduce over-selectivity in this group. It will also be important to study other types of category learning in TBI populations, such as relational category paradigms [25], using abstract relational properties (such as ‘bigger than’ and ‘smaller than’) based on inference learning, rather than specific dimensional sizes, when categorizing. As such, this work may also be integrated into broader models of categorization, based on cognitive and behavioural science [26], to allow for specific TBI intervention protocols being developed which could diagnose and remediate over-selectivity.

Further studies could explore milder forms of TBI to see whether similar cognitive deficits of over-selectivity occur, as there should be no expectation that there should be until empirically verified. Finally, an exploration could be made in terms of how these findings fit in terms of neurological mapping of over-selectivity through fMRI work. To date, fMRI work has not been conducted specifically for over-selectivity. This would potentially allow new ideas from empirical findings to further develop the theoretical and applied levels of research into cognitive dysfunction after brain injury. It would also allow for further understanding as to the very specific cognitive components involved in over-selectivity in TBI. For example, it could provide support for an attentional, retrieval or information process based theory. These are all exciting avenues of research for the future.

Declaration of interest

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

References

1. Demetras MJ, Post KN, Snow CE. Feedback to first language learners: the role of repetitions and clarification questions. Journal of Child Language 1986;13:275–292.
2. Bott L, Brock J, Brockdorff N, Boucher J, Lamberts K. Perceptual similarity in autism. The Quarterly Journal of Experimental Psychology 2006;59:1237–1254.
3. Bigler ED. The lesion(s) in traumatic brain injury: implications for clinical neuropsychology. Archives of Clinical Neuropsychology 2001;16:95–131.
4. Burgess PW. Strategy application disorder: the role of the frontal lobes in human multitasking. Psychological Research 2000;63:279–288.
5. Wood RLI. Understanding neurobehavioural disability. In: Wood RLI, McMillan TM, editors. Neurobehavioural disability and social handicap following traumatic brain injury. Hove (UK): Psychology Press; 2001. p 1–28.

6. Ord JS, Greve KW, Bianchini KJ, Aguerrevere LE. Executive dysfunction in traumatic brain injury: The effects of injury severity and effort on the Wisconsin Card Sorting Test. Journal of Clinical and Experimental Neuropsychology 2010;32: 132–140.
7. Wood RLI, Bigler ED. Assessment of neurobehavioural disability. In: McMillan TM, Wood RLI, editors. Neurobehavioural ability and social handicap. 2nd ed. London: Psychology Press; 2016.
8. Minda JP, Desroches AS, Church BA. Learning rule-described and non-rule-described categories: a comparison of children and adults. Journal of Experimental Psychology: Learning Memory & Cognition 2008;34:1518–1533.
9. Constantinidou F, Thomas RD, Scharp VL, Laske KM, Hammerly MD, Guitonde S. Effects of categorization training in patients with TBI during post-acute rehabilitation. Journal of Head Trauma Rehabilitation 2005;20:143–157
10. Wayland S, Taplin JE. Feature-processing deficits following brain injury. Over-selectivity in recognition memory for compound stimuli. Brain and Cognition 1985;4:338–355.
11. Edwards DJ, Perlman A, Reed P. Unsupervised categorization in a sample of children with autism spectrum disorders. Research in Developmental Disabilities 2012;33:1264–1269.
12. Dube WV, Lombard KM, Farren KM, Flusser DS, Balsamo LM, Fowler TR. Eye tracking assessment of stimulus over selectivity in individuals with mental retardation. Experimental Analysis of Human Behavior Bulletin 1999;17:8–14.
13. Leader G, Loughnane A, Mc Moreland C, Reed P. The effect of stimulus salience on over-selectivity. Journal of Autism and Developmental Disorders 2009;39:330–338.
14. Gibson JJ. The ecological approach to visual perception. Boston (MA): Houghton-Mifflin; 1979.
15. Pothos EM, Chater N. A simplicity principle in unsupervised human categorization. Cognitive Science 2002;26:303–343.
16. Murphy GL, Medin DL. The role of theories in conceptual coherence. Psychological Review 1985;92:289–316.
17. Wechsler D. Wechsler Adult Intelligence Scale – third UK edition. London (UK): The Psychology Corporation; 1998.
18. Edwards DJ. Unsupervised categorization with a child sample: category cohesion development. To be published in European Journal of Developmental Psychology/[Preprint] 2016 [cited 23 March 2016]. Available from: http://www.tandfonline.com/doi/abs/10.1080/17405629.2016.1158706?journalCode=pedp20.
19. Milton F, Longmore CA, Wills AJ. Processes of overall similarity sorting in free classification. Journal of Experimental Psychology: Human Perception and Performance 2008;34:676–692.
20. Wills AJ, Inkster AB, Milton F. Combination of differentiation? Two theories of processing order in classification. Cognitive Psychology 2015;80:1–33.
21. Pothos EM, Perlman A, Edwards DJ, Gureckis TM, Hines PM, Chater N. Modeling category intuitiveness. In Proceedings of the 30th Annual Conference of the Cognitive Science Society, LEA: Mahwah (NJ); 2008.
22. Pothos EM, Perlman A, Bailey TM, Kurtz K, Edwards DJ, Hines P, McDonnell JV. Measuring category intuitiveness in unconstrained categorization tasks. Cognition 2011;1:83–100.
23. Pothos EM, Edwards DJ, Perlman A. Supervised vs. unsupervised categorization: two sides of the same coin? Quarterly Journal of Experimental Psychology 2011;64:1692–1713.
24. Reed P, Gibson E. The effects of concurrent task load on stimulus over selectivity. Journal of Autism and Developmental Disorders 2005;35:601–614.
25. Edwards DJ, Pothos EM, Perlman A. Relational Vs. absolute representation in categorization. American Journal of Psychology 2012;125:481–497.
26. Edwards DJ. Integrating behavioural and cognitive psychology: a modern categorization theoretical approach. New York (NY): Nova Science Publishers; 2015.