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Categorization behaviour in adults, adolescents, and attention-deficit/hyperactivity disorder adolescents: A comparative investigation

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Although significant progress has been made with respect to our understanding of categorization and concept learning behaviour in adults, much less is known about how this key capacity plays out with respect to more restrictive populations. This is unfortunate because much may be revealed about the nature of concept learning by examining the limits exhibited by special populations. With this tenet in mind, in what follows, we investigated key aspects of concept learning in terms of the unexplored comparative performance of three populations—adults, adolescents, and adolescents with attention-deficit/hyperactivity disorder (ADHD). To do so, we employed a novel *parainformative* experimental task involving categorical stimuli with four objects defined over three dimensions. The learning difficulty ordering for these types of three-dimensional stimuli has proven robust and has been replicated by several researchers. Indeed, in our experiment, we observed the same concept learning ordering in adults and adolescents, but not in ADHD adolescents: For example, the latter group showed greatly impaired categorization performance on stimuli characterized by an “exclusive-or” rule. However, categorization performance on such type of stimuli indicated good reliability in discriminating between adolescents with and without ADHD (receiver-operating characteristic, $ROC = .82$). We accurately predicted and accounted for these results using generalized invariance structure theory (GIST; Vigo, 2013). The GIST of concepts. *Cognition*, 129, 138–162), which posits that organisms detect invariance patterns in stimuli that are necessary precursors to concept formation.

Keywords: Concept learning; Individual differences learning; Categorization; Attention-deficit/hyperactivity disorder; Generalized invariance structure theory; Cognitive modelling.

The ability to learn concepts is a cornerstone of human cognition. More than any other capacity, it reflects how various other key high-level cognitive facilities,

such as attention, similarity assessment, and memory, work in concert to achieve a singular aim: the sparse representation of complex information.

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Given this unique status, it is surprising that most of the robust and replicable findings concerning concept learning have involved only adult learners as the target population. Yet, there are key human populations, such as young children, adolescents, and those impaired by particular psychological disorders, that may or may not obey the same patterns of conceptual behaviour of the “average” adult. This is important because, if significant differences in performance are found between populations, theories of concept learning would be expected to be able to account for these differences. Indeed, such individual differences would serve not only to further test the validity of existing theories, but to better understand and identify the factors that influence the ability of humans to learn concepts. Thus, in what follows, we investigate the concept learning performance of three populations: adults, adolescents, and adolescents with ADHD. We believe that the study of these three populations in particular can help identify some of the cognitive limitations and factors that influence human concept learning.

For example, with respect to adolescents in general, psychologists have long hypothesized that humans experience gradual increases in their ability to comprehend the world around them—or in other words, in their ability to form concepts—from birth through adolescence, to adulthood. In fact, one of the most important open problems in developmental psychology concerns the factors that determine the exact nature of human concept learning performance throughout its developmental course. For example, Piaget (1952) was among the first psychologists to propose that children on the way to adulthood experience stages of conceptual development and do not begin to form logical concepts until the ages of 7 to 11. Furthermore, he believed that it is not until the ages of 11 to 16 and onwards that abstract reasoning concepts are acquired. These observations have been challenged and revised (Case, 1985, 1992a, 1992b; Furth & Wachs, 1974), but in spite of this debate the precise nature of the conceptual development of humans from the various stages of childhood through the stages of adolescence by and large has not been articulated with the same level of rigour and precision seen in formal theories of human categorization. These theories have focused only

on concept learning in adults. Yet, over the past 30 years, a number of significant empirical discoveries and mathematical models of concept learning (for a survey see Murphy, 2002) and classification behaviour have given researchers the tools necessary to probe into a key question about the nature of concept learning and classification performance—namely, what are the cognitive mechanisms that may account for the differences exhibited by children, adolescents, and adults in their ability to learn concepts?

There are three factors that have undermined progress toward answering this question: First, no concept learning and categorization data are available based on a set of standard and robust concept learning experimental paradigms that involve a wide range of developmental populations. Second, conceptual behaviour in children and adolescents has typically not been investigated using mathematical and computational models. Third, disorders/impairments that can provide insight and “negative knowledge” as to the nature of concept learning in children and adolescents have not been systematically and thoroughly studied from the standpoint of categorization performance.

Instead, much research regarding concept learning in children and adolescents has been qualitative in nature, involving a wide variety of real-world concepts, and focused on typical populations (for a historical survey see Borstelmann, 1974). In this report, we conduct a categorization experiment on adults and on adolescents with and without attention-deficit/hyperactivity disorder (ADHD) in order to gain insight into the range of behaviours underlying concept learning and categorization performance. In particular, we use a recent quantitative theory of concept learning named generalized invariance structure theory or GIST (Vigo, 2013) to predict and explain our empirical findings and to explore their potential in determining population membership.

Modes of stimulus processing

When processing compound stimuli, such as a set of objects, it has been argued that there are two modes of processing at play. One mode involves the analytic decomposition of objects into their features and dimensions in a deliberate and, often,

goal-oriented fashion; the second involves processing stimuli as whole entities in what may be construed as their object representation (Garner, 1974; Lockhead, 1972; Vigo, 2009a). Adults tend to be more fluent at the analytic aspect of stimulus processing, while children tend to be more holistic in their approach (Smith & Kemler, 1977; Ward, 1983). Although the underlying mechanisms for such developmental differences are not well known, it is known that adults also resort to more holistic forms of processing when stimulus complexity interferes with some rule-oriented problem-solving strategy. Furthermore, children may process some stimuli as whole entities because certain complex logical forms or logical concepts may not have been acquired at this early stage of cognitive development (Kemler Nelson, & Smith, 1989). Although this form of stimulus processing provides an important way of differentiating the capacity to discriminate features, it does not alone reflect the complex mechanisms responsible for concept acquisition. For example, there is converging theoretical and empirical evidence that such mechanisms may be grounded on core capacities of attention and similarity assessment (Nosofsky, 1986; Nosofsky, Gluck, Palmeri, McKinley, & Glauthier, 1994; Rehder & Hoffman, 2005; Vigo, 2013). More importantly, it has been recently proposed that a very specific kind of attention shifting mechanism (to be discussed later) responsible for the extraction of coherent (orderly) patterns from environmental stimulus serves as the fulcrum for concept acquisition (Vigo, 2013, 2014).

These deeper aspects of concept learning point at alternative causes for potential differences in concept learning performance between various populations. Indeed, failures in sustaining attention or in attending in specific ways to stimuli would account for such differences in concept acquisition in terms of the extent to which an observer is able to find organization or coherence in sets of object stimuli (i.e., categorical stimuli). Accordingly, it would be useful to study populations with suggested impairments to these aspects of concept acquisition. For example, ADHD sufferers have long been characterized as having difficulty

staying on task and organizing incoming perceptual data. In addition, in recent years, there has been a consensus among many investigators that executive functioning deficits are central to the disorder (Nigg, Blaskey, Huang-Pollock, & Rappley, 2002) and manifest as disorganization that compromises many areas of functioning (e.g., Storer, Evans, & Langberg, 2012). Thus, it would seem that any concept learning deficits displayed by adolescents with ADHD, compared to the adolescents without the disorder, could be due to an inability to detect the kinds of logical organization patterns that are intrinsic to complex stimuli.

The idea that both pattern detection and attention shifting play a key role in determining the ability to learn concepts was developed in a recent theory of human conceptual behaviour named “generalized invariance structure theory” (GIST; Vigo, 2013). GIST, and its core model (the GISTM), account for a wide variety of concept learning phenomena based on the idea that the ability to learn concepts is grounded on a process of qualitative pattern detection. The GISTM has been proposed as a potential law of conceptual behaviour due to its very accurate predictions with respect to several important datasets. We use GIST and the GISTM to attempt to account for the empirical findings in this paper.

Categorization performance as an ADHD benchmark

In our study, we used a classification task involving well-defined categorical stimuli as an instrument for teasing apart and determining the performance differences in conceptual behaviour from adolescence to adulthood and between ADHD-impaired adolescents and typical adolescents. Well-defined categorical stimuli are sets of objects or categories generated by a specific number of predetermined dimensions (e.g., size, colour, and shape). When the dimensions can only have one of two values, the categorical stimuli are binary in nature. We used these well-defined categorical stimuli because it is easy to identify and isolate in them the structural and qualitative aspects that contribute to their learnability. This aspect has made them the

focus of many rigorous concept learning investigations (e.g., Feldman, 2000; Medin, 1978; Nosofsky, 1986; Vigo, Zeigler, & Halsey, 2013; Vigo, 2013).

Shepard et al. (1961), in an influential study, investigated empirically the six category structures whose instances are categories containing four objects defined over three binary dimensions (instances of these six structures used in our experiment are illustrated in Figure 1). Shepard et al. found an empirical learning difficulty ordering among these six category structures measured by the number of classification errors made by participants with respect to each structure type. Specifically, in terms of increasing degree of learning difficulty, Shepard et al. (1961) found the following ordering: $I < II < [III = IV = V] < VI$. This result, referred to as the Shepard, Hovland, and Jenkins ordering or the “SHJ ordering”, is quite robust, as demonstrated by the fact that it has been replicated by several researchers (e.g., Love & Medin, 1998; Nosofsky, 1986; Nosofsky et al., 1994; Shepard et al., 1961; Vigo, 2011, 2013; Vigo et al., 2013) using different classification paradigms.

The experimental method used by Shepard and associates (Shepard et al., 1961) was based on a long-learning sequence of many blocks of trials per

category of objects. Each block involved the presentation of individual objects from a category of objects on a trial-by-trial basis with corrective feedback following each classification decision until a correctness criterion was met. In contrast, Vigo (2011, 2013; Vigo et al., 2013) used a simultaneous visual display of all members of the category and its complement (the nonmembers) for a fixed time period of 20 seconds and then individually presented each of the objects in the category (and its complement) at random, one after another, for a period of three seconds, within which the categorization decision had to be made. Vigo (2013) refers to the former task as a *serioinformative* task and the latter as a *parainformative* task. The parainformative task places emphasis on the ability of participants to perceive relationships “online” (i.e., as participants scan all the stimulus information), thereby highlighting the attention shifting that is necessary to make complicated comparisons. We use this approach on the SHJ structures to examine typical versus impaired performance in adolescents.

Although we believe that the robustness of the SHJ ordering makes the $3_2[4]$ category structures (i.e., the six structures defined over 3 binary dimensions (the subscript 2 denotes binary) and 4 objects) a powerful standard for benchmarking categorization performance, not all researchers, and most notably Feldman (2000), have empirically observed the SHJ ordering in parainformative tasks. Indeed, the generality of the ordering was recently called into question (Kurtz, Levering, Stanton, Romero, & Morris, 2013). Kurtz et al. (2013) suggested that the classic Type II advantage (the finding that Type II is learned more quickly and with fewer errors than Types III–V) occurs only under specific circumstances—when the stimuli are composed of dimensions that are not equally salient and when the instructions encourage participants to selectively attend to relevant dimensions. Note that neither of these conditions was met in the experiment reported in this paper. Yet, we feel that we have gathered converging evidence in support of an overall Type II structure advantage.

A possible cause for this discrepancy has been proposed in Vigo (2013) where it is argued that the reason Feldman (2000) did not observe the

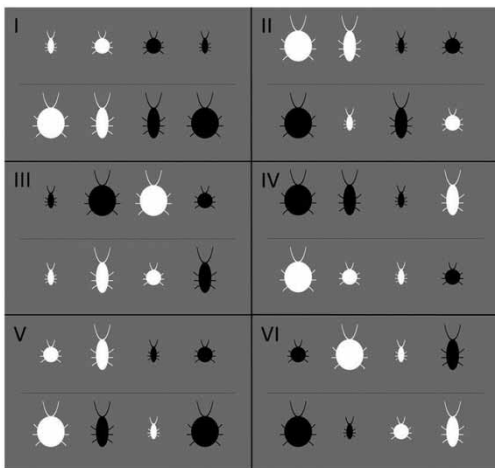


Figure 1. Examples of the six types of categorical stimuli used in the classification experiment.

classic SHJ ordering in his experimental protocol is because he did not sample from the entire population of category instances associated with each of the six structures. This is a critical step that seems necessary in order to avoid dimensional biases. In fact, Kurtz and associates (2013) acknowledge that this limitation is also present in their study and that it may influence patterns of behaviour. In addition, Kurtz et al. use seroinformative tasks, while the categorization tasks used in Vigo (2013) and in our study are parainformative, thereby potentially rendering some comparisons between results as inappropriate. Other plausible causes for the discrepancy may be found in Vigo (2013, 2014). In spite of any potential discrepancies between the SHJ categorization study conducted by Kurtz et al. and our study, the $3_2[4]$ family of structures still represents the best available standard in the field, and more so when considering the comparative nature of our study.

EXPERIMENTAL STUDY

We asked participants from each of the three populations to classify individual insects from a training set of four insects and its complement. Twenty-four such sets were used: four per each of the six SHJ category structures. Figure 1 contains six examples of these sets. Note that the second set of insects underneath the faint grey separating line is the complementary set.

Method

Participants

Twenty-eight undergraduate students from Ohio University between the ages of 18 and 22 years (the adult group), 38 adolescents between the ages of 11 to 15 years who did not meet the diagnostic criteria for ADHD, and 44 adolescents between the ages of 11 and 16 years who met the diagnostic criteria for ADHD participated in the study. In accordance with recommended diagnostic procedures (Pelham, Fabiano, & Massetti, 2005), all participants diagnosed with ADHD completed a comprehensive research evaluation that included

a semistructured diagnostic interview with a parent (Parent Children's Interview for Psychiatric Syndromes; Weller, Weller, Teare, & Fristad, 1999) combined with parent and teacher ratings of symptoms on the Disruptive Behavior Disorders Rating Scale (DBD; Pelham, Gnagy, Greenslade, & Milich, 1992) and parent and teacher ratings on the Impairment Rating Scale (IRS; Fabiano et al., 2006). These data were used to determine diagnoses according to criteria in the *Diagnostic and Statistical Manual for Mental Disorders—Fourth Edition, Text Revision (DSM-IV-TR;* American Psychiatric Association, APA, 2000; see rating scale data in Table 3 in the Supplemental Material). Participants taking stimulant medications (28 or 63.6% of the 44 participants) were asked to refrain from taking stimulant medication on the day of the assessment so performance was not influenced by psychoactive medication.

Stimuli

A Lenovo Thinkpad W500 laptop with a 15" flat panel LCD display (5-ms response time) was used to display eight "insects" defined over three binary dimensions: colour (black or white), shape (round or oval), and size (large or small) and separated by a line into the target category and its complement. Each stimulus was displayed on a neutral grey background. The stimuli were generated in accord with the six types of category structures of the SHJ family using a computer program written in Matlab 7 and Psychophysics Toolbox 3.1. A total of 24 stimuli, four per structure type, were used in the experiment. Figure 1 shows six of these 24 stimuli.

Procedure

Participants from the three groups were tested on each of the 24 insect categories described above. The experiment was executed in the same manner for all three groups. The 24 categories were presented in random order to each participant. Each category and its complement were presented for a training period of 20 seconds followed by a random sequence of the category's members and nonmembers, displayed one at a time for three

seconds. Participants were instructed to provide a response within this time window. Nonresponses and late responses counted as incorrect responses. Before the start of the experiment, participants were told that for each block of categorization trials, an insect collector liked the set of four insects located above a line and disliked the four below the line. Furthermore, they were told that the eight insects shown would be presented individually one at a time and that their task was to click on one of two round buttons (four inches in diameter each): the right button if the insect was liked by the insect collector and the left button if not. As soon as a response was entered, a new trial displaying one of the eight insects began. Once a choice was made participants were not able to change it. After each block of eight classification trials, a new block would start immediately with the introduction of a new category of insects. This continued until all 24 categories were tested for a total of 192 (24 × 8) categorization trials.

Results

As illustrated in Table 1, both the non-ADHD adolescents and adults exhibited the robust learning difficulty ordering observed by Shepard et al. (1961). More specifically, the ordering of error rates observed was I (.02) < II (.12) < [III (.17), IV (.19), V (.20)] < VI (.30) for the adults and I (.03) < II

(.20) < [III (.26), IV (.26), V (.25)] < VI (.40) for the non-ADHD adolescents. Pairwise *t*-tests showed significantly fewer classification errors for Type I than for Type II [adults, $t(27) = -6.12$, $p < .001$, $d = -1.12$; non-ADHD adolescents, $t(37) = -7.45$, $p < .001$, $d = -1.17$]; significantly fewer errors for Type II than for Types III, IV, and V [adults average $t(27) = -2.67$, $p < .05$, $d = -0.40$; non-ADHD adolescents average $t(37) = -3.08$, $p < .05$, $d = -0.29$]; and significantly fewer errors for Types III, IV, and V than for Type VI [adults average $t(27) = -4.46$, $p < .001$, $d = -0.45$; non-ADHD adolescents average $t(37) = -7.43$, $p < .001$, $d = -0.42$]. There were no significant differences among Types III, IV, and V for either group [adults average $t(27) = 0.82$, $p > .05$, $d = 0.09$; non-ADHD adolescents average $t(37) = 0.45$, $p > .05$, $d = 0.04$]. Upon applying a Holm–Bonferroni correction procedure, differences between the two groups on Types II and IV become statistically nonsignificant. However, as it is explained in the statistical notes in the Supplemental Material III, such corrections are likely inappropriate and too aggressive given the implausibility of their underlying assumptions and the nature of our empirical tests.¹ Thus, the probability of making at least one Type I error may be much lower than such corrections estimate. Please refer to Tables 4 and 5 in the Supplemental Material for detailed summaries of these statistics.

In spite of both of these groups (i.e., the non-ADHD adolescents and adults) having exhibited or approximated the SHJ ordering, the adults attained a 12% classification error rate with respect to the instances of the Type II structure involving an “exclusive-or” rule while the non-ADHD adolescents achieved a nearly twice as high 20% classification error rate. In fact, classification performance was significantly better for the adults for Type II, $t(64) = -2.37$, $p < .05$, $d = -0.59$, Type III, $t(64) = -2.85$, $p < .01$, $d = -0.71$, Type IV, $t(64) = 1.95$, $p = .056$, $d = -0.49$, Type V, $t(64) = -2.59$, $p < .05$, $d = -0.64$, and Type VI, $t(64) = -3.08$, $p < .01$, $d = -0.77$, structures. Again, refer to Tables 4 and 5 in the Supplemental Material for detailed summaries of these statistics.

Table 1. The learning difficulty ordering for each of the three groups based on the proportion of classification errors

Group	SHJ structures					
	I	II	III	IV	V	VI
Adults	.02	.12	.17	.19	.20	.30
Non-ADHD adolescents	.03	.20	.26	.25	.27	.40
ADHD adolescents	.10	.36	.35	.35	.37	.47

Note: The ordering for the non-ADHD (attention-deficit/hyperactivity disorder) adolescents and for the adults conformed to the SHJ ordering—namely, I < II < [III = IV = V] < VI. However, there were considerable differences in performance between all three groups across the six category structures.

On the other hand, ADHD adolescents' categorization behaviour clearly did not conform to the classic SHJ learning difficulty ordering. Instead, performance on Type II structures was not significantly different from that of Types III, IV, and V structures [average $t(43) = -0.51$, $p > .05$, $d = -0.07$]. More specifically, the ADHD adolescents achieved the following performance ordering for the six structures: I (.10) < [II (.36), III (.35), IV (.35), V (.37)] < VI (.47). Please refer to Table 6 in the Supplemental Material for detailed summaries. This confirms that Type II structures seem to be relatively more difficult for children with ADHD than for adults, $t(70) = 6.78$, $p < .001$, $d = 1.64$, and non-ADHD adolescents, $t(80) = 4.74$, $p < .001$, $d = 1.05$. We provide an account of this phenomenon in the next section. Among adolescents with ADHD, tests further revealed that instances of Type I were associated with a significantly lower proportion of classification errors than each of the other five types [average $t(43) = -13.9$, $p < .001$, $d = -2.24$]. Additionally, there was a significantly higher proportion of classification errors associated with instances of Type VI than with each of the other five types [average $t(43) = 8.77$, $p < .001$, $d = 1.42$].

Classification results for all three populations across all six category structures are summarized in Table 1. With respect to Type I structures, performance by the non-ADHD adolescents and the adults was not significantly different, $t(64) = 0.67$, $p > .05$, $d = 0.17$. For the remaining five structures, performance was significantly different across the three groups [least favourable: $t(64) = 1.95$, $p = .56$, $d = 0.49$]. Also, there were significant differences between the average classification performance on all six structures by each group [ADHD vs. non-ADHD adolescents: $t(80) = 4.28$, $p < .001$, $d = 0.95$; ADHD adolescents vs. adults: $t(70) = 7.15$, $p < .001$, $d = 1.73$; non-ADHD adolescents vs. adults: $t(64) = 3.32$, $p < .01$, $d = 0.83$]. Please refer to Table 7 in the Supplemental Material for detailed summaries of the independent-samples t -test results amongst the three groups.

Although, usually, categorization data involving a single group performance on these six structures

are analysed using pairwise t tests as was done above, given that our analysis extends to three different groups, we wish to minimize the risk of making a Type I inferential error. Thus, we also conducted a repeated measures analysis of variance (ANOVA) with the within-subjects factor structure type and between-subjects factor group (ADHD, non-ADHD, adults), which revealed a significant main effect of type, $F(5, 103) = 146.55$, $p < .001$, $\eta_p^2 = .88$, and a significant main effect of group, $F(2, 107) = 27.52$, $p < .001$, $\eta_p^2 = .34$. Additionally, there was a significant interaction between group and type, $F(10, 535) = 3.35$, $p < .001$, $\eta_p^2 = .06$, which arises due to the substantial classification performance differences observed with regards to Type II structures across the three groups. Notwithstanding, further analyses revealed that, on average, ADHD adolescents had a higher proportion of classification errors per type ($M = .33$, $SD = .11$) than did non-ADHD adolescents ($M = .24$, $SD = .09$), $F(1, 80) = 18.13$, $p < .001$, $\eta_p^2 = .19$, and adults ($M = .17$, $SD = .07$), $F(1, 70) = 51.05$, $p < .001$, $\eta_p^2 = .42$. Additionally, non-ADHD adolescents had a higher proportion of classification errors per type, on average, than did adults, $F(1, 64) = 11.17$, $p < .01$, $\eta_p^2 = .15$.

Between-groups ANOVAs were conducted to determine the extent of the differences between each of the category types among the groups (see Table 8 in the Supplemental Material). Results indicate that adolescents with ADHD had a significantly higher proportion of classification errors for each of the six category types than did either the adolescents without ADHD [average $F(1, 80) = 10.9$, $p < .05$, $\eta_p^2 = .12$] or the adults [average $F(1, 70) = 28.6$, $p < .01$, $\eta_p^2 = .28$]. Additionally, adolescents without ADHD were found to have a significantly higher proportion of classification errors for Types II, III, V, and VI than did the adults [average $F(1, 64) = 7.58$, $p < .05$, $\eta_p^2 = .10$]. However, there were no significant differences when comparing classification performance between adolescents without ADHD and adults among Type I, $F(1, 64) = 0.37$, $p > .05$, $\eta_p^2 = .01$, and Type IV, $F(1, 64) = 3.84$, $p > .05$, $\eta_p^2 = .06$. When using the Holm-

Bonferroni procedure to control for Type I error, the aforementioned differences between the adolescents without ADHD and the adults on Type II become statistically nonsignificant.

Model fits and predictions

In GIST, a specific kind of pattern detection named “invariance detection” is the basis of concept formation. It also determines the perceived degree of difficulty of a concept. The equations describing the process of invariance detection and perceived degree of learning difficulty are defined in Supplemental Material I; however, we next give a brief nontechnical explanation of the basic ideas. In short, invariance detection is the process of assessing the “partial similarity” between object stimuli in a category of objects by binding or suppressing, one at a time, each of their dimensions. This process is referred to in GIST as *dimensional binding*. The process not only involves rapid attention shifting from one dimension to another, but also involves sustained and deliberate “unattending” or “suppression” with respect to each dimension. Ultimately, the described process results in the detection of categorical invariants. Concept or categorical invariants are the object exemplars that determine which features (and more generally, dimensions) of the categorical stimulus should be used in rule formation (see Vigo, 2009b, 2011, 2013, 2014, for a detailed explanation). The categorical invariants of a categorical stimulus are then represented as an “ideotype” in psychological space (i.e., ideotypes contain the structural information necessary to form concepts; see Table 2 in Supplemental Material I).

In other words, in order to form explicit language-oriented categorization rules, humans must first implicitly detect these invariance patterns. The reason is that these patterns make it possible for an observer to ascertain which dimensions associated with a particular categorical stimulus best predict category membership or, in other words, which dimensions are most diagnostic. If the diagnostic dimensions of the categorical stimulus are fully detected by the observer and amount to

one or two, then the categorical stimulus is simple to learn, otherwise it is not. In short, in GIST, when the observer is a good detector of categorical invariants, he or she is a good concept learner and classifier; in turn, these patterns of invariance reduce stimulus complexity by revealing only the key information necessary for correctly classifying the members of a categorical stimulus. Clearly, the process of invariance pattern detection requires the analytic ability to dissect objects in terms of their dimensions in the first place, and not just the ability to shift attention rapidly while deliberately ignoring a particular dimension. But evidence from the literature suggests that individuals with analytic deficits (e.g., young children when compared to adolescents and adolescents when compared to adults) presumably lack the ability to break down stimuli into their featural components (Smith & Kemler, 1977; Ward, 1983).

Thus, according to GIST, this inability of individuals with such deficits will interfere with the pattern detection process necessary for the formation of classification rules. Accordingly, adolescents should exhibit gradual increases in classification performance as their analytic skills increase over the years. Yet, given that the dimensional make-up of the categorical stimuli of our experiment is so simple (consisting of three easily recognizable dimensions), such ability would not seem sufficient to, in and of itself, account for group differences. However, we think that it would play a role when large differences in concept learning performance are observed.

This supposition is supported by the core law in GIST, which predicts the degree of learning difficulty of a concept (see x -axis of Figure 2). The law contains a scaling parameter k (where k is a real number greater than or equal to zero) that accounts for individual differences in categorization performance by capturing some of the aforementioned pattern discrimination capacities as a function of dimensional discrimination. In other words, k tells us the overall ability of an observer to extract invariance patterns from categorical stimuli of different dimensionality. More specifically, the parameter k is an index that summarizes concept learning performance by indicating an observer's overall degree

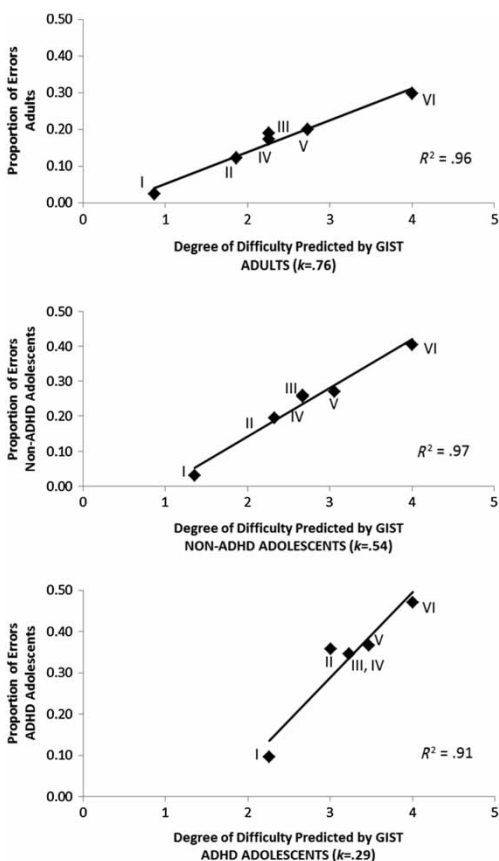


Figure 2. The three graphs depict the generalized invariance structure theory (GIST) core model (GISTM) predictions as to the perceived degree of learning difficulty (x-axis) of the six category structures. The first graph depicts a fit to the adults' data, the second to the non-ADHD (attention-deficit/hyperactivity disorder) adolescents' data, and the third to the ADHD adolescents' data. The variant of the GISTM used here contains a single scaling parameter value (the pattern discrimination parameter k). This parameter is different for each group, indicating that adults have the more effective pattern detection system, followed by the adolescents and finally the ADHD adolescents.

of discrimination between the invariance patterns detected in different categorical stimuli.

Admittedly, the parameter k is not very revealing unless the model can provide accurate fits to the data. As Figure 2 shows, the GISTM accounts accurately for virtually all of the variance in the classification data of each of the three groups tested (adults, $R^2 = .96$, $p < .0001$, $k = .76$; non-ADHD adolescents, $R^2 = .97$, $p < .0001$, $k = .54$; ADHD

adolescents, $R^2 = .91$, $p < .0001$, $k = .29$). We used the SOLVER parameter estimation platform built in EXCEL, which estimates parameters by maximizing the coefficient of determination using the gradient descent method, to estimate a single k value for each of the three groups tested. As mentioned, the ability to extract invariance patterns at different dimensional levels is captured by this parameter, where higher values indicate better discrimination. Because our stimuli are three-dimensional, the value for the adult group of $k = .76$ indicates a relatively greater ability to extract key patterns from three dimensional categorical stimuli than that exhibited by the non-ADHD adolescents with a discrimination index of $k = .54$. Likewise, the non-ADHD adolescents have a significant edge over the ADHD adolescents whose discrimination index is .29.

Under GIST, this suggests that adolescents with ADHD lack the ability to find invariance patterns involving three-dimensional stimuli, whereas adolescents without ADHD do not seem to experience the same difficulty. This is particularly important because Types I and II are the most patternful or coherent of the structures by a large margin. In close agreement with GIST, these are the two structures for which there are, generally speaking, pronounced relative or ratio differences in performance between the three populations: For example, as shown in Table 1, the ADHD adolescents are performing at three times the error rate of the adults on Structure Types I and II.

These results are consistent with results obtained when the data were analysed from the standpoint of individual differences between participants. For example, we estimated the parameter k on a per subject basis for all six structures (i.e., at the structure family level). Furthermore, we estimated the parameter k on a per subject basis for each of the six structures (i.e., at the structure instance level). The pattern of discrimination observed may be characterized by the cumulative distribution of discrimination levels k or, in other words, the cumulative proportion of subjects operating at a particular estimated discrimination level or below, as shown in Figures 3 and 4.

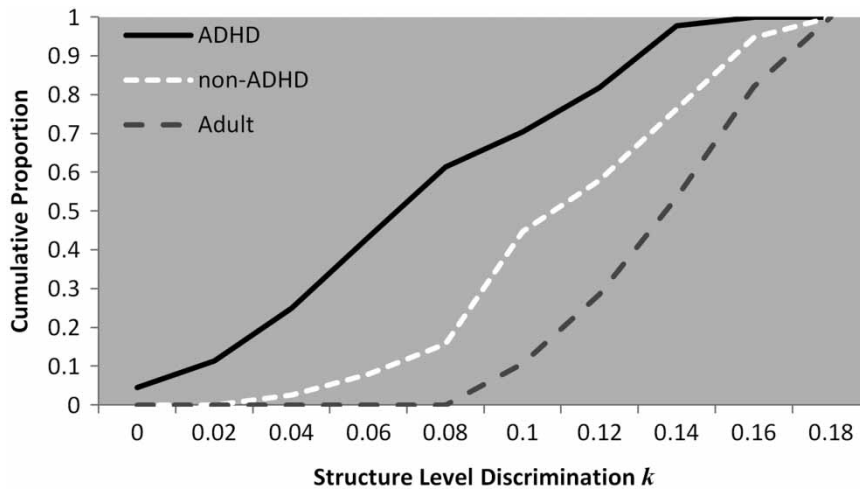


Figure 3. Cumulative proportion of ADHD (attention-deficit/hyperactivity disorder) adolescents, non-ADHD adolescents, and adults for predicted degrees of discrimination between the structures of the $3_2[4]$ family of structures. A single k value is estimated for all six structures, per subject.

For example, by Figure 3, the cumulative proportion of ADHD adolescents that discriminate at a level of .13 or below is nearly .9 for our sample, while the approximate cumulative proportion of adults that discriminate at the same level or below would be roughly .35.² In addition, note the much smaller discrimination performance range of the adults in Figure 3 when compared to those of the ADHD adolescents and the non-ADHD adolescents. Also, note that about .25 of the non-ADHD adolescents are predicted to discriminate at a level of .9 and below, while about .65 of the ADHD adolescents are predicted to discriminate at the same level and below.

Accordingly, Figure 4 exhibits equally consistent and interesting patterns. In particular, note the graph corresponding to individual discrimination performance on Type II structures. Here we can clearly see the most drastic separation between the ADHD performance distribution curve and the curve corresponding to the adults. Furthermore, as we would expect for Type VI structures, given their lack of inherent patternfulness, we see that pattern discrimination performance between their category instances coincides.

Finally, in making the above predictions, GIST assumes that the same basic pattern detection mechanism involving dimensional binding is the same for

all the three groups, and that the scaling parameter k captures a higher order process of discrimination, which is a consequence of the overall ability to extract invariance patterns from categorical stimuli. Differences between subjects with respect to this ability may be traced to differences in achieving the proper coordination or cadence during the dimensional binding process (for details, see Vigo, 2013). In short, attention per se is not the critical factor in determining individual differences between observers; instead, it is the ability of observers to rapidly and implicitly shift or distribute attentional control (i.e., dimensional suppression or amplification) properly in order to achieve optimal levels of invariant pattern detection.

GENERAL DISCUSSION

A few key questions emerge from the above research: Why are there significant classification performance differences between adults, non-ADHD adolescents, and ADHD adolescents? Secondly, why is performance on Type II structures so dramatically different between the two adolescent populations? Finally, what cognitive facilities explain these gradual differences in performance as a function of chronological age? To answer these questions, we

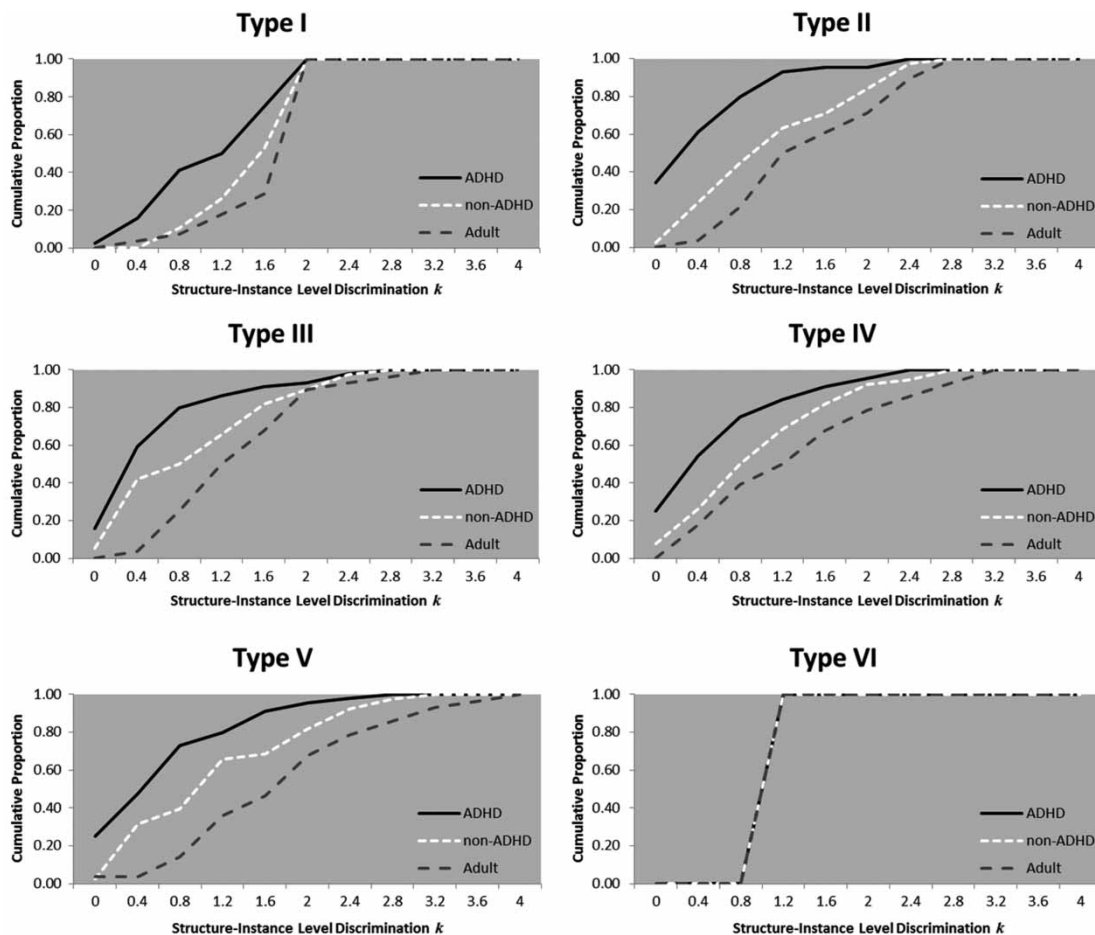


Figure 4. Cumulative proportion of ADHD (attention-deficit/hyperactivity disorder) adolescents, non-ADHD adolescents, and adults for predicted degrees of discrimination by the generalized invariance structure theory (GIST) core model (GISTM) at the level of structure instances. A single k value is estimated for all four instances of each structure, per subject.

used a theory of categorization and concept learning performance referred to as GIST (generalized invariance structure theory; Vigo 2013). GIST, and, its core mathematical model, the GISTM, have accurately predicted categorization performance for a wide variety of categorical stimuli. In fact, the GISTM accounts for about 90% of the variance in classification data involving 84 category structures (see Vigo, 2013).

An important feature of the GISTM is its single scaling parameter k (free or bound depending on the variant of the model being used) discussed in the previous section. It allowed us to confirm our

hypothesis that adults would probably be better categorizers than adolescents, and that adolescents with ADHD, due to cognitive impairments associated with the core facilities essential for the detection of invariance patterns in GIST (working memory, attention shifting, and similarity assessment) would experience the most difficulty.

In particular, GIST predicts that adolescents with ADHD should not be able to perform as well as adolescents and adults without ADHD because they will not be able to maintain the systematic and goal-oriented attention shifting required to detect the patterns necessary for the

subsequent formation of classification rules (Vigo, 2011, 2013). More specifically, some of these dimensionally grounded patterns in the category can only be detected by deliberate attention shifting across *all* its dimensions (i.e., a complete pattern search). In this respect, Type II structures (see Figure 1) will pose a particular challenge. These types of structures are also referred to as “exclusive-or structures”. The insects in this category can be white or small but not both; likewise, they can be black or large but not both. Thus, no single feature (white, small, black, large) may be used to determine category membership.

According to GIST, Type II structures are particularly challenging because there are many redundant patterns or invariants associated with one of the three dimensions that define the structure. Indeed, this is the only three-dimensional structure with this property. The remaining two dimensions are associated with zero-invariance patterns. Thus, it is essential not to give up a pattern search after the first two dimensions have been scanned. Otherwise, an observer is likely to miss the fact that there are two maximally diagnostic dimensions

revealed in the stimulus structure. Accordingly, under GIST one would expect exceptionally poor performance from the adolescents with ADHD because they perhaps will give up too early in the process of goal-oriented attention shifting underlying dimensional binding. This condition may be reflected in an inability to organize entities in the surrounding environment and in the mind. The pattern discrimination distribution graph corresponding to Type II structures (see Figure 4) attests to this difficulty. Accordingly, the receiver-operating characteristic (ROC) curve in Figure 5 illustrates the effectiveness of Type II structures in discriminating classification performance between adolescents with and without ADHD. Note that the area under the ROC curve for the performance (proportion of errors) on Type II category structures was .82. In other words, Type II structure performance is a reliable index for discriminating between the two populations. This indicates the potential of the implemented empirical paradigm as a diagnostic instrument for ADHD: a critical finding that warrants further research.

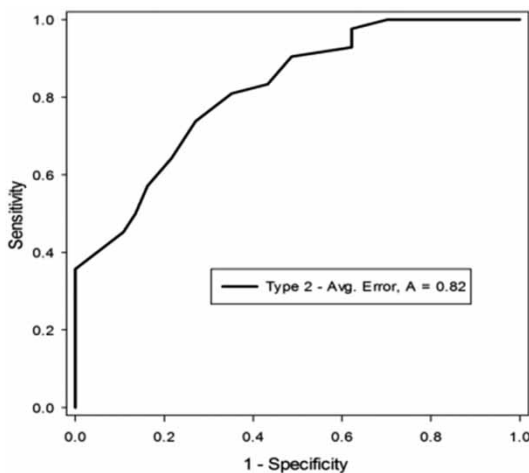


Figure 5. The receiver-operating characteristic (ROC) curve, illustrating the effectiveness of a structure Type II task (labeled “Type 2” in the Figure above) in discriminating between ADHD (attention-deficit/hyperactivity disorder) and non-ADHD adolescents in terms of their categorization performance on Type II structures. The area under the curve is .82 (95% confidence interval, CI [0.663, 0.855]; $z = 5.21$, $p < .0001$), which is indicative of good discrimination performance.

CONCLUSION

In conclusion, results from our categorization experiment and modelling approach indicate that: (a) there are significant differences in the categorization performance of adolescents with and without ADHD; (b) both the categorization performance of adolescents without ADHD and adults appear to conform to the empirically robust concept learning difficulty ordering for four-object category structures defined over three dimensions (i.e., SHJ ordering); however, there are significant differences in performance between the two groups; (c) the categorization performance of adolescents with ADHD does not conform to the empirically robust SHJ ordering; (d) there are marked differences in categorization performance between adolescents with and without ADHD with respect to Type II category structures (this latter finding suggests the potential of a diagnostic test for ADHD based on this single category structure); and (e) the GISTM fits the data for each of the three groups accurately and with its scaling/

discrimination parameter k (the only parameter in the model) it is able to account for individual differences in performance within each group.

As far as we know, each of the findings above is new to the concept learning literature. In addition to these first-time findings, we proposed a cognitively feasible explanation for each finding using GIST. Although other classification theories and models that emphasize attention processes via weighted features may offer alternative explanations (e.g., Kruschke, 1992; Nosofsky, 1986), GIST is the only one that offers a direct explanation of categorization performance in terms of the ability of subjects to find invariance patterns between the dimensional make-up of categorical stimuli.

In addition, unlike GIST, these alternative theories and models incorporate in their formulations negative exemplars (i.e., category instances not in the category) in order to make their predictions. Moreover, it has been shown that models from the aforementioned theories do not fit categorization data on a wide range of category structures nearly as accurately as the GISTM or its ancestral models (Vigo, 2013). Furthermore, the significant differences in categorization performance that we found between the three populations tested are also consistent with predictions made by GISTM and with the assumption that the processing of pattern-rich categories requires a greater sustained cognitive cadence or “rhythmic processing” in the form of sustained dimensional binding. But they also require the analytic capacity to break down dimensional and featural information—a capacity that has been developmentally differentiated in the literature. Finally, with respect to Type II structures, our experimental results were also consistent with GIST, which suggests that their unique structural nature requires an even more diligent dimensional pattern search by subjects than the rest of the six structures studied. This indicates that Type II categories could play an important role as a diagnostic instrument for ADHD and may provide clues for intervention development.

We hope that this finding, along with the proposed methods in this report, is applied to better understand the entire developmental course of

concept learning in humans: from infancy, through childhood and adolescence, to late adulthood.

Supplemental material

Supplemental content is available via the “Supplemental” tab on the article’s online page (<http://dx.doi.org/10.1080/17470218.2014.974625>, 2014).

Notes

1. The Holm-Bonferroni corrections assume that all the hypothesis tests are statistically independent. But we assume that our categorization tests are influenced by the same mental ability to learn concepts and that performance on particular structures is not necessarily totally independent from performance on other structures (recall that instances of different structures are presented at random during a single experimental session).
2. To better appreciate the utility of these distributions, one could very roughly construe them (to the extent that the samples capture the population characteristics) as potentially giving the probability associated with finding a pattern discrimination value of x or below for the particular group. For example, according to Figure 3, the approximate probability that an ADHD adolescent discriminates at a level of .13 or below would then be nearly .9, while the approximate probability that an adult discriminates at the same level or below would be roughly .35.

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