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Behavioral and Neural Predictors of Individual Differences in Concept Generalization

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ABSTRACT

Concept learning involves linking related pieces of information to a shared label, such as learning that furry creatures that bark are called "dogs." People vary in how well they learn concepts and apply them to new situations (generalization). What factors drive these individual differences? In the present study, we tested whether stable aspects of intelligence or transient activations in the brain best predicted concept generalization abilities. To measure aspects of intelligence, subjects underwent an assessment that included measures of working memory, processing speed, perceptual reasoning, and verbal comprehension, which could be combined into an overall IQ. Subjects also completed a concept generalization task while undergoing functional MRI, allowing us to measure activations in brain regions that are part of the explicit rule-learning system (hippocampus, prefrontal cortex) or part of an implicit system that learns without awareness (caudate, posterior visual cortex). To elucidate the shared or dissociable roles of behavioral and neural predictors in concept generalization, we tested the relationship between accuracy in concept generalization and individual differences in measures of intelligence and activation in each brain region of interest. Behaviorally, we found that overall IQ, but not its subcomponents, predicted concept generalization abilities. Neurally, we found that only the activation in the hippocampus predicted concept generalization abilities. Finally, we found that IQ and hippocampal activation each predicted concept generalization independent of each other, indicating that they represent two separate processes that both contribute to generalization success. These results show dissociable contributions of behavioral and neural predictors of concept generalization, suggesting that both stable cognitive abilities and transient brain states influence the ability to learn new concepts.

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Every day, people make associations between the *commonalities* of different experiences to form general conceptual knowledge. For example, a child learns what a dog is after noticing common features across many encounters with individual dogs. Successful concept mastery involves being able to recognize new examples as being members of a given category (concept generalization). However, concept generalization abilities vary among individuals, and it is still unclear what drives these individual differences.

1. BEHAVIORAL PREDICTORS OF CONCEPT GENERALIZATION

Individual differences in cognition, historically known as cognitive style, involve stable variability in cognitive processes (e.g., memory, perception, and logical reasoning) across people (Ausburn & Ausburn, 1978). Although this specific term is no longer commonly used, individual differences in various aspects of cognition have still been studied extensively since they are a useful tool for understanding the mechanisms of cognition. One of the well-studied individual differences in cognition is intelligence, which is the ability to solve problems and learn from experience. Intelligence quotient (IQ) is the score that is most commonly used as a measure of general intelligence (Nessier et al., 1996). In the past, IQ has been a good predictor of cognitive performance in separate tasks, such as explicit learning processes and executive functions (Friedman et al., 2006; Reber, Walkernfeld, & Hernstadt, 1991). Here, we focus on IQ as a general cognitive ability that is derived from multiple component processes, such as working memory capacity, logical reasoning, and verbal comprehension.

Past work investigating how cognitive abilities relate to concept generalization has largely focused on working memory capacity. Working memory is "the system that is necessary for the concurrent storage and manipulation of information" (Baddeley, 1992). Studies have shown that differences in working memory capacities are related to concept learning abilities (DeCaro, Carlson, Thomas, & Beilock, 2009; DeCaro, Thomas, & Beilock, 2008; Lewandowsky, 2011; Tharp & Pickering, 2009). However, there are conflicting views in the literature as to whether individuals with high working memory capacity will always be better at concept generalization (or categorization) than those with low working memory capacity. Previous research has indicated that people with higher working memory capacity could be better at generalizing concepts because they can better track the features and their relationship across items (e.g., Craig & Lewandowsky, 2012). However, some suggest that better generalization results when information is discarded and only the most relevant features are maintained in memory. Those with higher working memory capacity may be less likely to discard details (DeCaro et al., 2009; DeCaro et al.,2008; Tharp & Pickering, 2009). Thus, the nature of the relationship between concept learning and working memory remains an open question.

Besides working memory, past research shows that individual differences in logical reasoning abilities and semantic knowledge can predict some types of concept learning. Better logical reasoning skills are associated with better discovery of category structures, especially when there are explicit rules behind them (Ashby & O'Brien, 2005). Regarding semantic knowledge, Varga and Bauer (2017) demonstrated that the ability to comprehend semantic information (i.e., passage comprehension and concept formation) was correlated with successful self-derivation of a novel fact by integrating two studied related facts (memory integration). Concept-learning abilities have been linked to a number of other cognitive abilities; hence, investigating the relationship between concept learning and different aspects of intelligence is imperative to know if any of them are stronger predictors than the others.

2. NEURAL PREDICTORS OF CONCEPT GENERALIZATION

The most common way to study human behavior in the brain is to examine its task-based activations. Task-based activations index how strongly the level of brain activation in a given region fluctuates on a trial-by-trial basis with the task that is being performed. Task-based activation has been shown to track various transient cognitive states such as levels of sleep deprivation and task engagement (Berka et al., 2007; Mu et al., 2005). Thus, task-based activation may predict concept generalization performance by indexing task engagement.

Research shows that two memory systems are involved in concept learning: a procedural learning system that learns without awareness and a declarative memory system that supports explicit learning (Ashby & O'Brien, 2005; Seger & Miller, 2010). Among procedural memory regions, activation of the striatum has often been observed when individuals perform categorization tasks regardless of the levels of task familiarity (Seger & Cincotta 2002). Particularly, recruitment of the caudate, a sub-region of the striatum, is often found in implicit category learning tasks (Seger, Dennison, Lopez-Panigua, Peterson, & Roark, 2011), especially when subjects learn incrementally (Ashby & O'Brien, 2005) or through feedback (Cincotta & Seger, 2007). Another procedural learning region that has been implicated in concept learning is the visual cortex. Visual areas responsible for processing of low-level features are thought to be involved in indexing familiarity with individual category members when learning visual categories. For instance, Aizenstein et al. (2000) examined the task-related activation of the extrastriate visual cortex (V3), and found changes in activation through learning, with decreased activation during the implicit tasks and increased activation during the explicit tasks. Thus, differences across individuals in caudate and early visual activations may index how strongly they rely on implicit learning when forming new concepts.

In addition, recent research in concept learning has shown the involvement of regions typically associated with memory for individual episodes: the ventromedial prefrontal cortex (VMPFC) and hippocampus. In concept learning tasks, neuropsychological patients with damage in their hippocampus (amnesiac disorder and Alzheimer's disease patients) have performed significantly worse than their healthy counterparts (Zaki, Nosofsky, Jessup, & Unverzagt, 2003). Also, a study showed that patients with impaired VMPFC performed worse on concept learning tasks compared to healthy controls (Schnyer et al., 2009). These two regions (the hippocampus and the VMPFC) have also been studied together in categorization research. Previous studies have demonstrated task-based activations of these regions during concept-learning tasks (Bowman & Zeithamova, 2018; Zeithamova, Maddox, & Schnyer, 2008). Hence, individual differences in hippocampal and VMPFC activations may index how strongly they rely on declarative memory systems during concept learning.

3. THE PRESENT STUDY

We investigated the relationship between cognitive abilities, neural categorization effects, and concept generalization. Subjects completed neuropsychological testing to assess their IQ and the subcomponents of IQ (working memory, processing speed, perceptual reasoning, and verbal comprehension). On a separate day, subjects performed a task where they learned to classify cartoon animals into two imaginary species. Subjects completed both concept learning and generalization testing during functional magnetic resonance imaging (fMRI) that allowed us to measure the brain processing underlying conceptual knowledge. This study focused on the final concept generalization (categorization) tests, where subjects were asked to classify novel cartoon animals that had not been given a species label previously. From this data, we measured task-related activations in several brain regions of interest (hippocampus, VMPFC, caudate, and posterior visual cortex) and behavioral accuracy in the generalization task. We then tested whether cognitive predictors generated from the IQ testing and/or neural predictors generated from the categorization task predicted concept generalization abilities.

3.1. METHOD

3.1.1 SUBJECTS

Forty volunteers were recruited from the University of Oregon and surrounding community and were financially compensated for their research participation. All subjects were provided with and signed a written informed consent form and were screened for neurological conditions and medications known to affect brain function. Research Compliance Services at the University of Oregon approved all experimental procedures prior to data collection. Two subjects did not complete the tasks due to discomfort in the scanner, and two subjects were excluded due to poor performance (less than 50% correct, where 50% correct corresponds to accuracy achieved by simply pressing one of two response keys randomly). This resulted in a sample size of 36 subjects (age: range=18-32, M=22.03, SD=3.53; 23 females) for behavioral analyses. For the fMRI analyses, one more subject was excluded because of excessive motion, which left 35 subjects reported in all fMRI analyses (age: range=18-32, M=22.09, SD=3.57; 22 females). One participant scored very high on behavioral measures: 100% accuracy and IQ of 147. While 100% categorization score was within a normal range (within two standard deviations away from the mean of our sample), his or her IQ was outside a normal range (more than three standard deviations away from the population mean of μ=100, σ=15). Because regression can be strongly affected by extreme values, we computed all regression analyses with and without this particular subject. As the sample size is relatively low for an individual differences analysis, the current study should be considered as preliminary. A larger scale fMRI study would be necessary to ensure the robustness of the findings (Button et al., 2013).

3.1.2. MATERIALS

WECHSLER ADULT INTELLIGENCE SCALE: To assess the intelligence scores for each subject, we used the Wechsler Adult Intelligence Scale Fourth Edition (WAIS-IV) (Wechsler, 2008). It measures the IQ of individuals based on its four subcomponents: verbal comprehension, perceptual reasoning, working memory, and processing speed. Each subcomponent is derived by combining scores across two subscales. The working memory subcomponent is made up of digit span (recalling a sequence of numbers read by an experimenter in either the same order, reverse order, or ascending order) and arithmetic (solving a series of mathematical problems within a specified time limit). The processing speed subcomponent consists of symbol search (indicating if one of the target symbols is in the search group in a predefined time limit) and coding (drawing symbols that are previously paired with numbers in a certain time limit). The verbal comprehension subcomponent is made up of vocabulary (defining words that are presented visually and orally) and information (answering questions about general knowledge in various areas). The perceptual reasoning subcomponent involves matrix reasoning (completing incomplete visual matrices and series) and visual puzzles (reconstructing a puzzle based on a completed puzzle). The WAIS-IV subscales were administered in the following order: digit span, matrix reasoning, vocabulary, arithmetic, symbol search, visual puzzles, information, and coding. Also, the WAIS-IV has demonstrated to be a highly reliable measure of IQ. The test-retest reliability for the general intelligence is r=.96, and four main components also have high test-retest reliability: verbal comprehension (r=.96), perceptual reasoning (r=.87), working memory (r=.88), and processing speed (r=.87) (Wechsler, Coalson, and Raiford, 2008).

CATEGORIZATION STIMULUS SET: Stimuli consisted of cartoon animals (Bozoki et al., 2006; Bowman & Zeithamova, 2018) that differed on eight features with two possible versions of each feature (Figure 1a): neck (short or long), tail (straight or curled), feet (fingers or round), snout (rounded or pig), head (ears or antennae), color (purple or red), body shape (hexagon or round), and pattern of a body (polka dots or stripes). All the animals were classified as either Febbles or Badoons based on the combination of the aforementioned features. Each category was organized around a prototype – the stimulus that contained the most common feature values for that category. There were two prototypes whose eight features were different from each another. Animals were labeled as one category or the other based on the number of features they shared with either prototypes (i.e., category A members shared more features with prototype A than prototype B). There was no one feature that defined a given animal as either a Febble or a Badoon.

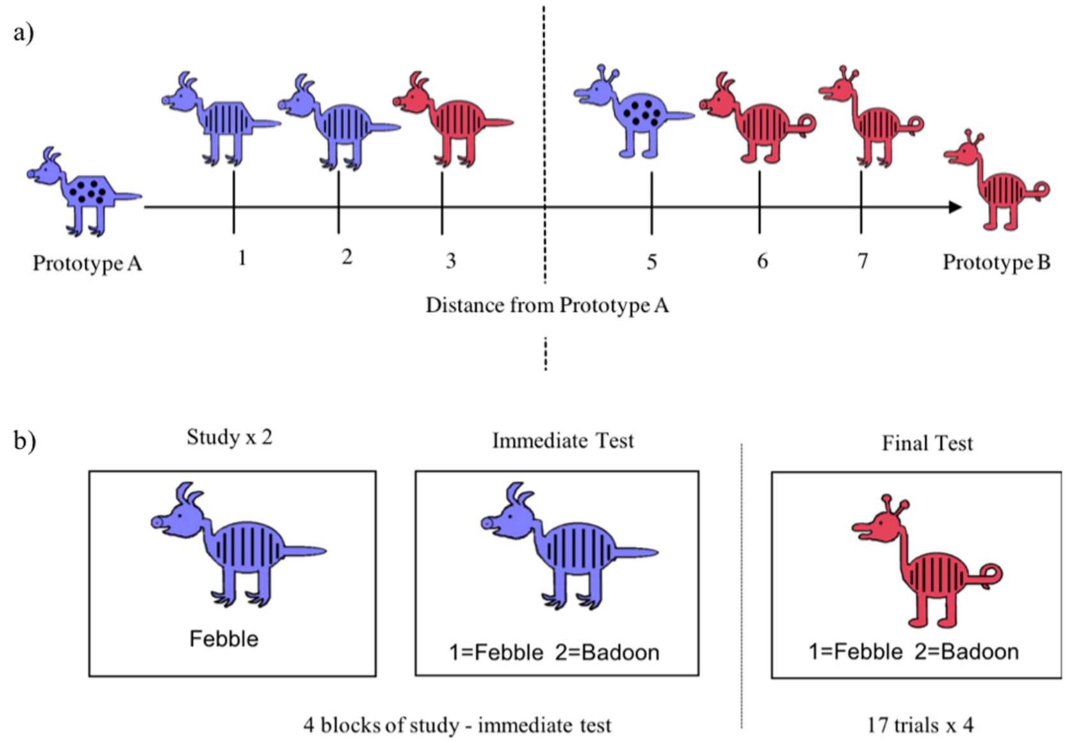

Figure 1: a) Example of stimulus set. There were two prototypes whose eight features were different from each other. Animals were classified as one category of the other based on the number of features they shared with either prototypes (i.e., category A members shared more features with prototype A than prototype B). b) Study design.

3.1.3. EXPERIMENTAL DESIGN

Our study was divided into two sessions. Subjects first came into the lab and met with one of the researchers individually to complete the WAIS as part of a larger cognitive battery. After completing all neuropsychological tests, subjects were then given instructions about the scanner. The entire first session lasted approximately an hour and a half.

For the second session, subjects entered the scanner and first completed a learning phase. They were told to learn two imaginary species of cartoon animals (Febbles and Badoons). Subjects completed four study-test cycles. In each cycle, subjects completed two blocks of observational study where they saw individual animals with their species label and were told to try to learn what makes some Febble and some Badoon. They then completed a single test block to assess how well they had learned the concepts so far. Then, four runs of a final generalization test followed (Figure 1b). Subjects were asked to categorize 68 animals into one of the two imaginary species (Febbles and Badoons) using the same button press while the stimulus was on the screen. Within 68 stimuli, 16 of them were from the 8 training exemplars presented twice, and 4 stimuli were repeatedly presented two prototypes. 48 stimuli were 8 exemplars for each 6 distances from prototypes. These stimuli were presented for 5 seconds with 7 seconds inter-trial interval (ITI) where subjects viewed a fixation cross. Lastly, following the scan, subjects were verbally debriefed about the study.

3.1.4. fMRI DATA ACQUISITION

Scanning was completed on a 3T Siemens MAGNETOM Skyra (high-resolution MRI) scanner at the University of Oregon Lewis Center for Neuroimaging using a 32-channel head coil. The scanning sessions started with two anatomical scans to reveal the structure of participant's brain which allowed us to localize their activation into specific brain regions. This was followed by 16 functional scans while participants performed experimental tasks. Functional scans measured signal related to the blood oxygen level (a marker of neuronal activity) every two seconds to track the changes in brain activation related to task performance. A detailed description of fMRI data acquisition method has been reported previously (e.g., Bowman & Zeithamova, 2018). The analyses presented here focus on task-related activation during the final 4 functional runs, while participants were tested on their category knowledge.

3.1.5. BEHAVIORAL STATISTICAL ANALYSIS

We examined final concept generalization test data using MATLAB (MATLAB_2017b, MathWorks) and SPSS (version 24, IBM). First, each subject's overall concept generalization accuracy was computed by averaging all four runs of the final generalization test. We only included new trials whose stimuli subjects had not seen during the learning phase. Then, a one-sample t-test was conducted to compare generalization accuracy to chance. As cognitive (behavioral) predictors, we used the overall IQ and its four subcomponents. We also compared our sample's scores with the population mean (100) using one-sample t-tests to test whether our college sample was above the population average for their age group.

3.1.6. fMRI ANALYSIS

Data were prepared for analysis using standard procedures (e.g., Bowman & Zeithamova, 2018). We then used functional MRI analysis program FSL to obtain estimates of brain activation related to the performance of the categorization task for each participant. To localize regions of interest (ROIs) in individual participants' brains, we used a tool called Freesurfer that automatically segmented anatomical images into different brain regions. We then extracted for each participant's task-related brain activity in each ROI. We focused on four ROIs: hippocampus, VMPFC, caudate, and lateral occipital (Figure 2).

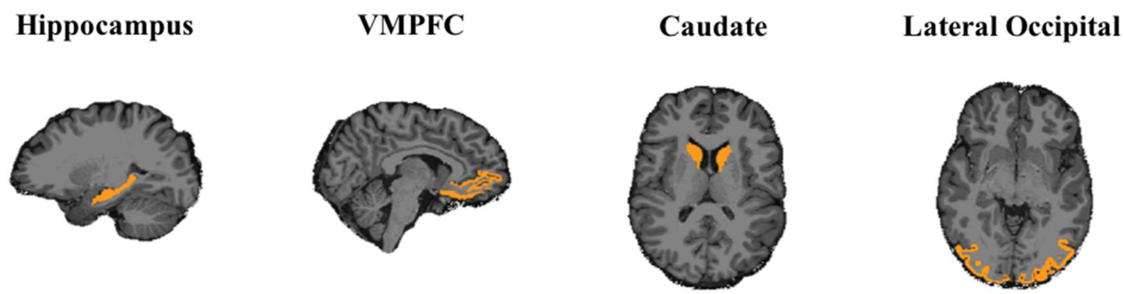

Figure 2: We examined the task-based activations of the declarative memory regions (hippocampus and the VMPFC) as well as procedural learning regions (caudate and lateral occipital)

3.1.7. REGRESSION ANALYSES

To investigate how behavioral/cognitive predictors would track individual differences in concept learning, we conducted a single linear regression to identify if IQ would predict generalization accuracy. Then, a multiple regression was performed. All four subcomponents of IQ were entered as predictor variables to determine whether it is overall IQ or a specific component that predicts generalization. For our neural predictors, we performed a multiple regression using task-related activation in each ROIs as predictors and generalization accuracy as outcome. Lastly, as an exploratory analysis, another multiple regression was performed to test whether significant behavioral and neural predictors would predict shared or distinct variance in concept generalization.

3.2. RESULTS

3.2.1. BEHAVIORAL PREDICTORS

Table 1. One-sample t-test of behavioral variables

	Mean	Std.Deviation	t
IQ	111.19	13.44	5.06**
WM	104.84	16.29	1.81
PS	106.84	13.98	2.98**
VC	117.97	17.72	6.17**
PR	105.51	1051	3.19**
Generalization	.82	.08	24.01***

*p<.05, **p<.01, ***p<.001

Means, standard deviations, and results from one-sample t-tests comparing these results to population averages are presented in Table 1. Our sample showed above-chance generalization accuracy and above-average IQ scores for everything except working memory. A single linear regression was conducted to test if IQ was a significant predictor of individual differences in concept learning. The result revealed that IQ significantly positively predicted generalization accuracy (b=.002, r=.38, p=.024; Figure 3a). To further investigate if this relationship was driven by any of the subcomponents of IQ (working memory, processing speed, verbal comprehension, and perceptual reasoning), a multiple regression was performed. The model including all of the subcomponents of IQ as predictors of generalization accuracy was not significant ($F(4,31)=1.72$, R^2=.18, p=.172) and none of the individual predictors were significant (all ps>.158). This indicates that the contribution of IQ to generalization is not driven by any single one IQ subcomponent. However, when the subject with the highest IQ and generalization score was excluded from the analyses, neither the single regression (p=.160) nor multiple regression (all ps>.189) reached significance.

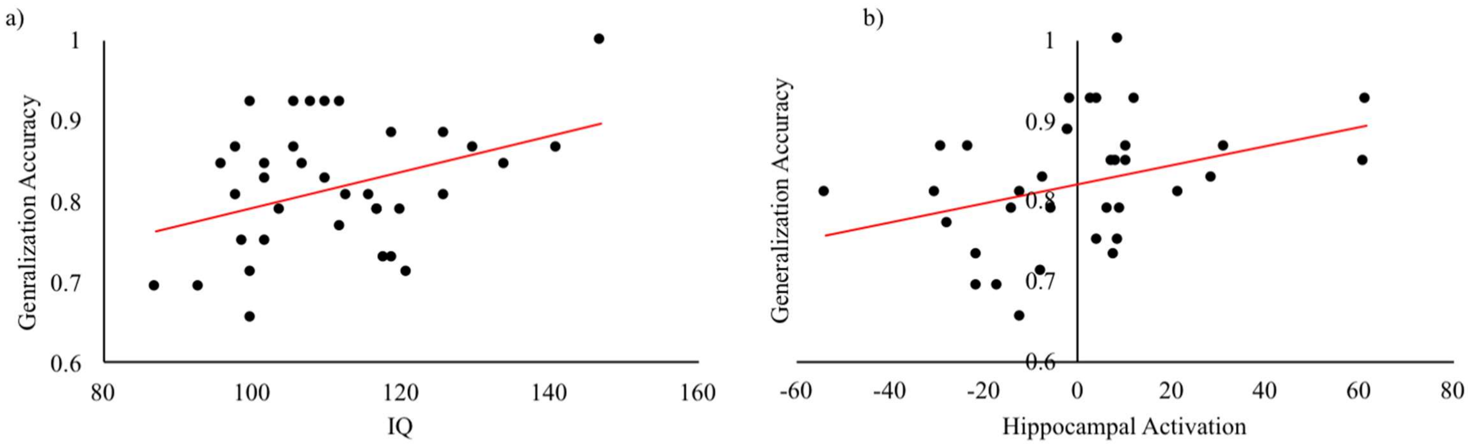

Figure 3: IQ (a) and hippocampal activation (b) tracking individual differences in concept learning.

3.2.2. NEURAL PREDICTORS

We then examined if task-based ROI activations predicted generalization accuracy using a multiple regression analysis.

While the overall model did not reach significance ($F(4,30)$ =2.14, R^2=.22, p=.100), hippocampal activation significantly tracked individual differences in concept learning (b=.003, p=.017; Figure 3b). The VMPFC, caudate, and lateral occipital activation predictors were not significant (Table 2). The pattern of results remained the same even after excluding the participant with the highest generalization score, indicating that the significant hippocampal contribution to generalization was not driven by data of a single participant.

Table 2. Task-related activations of ROIs predicting the categorization accuracy

Predictors	Beta	t	p
Hippocampus	.003	2.53	.017
VMPFC	-.001	-.92	.365
Caudate	-.001	-1.04	.306
Lateral occipital	<.001	-.01	.995

Lastly, we conducted an exploratory analysis to test whether cognitive and neural predictors explain common or complementary variance in concept learning by putting IQ and hippocampal activation in one model to predict generalization accuracy. The model significantly accounted for 28.0% of the variance in generalization scores ($F(2,32)=6.32$, $p=.005$). The result also revealed that IQ ($b=.002$, $p=.012$) and hippocampal activation ($b=.001$, $p=.013$) both remained significant when the other was controlled for. Thus, IQ and hippocampal activation tracked unique aspects of concept learning. When excluding the positive outlier, the model was still significant ($F(2,32)=6.32$, $R^2=.20$, $p=.005$); however, only hippocampal activation remained a significant predictor of generalization accuracy ($b=.001$, $p=.019$). Thus, while the hippocampal activation predicted generalization success robustly, the IQ results were to some degree driven by a participant with an extreme IQ score who also achieved perfect generalization accuracy.

3.3. DISCUSSION

We investigated concept learning from several angles. First, we were interested in how concept-learning ability would be related to other cognitive activities (IQ, working memory, processing speed, verbal comprehension, and perceptual reasoning). We found that overall IQ positively predicted generalization accuracy, and this was not driven by any single subcomponent of IQ. However, the relationship between IQ and generalization accuracy was partially driven by a subject with an extreme IQ score and did not reach significance when that participant was excluded from analysis, though it remained in the right direction. Our findings are not in accordance with previous studies on the relationship between working memory capacity and concept-generalization abilities. Regardless of the direction of the relationship, previous work supports the notion that individuals' working memory capacities are correlated with their concept generalization accuracy (e.g., Craig & Lewandowsky, 2012; DeCaro et al.,2008; Tharp & Pickering, 2009). However, we did not find any significant correlation between generalization accuracy and working memory capacity nor any other subcomponents of IQ such as logical reasoning and semantic knowledge. While other studies have identified individual cognitive abilities that predict concept learning (Ashby & O'Brien, 2005; Lewandowsky, 2011; Varga & Bauer, 2017), we found that a more holistic measure of overall cognitive abilities was the best predictor of concept generalization. This may be because there are multiple routes to acquire concept knowledge and no single ability captures the multifaceted process of learning a new concept.

Secondly, we examined task-related activations of concept learning regions and found that only the activation in the hippocampus tracked individual differences in concept learning. Importantly, the hippocampal finding was independent of the activation in other ROIs (the VMPFC, caudate, lateral occipital). This finding supports the important role of the hippocampus in concept learning as previous work also indicated (e.g., Zaki et al., 2003) However, in contrast with previous studies with similar stimuli sets, we did not find any significant activations in the VMPFC, caudate, or lateral occipital. The lack of activation in the VMPFC found here is not in line with previous studies in this field, which found the VMPFC to be activated with the hippocampus during concept-learning tasks (Bowman & Zeithamova, 2018; Zeithamova, Maddox, & Schnyer, 2008). Moreover, we did not find any significant activations in procedural learning regions. In our study, subjects learned by observing category labels rather than by learning through guessing and receiving feedback. Procedural learning regions contribute primarily to feedback-based learning (Cincotta & Seger, 2007; Seger & Miller, 2010). This might explain why they did not show a strong relationship to individual differences in performance in our task. Therefore, our results suggest that the extent to which individuals' task engagement in the hippocampus is a key determinant of how well they perform in generalization.

In addition, both IQ and hippocampal activation individually predicted unique variance in concept generalization, suggesting that each captures a distinct aspect of what makes individuals vary in their concept-generalization abilities. The role of IQ needs to be verified or refuted in a larger-scale study, as this result did not reach significance without the positive outlier. However, the current study is one of the few, if not the only one, that speculates both stable cognitive abilities and task-based brain states are responsible for the learning of new concepts. If confirmed by future studies, our results indicate that both stable aspects of cognition (IQ) and transient activations of the brain are important for successful concept learning. One possible explanation of our finding that IQ and hippocampal activation explain distinct variance is that our IQ measures and our regions of interest in the brain were not well-aligned. Since IQ is complex and consists of different subcomponents (i.e., in WAIS-IV, working memory, processing speed, verbal comprehension, and perceptual reasoning), we could not find any specific "IQ region(s)". Instead, differences in IQ likely arise from complex interactions between networks of brain regions. Similarly, the relationship between hippocampal activation and generalization might have remained significant even when IQ was included in the regression model because the WAIS-IV does not capture the episodic memory process that the hippocampus is responsible for. Thus, without a better alignment of the behavioral and neural predictors, it is difficult to definitively conclude that each variable uniquely contributes to concept generalization abilities.

3.4. LIMITATIONS

A primary concern arisen from our behavioral results was that the significant relationships we found between IQ and concept generalization accuracy were driven by a subject with a 100% accuracy and IQ of 147. When computing the same statistics without this particular subject, the relationship between IQ and categorization performance did not reach significance. Thus, our behavioral results were largely driven by this one subject. This issue is compounded by the small sample size of our current study. With only 36 subjects included in the behavioral analyses and

35 subjects in the exploratory analysis before excluding the positive outlier, a relatively large effect size was required to reach statistical significance. With a bigger sample size, we would be able to attain more reliable data on the relationship between stable aspects of intelligence (e.g., IQ and working memory capacity) and concept learning (e.g., DeCaro et al., 2008; Little & McDaniel, 2015). Thus, a future study with a larger sample size is necessary to more decidedly determine the contribution of IQ to concept learning. Although the current study is preliminary given its small sample size, the results we presented in this paper detailing the relationship between IQ and individual differences in concept learning are an important first step in determining the relative contribution of both stable cognitive abilities and transient task-related brain states to performance.

3.5. CONCLUSION

In the present study, we demonstrated the possible role that overall intelligence plays in concept learning. We show that a composite IQ score, rather than its separate subcomponents, predicts concept generalization abilities across individuals. Our results also support the contribution of a declarative memory region in concept learning – the hippocampus. Finally, we have initial evidence that concept generalization is supported by both broad cognitive abilities and activation in a core long-term memory region. Thus, we suggest that both stable cognitive abilities and transient brain states influence the ability to learn new concepts.

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REFERENCES

Aizenstein, H. J., MacDonald, A. W., Stenger, V. A., Nebes, R. D., Larson, J. K., Ursu, S., & Carter, C. S. (2000). Complementary category learning systems identified using event-related functional MRI. *Journal of Cognitive Neuroscience*, *12*(6), 977-987.

Ashby, F. G., & Ell, S. W. (2001). The neurobiology of human category learning. *Trends in cognitive sciences*, *5*(5), 204-210.

Ashby, F. G., & O'Brien, J. B. (2005). Category learning and multiple memory systems. *Trends in cognitive sciences, 9*(2), 83-89.

Ausburn, L. J., & Ausburn, F. B. (1978). Cognitive styles: Some information and implications for instructional design. *Ectj*, *26*(4), 337-354.

Baddeley, A. (1992). Working memory. *Science*, *255*(5044), 556-559.

Berka, C., Levendowski, D. J., Lumicao, M. N., Yau, A., Davis, G., Zivkovic, V. T., ... & Craven, P. L. (2007). EEG correlates of task engagement and mental workload in vigilance, learning, and memory tasks. *Aviation, space, and environmental medicine*, *78*(5), B231-B244.

Bowman, C. R., & Zeithamova, D. (2018). Abstract memory representations in the ventromedial prefrontal cortex and hippocampus support concept generalization. *Journal of Neuroscience*, 2811-17.

Button, K. S., Ioannidis, J. P., Mokrysz, C., Nosek, B. A., Flint, J., Robinson, E. S., & Munafò, M. R. (2013). Power failure: why small sample size undermines the reliability of neuroscience. *Nature Reviews Neuroscience*, *14*(5), 365-376.

Cincotta, C. M., & Seger, C. A. (2007). Dissociation between striatal regions while learning to categorize via feedback and via observation. *Journal of cognitive neuroscience*, *19*(2), 249-265.

Craig, S., & Lewandowsky, S. (2012). Whichever way you choose to categorize, working memory helps you learn. *The Quarterly Journal of Experimental Psychology*, *65*(3), 439-464.

Daneman, M., & Carpenter, P. A. (1980). Individual differences in working memory and reading. *Journal of verbal learning and verbal behavior, 19*(4), 450-466.

DeCaro, M. S., Carlson, K. D., Thomas, R. D., & Beilock, S. L. (2009). When and how less is more: Reply to Tharp and Pickering. *Cognition*, *111*(3), 415-421.

DeCaro, M. S., Thomas, R. D., & Beilock, S. L. (2008). Individual differences in category learning: Sometimes less working memory capacity is better than more. *Cognition*, *107*(1), 284-294.

Friedman, N. P., Miyake, A., Corley, R. P., Young, S. E., DeFries, J. C., & Hewitt, J. K. (2006). Not all executive functions are related to intelligence. *Psychological science, 17*(2), 172-179.

Grill-Spector, K., Kourtzi, Z., & Kanwisher, N. (2001). The lateral occipital complex and its role in object recognition. *Vision research*, *41*(10-11), 1409-1422.

Knowlton, B. J., Mangels, J. A., & Squire, L. R. (1996). A neostriatal habit learning system in humans. *Science*, *273*(5280), 1399-1402.

Lewandowsky, S. (2011). Working memory capacity and categorization: Individual differences and modeling. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *37*(3), 720-738.

Little, J. L., & McDaniel, M. A. (2015). Individual differences in category learning: Memorization versus rule abstraction. *Memory & cognition*, *43*(2), 283-297.

Mu, Q., Mishory, A., Johnson, K. A., Nahas, Z., Kozel, F. A., Yamanaka, K., ... & George, M. S. (2005). Decreased brain activation during a working memory task at rested baseline is associated with vulnerability to sleep deprivation. *Sleep, 28*(4), 433-448.

Neisser, U., Boodoo, G., Bouchard Jr, T. J., Boykin, A. W., Brody, N., Ceci, S. J., ... & Urbina, S. (1996). Intelligence: Knowns and unknowns. *American Psychologist*, *51*(2), 77-101.

Reber, A. S., Walkenfeld, F. F., & Hernstadt, R. (1991). Implicit and explicit learning: Individual differences and IQ. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *17*(5), 888-896.

Schnyer, D. M., Maddox, W. T., Ell, S., Davis, S., Pacheco, J., & Verfaellie, M. (2009). Prefrontal contributions to rule-based and information-integration category learning. *Neuropsychologia*, *47*(13), 2995-3006.

Seger, C. A. (2008). How do the basal ganglia contribute to categorization? Their roles in generalization, response selection, and learning via feedback. *Neuroscience & Biobehavioral Reviews*, *32*(2), 265-278.

Seger, C. A., Dennison, C. S., Lopez-Paniagua, D., Peterson, E. J., & Roark, A. A. (2011). Dissociating hippocampal and basal ganglia contributions to category learning using stimulus novelty and subjective judgments. *Neuroimage*, *55*(4), 1739-1753.

Seger, C. A., & Miller, E. K. (2010). Category learning in the brain. *Annual review of neuroscience*, *33*, 203-219.

Tharp, I. J., & Pickering, A. D. (2009). A note on DeCaro, Thomas, and Beilock (2008): Further data demonstrate complexities in the assessment of information–integration category learning. *Cognition*, *111*(3), 410-414.

Varga, N. L., & Bauer, P. J. (2017). Using event-related potentials to inform the neurocognitive processes underlying knowledge extension through memory integration. *Journal of cognitive neuroscience*, *29*(11), 1932-1949.

Vogel, E. K., & Machizawa, M. G. (2004). Neural activity predicts individual differences in visual working memory capacity. *Nature*, *428*(6984), 748-751.

Wechsler, D. (2008). *Wechsler adult intelligence scale–Fourth Edition (WAIS–IV)*. San Antonio, TX: Pearson.

Wechsler, D., Coalson, D. L., & Raiford, S. E. (2008). *WAIS-IV: Technical and interpretive manual*. San Antonio, TX: Pearson.

Zaki, S. R., Nosofsky, R. M., Jessup, N. M., & Unverzagt, F. W. (2003). Categorization and recognition performance of a memory-impaired group: Evidence for single-system models. *Journal of the International Neuropsychological Society*, *9*(3), 394-406.

Zeithamova, D., Dominick, A. L., & Preston, A. R. (2012). Hippocampal and ventral medial prefrontal activation during retrieval-mediated learning supports novel inference. *Neuron*, *75*(1), 168-179.

Zeithamova, D., Maddox, W. T., & Schnyer, D. M. (2008). Dissociable prototype learning systems: evidence from brain imaging and behavior. *Journal of Neuroscience*, *28*(49), 13194-13201.