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Article

The influence of working memory on auditory category learning in the presence of visual stimuli

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SUMMARY

In our daily lives, our brains process categories of information that allow us to recognize and respond appropriately to objects and situations. For example, auditory category learning involves differentiating between sounds and learning the optimal strategy for sorting sounds into various categories. In the complex, multimodal world, we learn under distracting conditions, with both relevant and irrelevant information. However, in the lab, learning is often studied under quiet and focused conditions with limited distractions. In this study, we explored the association between working memory capacity and auditory category learning in the presence of visual distractor stimuli. We trained participants on one of two types of auditory categories that are linked to distinct neural learning mechanisms, rule-based or information-integration, in the presence of simple or complex visual distractors. We assessed working memory capacity using an operation span task, which includes answering simple math questions while memorizing a sequence of letters. We found that individuals with higher working memory capacity had higher overall task accuracy, regardless of the type of category they learned or the type of visual distractors they had to process. Higher working memory capacity was also associated with higher accuracy on questions about the visual distractors. These results shed light on how auditory category learning proceeds under distracting conditions and the importance of understanding the implications. While some students may be less affected by distracting stimuli, such as music, TV, and conversation, others may be more impacted by distractions.

INTRODUCTION

How can we differentiate between apples and oranges, domestic pets and wild animals, a cry of surprise and a cry of pain? The answer is by category learning. If our brain were to store every independent record of an encounter with a fruit to differentiate between an apple and an orange, then it would require a tremendous amount of storage capacity. Instead, our brain can detect the higher-level structures of our experiences and the commonalities between them and group them into meaningful categories. This allows us to recognize and respond appropriately even to objects and situations that we may not have come across earlier (1). Categorization is thus a common phenomenon in one's daily life. It is the simple act of differentiating between objects or stimuli and making sense of the stimulus in your brain. Category learning identifies the optimal strategy for sorting objects into various categories (2).

Although category learning is essential, people have varying aptitudes for it. While some may be able to quickly pick up the optimal strategies for categorization, others may struggle to learn (3). There may also be differences in the ability to learn categories in different modalities, meaning forms of sensory perception, such as auditory and visual stimuli. Selectively attending to visual dimensions may be easier than selectively attending to acoustic dimensions, due to easy-to-verbalize categorization rules in the visual modality compared to difficult-to-verbalize rules in the auditory modality (4, 5). Dimensions are a way to define features of stimuli. For example, visual dimensions include color and shape and auditory dimensions include pitch frequency and duration (6). Working memory capacity influences how well participants learn nonspeech rule-based (RB) and information-integration (II) categories (7, 8), RB categories rely on working memory and selective attention processing, where the differences between the categories are easy to verbalize (2). II categories rely on procedural learning mechanisms instead of working memory where the differences between the categories are more implicit (2). Other category types include weather prediction (predicting "rain" or "sun" based on four clues) and prototype distortion (sorting random patterns of dots) (2). Working memory is a form of short-term memory that holds a small amount of information in mind for a short amount of time (7, 8). Working memory is used to execute cognitive tasks and plays a large role in an individual's intelligence, processing, comprehension, and learning (9). Auditory working memory is used to preserve auditory stimuli in one's memory for short periods of time (10). Visual working memory is used to keep colors, shapes, and other visual stimuli in one's short-term memory (11).

One theory about category learning, the Competition between Verbal and Implicit Systems (COVIS) theory, suggests that there are two separate systems involved in category learning: implicit and explicit (12). The implicit system supports learning primarily through procedural reflexive learning, and the explicit system supports reflective learning primarily through hypothesis testing, selective attention, and working memory mechanisms (13, 14). Through this dual learning systems perspective, it has been suggested that procedural learning, the basis for implicit categorization, occurs when an association is formed between a group of sensory cells and an abstract cognitive or cortical-motor response (15). As a result, implicit categorization is more difficult to verbalize. In the lab, we can study implicit categorization by training participants on information-integration (II) categories. On the other hand, working memory is a critical skill for explicit categorization because when learning, one must actively remember the previous stimuli and the feedback they have received to find the optimal rule separating the categories. In the lab, we can study explicit categorization by training participants on rule-based (RB) categories. Although the COVIS theory was originally developed to explain category learning in the visual modality, it was recently extended to the auditory modality (15, 16).

Working memory is important for category learning and higher working memory is associated with better learning performance (17). Individuals differ in both working memory capacity and the efficiency with which they use their working memory capacity (18). Generally, higher working memory has been linked to better RB and II learning, but there is evidence that working memory may be more important for RB than II learning due to RB's dependence on the explicit system and selective attention (19-22-).

Working memory is especially important when distractions are present. Typically, visual stimuli typically take more resources to process, and attention is often turned toward the visual modality, resulting in inattentional deafness, or a lack of attention toward the auditory modality (23). Prior studies found that during conditions of high visual load, task performance is poorer when the auditory stimuli were predictable, implying that working memory significantly influences task performance when there are distracting stimuli present (24).

In the current study, we are interested in understanding how working memory relates to auditory category learning in the presence of visual distractors, as one might encounter in the complex, multisensory world, such as in a classroom. Prior work has shown that having increased working memory ability coincides with being better able to filter irrelevant visual distractors processed during visual tasks and reduce the interference of irrelevant auditory distractors during auditory tasks (25, 26).

This paper seeks to shed light on the debate about cross-modal distraction by studying the impact of working memory in auditory category learning in the presence of competing visual stimuli. Specifically, an individual with an innately higher working memory capacity will fare better in increasingly complicated visual tasks than would an individual with a lower working memory capacity (27, 28). However, it is still unclear how visual distractors during auditory-centered tasks affect higher working memory capacity.

We tested two alternative hypotheses about the association of working memory capacity and auditory category learning in the presence of visual distractors. In the experiment, participants were randomly assigned to learn one type of category (RB or II) in one condition of competing visual information (simple or complex). The participants learned to sort complex auditory stimuli (static ripples that varied in spectral modulation and temporal modulation) into one of two categories in the presence of visual distractors.

The first hypothesis was that the higher an individual's working memory capacity, the higher their accuracy would be for both RB and II categories, regardless of the type of visual distractor. The second hypothesis was that working memory capacity would interact with the complexity of visual distractors, such that with more complex visual distractors, the learner would have fewer working memory resources to use in the auditory category learning task. As a result, auditory category learning may be worse in complex than simple visual distraction conditions and higher working memory may not be associated with better auditory category learning performance. We found that individuals with higher working memory capacity had better learning performance, regardless of the type of category they learned or the type of visual distractors they had to process.

RESULTS

In this experiment, we examined the effect of working memory capacity on auditory category learning in the presence of competing visual information. Participants were randomly assigned to learn one type of category, RB or II **(Figure 1A-B)**, with either simple or complex visual competing information **(Figure 1C)**. During learning, participants heard a stimulus while seeing visual stimuli on the screen, responded which category they thought the auditory stimulus belonged to, and received feedback about whether they were correct or incorrect. We measured correct identification of the category stimuli as participants' ability to learn the categories. RB sounds differed in their temporal modulation alone, while II differed in both temporal modulation and spectral modulation **(Figure 1)**. As a result, for the RB categories, a simple rule on temporal modulation rate could determine category identity. For example, category 1 has a faster temporal modulation rate than category 2 **(Figure 1B)**. In contrast, for II categories, a simple rule is not sufficient to determine category identity and participants need to use both temporal and spectral modulation dimensions to determine category identity **(Figure 1A)**. On a small subset of trials, participants responded to questions about the visual distractor stimuli to ensure they were paying attention to them. After participants completed the category learning task, we recorded participants' operation span (OSPAN) scores as a measure of their working memory capacity **(Figure 2)**.

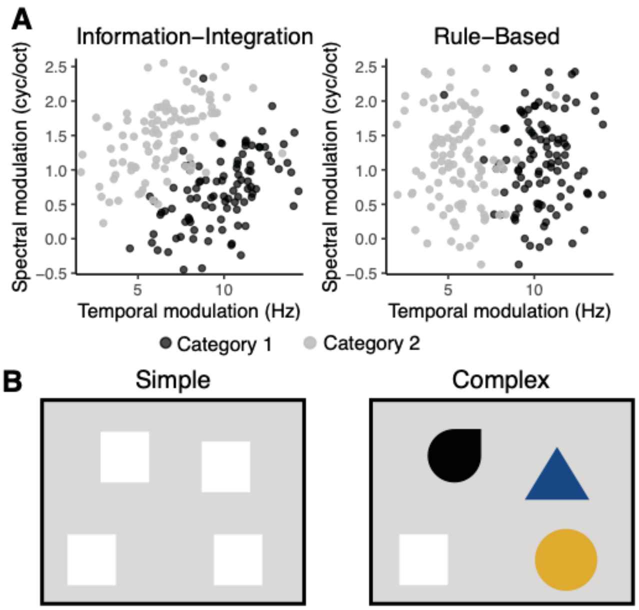

Figure 1: Category distributions for auditory stimuli and examples of visual distractors. A. Auditory stimuli for Information-Integration and Rule-Based categories. Each dot represents an individual sound with a particular temporal modulation rate (x-axis) and spectral modulation rate (y-axis). **B.** Examples of simple and complex and visual distractors shown at the same time as the auditory stimuli. The simple distractors consisted of four of the same shapes (square, drop, triangle, or circle) of the same color (white, black, blue, yellow, red) and complex distractors consisted of four different shapes, each with a different color.

Stimuli

The auditory stimuli consisted of static ripples that varied in spectral modulation and temporal modulation. These dimensions are complex dimensions of sound, underlying music and speech perception (29). Interested readers can find examples of the stimuli can be found in the online repository (30). The visual stimuli were images consisting of four shapes (squares, circles, teardrops, or triangles) of a single or different colors (blue, red, black, white, yellow) in different locations on the screen and varied in their complexity **(Figure 1B)**. The images were either all the same shape and color (simple) or all different shapes and colors (complex). All stimuli were created by the experimenters.

Summary of Task Performance

Overall, participants learned the auditory categories, evidenced by their better-than-guessing (50%) performance **(Figure 3A)**. To understand how well participants were able to learn these categories in the presence of visual distractors, we compared the ability to correctly categorize the auditory stimuli (i.e., accuracy) across conditions. Participants learned the RB and II categories to similar levels of accuracy (mixed-model ANOVA, $F(1, 143) = 2.55$, $p = .12$, $\eta_G^2 = 0.012$). The visual complexity of the distractors (simple vs. complex) did not significantly affect participants' accuracy ($F(2, 143) = 0.61$, $p = .55$, $\eta_G^2 = 0.006$). Accuracy also did not differ when considering category and visual complexity type together ($F(2, 143) = 0.03$, $p = .97$, $\eta_G^2 = 0.0003$).

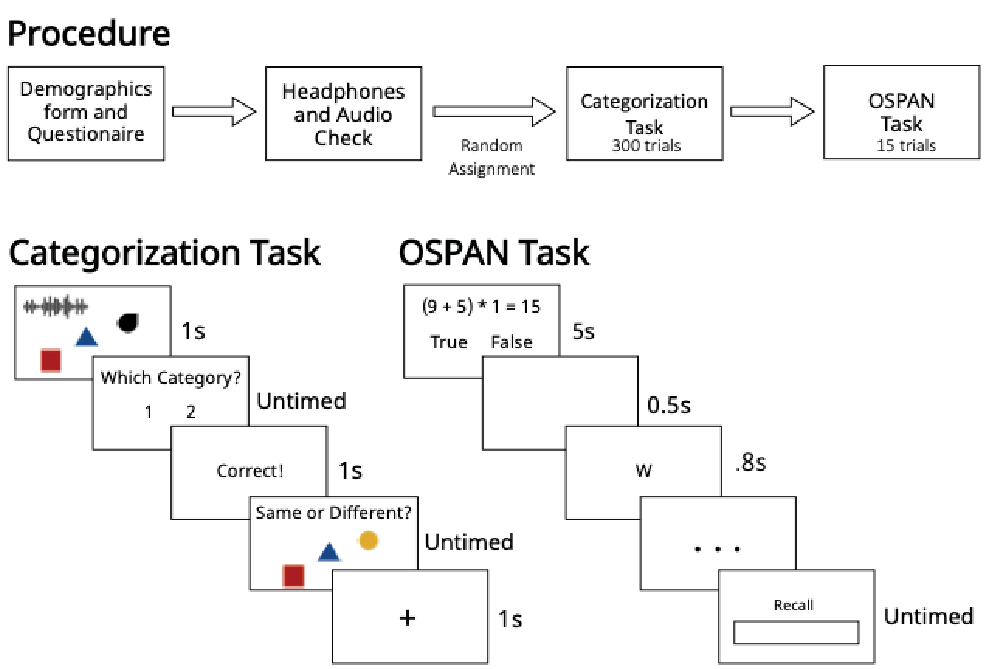

Figure 2: Experiment and task procedures. Overview of the full experiment procedure and the trial procedures for the categorization task and the operation span (OSPAN) working memory task.

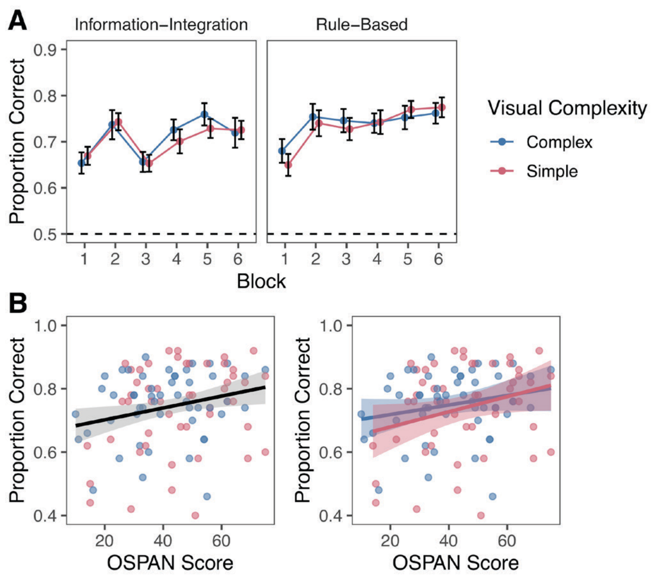

Figure 3: Category learning performance and relation with working memory. A. Mean proportion of correct answers for each block for Information-Integration (II) and Rule-Based (RB) categories. Error bars reflect SEM and the dashed line reflects chance performance (50%). **B.** Regression results for the relationship between working memory and category learning averaged across both categories and visual complexity conditions (left) and separately by complexity of visual distractors (right).

However, we found that performance differed across blocks for the RB and II categories, evidenced by a significant interaction between block and category ($F(3.95, 564.3) = 0.62$, $p = .001$, $\eta_G^2 = 0.01$). To further examine this, we ran Bonferroni-corrected post hoc tests on the effect of category in each block. We found that the accuracy in RB tasks (mean = 73%) was significantly higher than the accuracy in II (mean = 65%) tasks in the third block only ($p = .000438$) with no other block had a significant difference between the two ($p > .61$). In other words, there was no significant difference in the participants' task accuracy between RB and II categories in most of the blocks except for the third block, in which participants had a higher RB accuracy than II accuracy.

We also examined whether participants attended to the visual distractor stimuli. Specifically, on 10% of trials (30/300 trials), after categorizing the sound and receiving feedback, participants were given a visual array that was either identical to or different from the previous visual array. Participants responded whether this new array was exactly the same or different from the previous array. Participants also attended to the visual distractor stimuli, evidenced by their above-chance accuracy on the same-different questions in both the simple ($t(50) = 14.2$, $p < .001$, $d = 1.98$) and complex conditions (**Figure 4A**; $t(50) = 14.7$, $p < .001$, $d = 2.06$). Performance on the visual distractor questions was significantly better for the simple stimuli (mean = 76%) than the complex stimuli (mean = 71%; $F(1, 98) = 5.53$, $p = .021$, $\eta_G^2 = 0.053$). There was no significant difference based on the type of category participants learned ($F(1, 98) = 0.50$, $p = .48$, $\eta_G^2 = 0.0050$) and there were no significant differences based on consideration of both the type of distractor (simple vs. complex) and category type together ($F(1, 98) = 0.02$, $p = .89$, $\eta_G^2 = 0.00021$).

Relationship between Working Memory and Category Learning

The main question we investigated was whether working memory capacity impacts one's category learning ability under visually distracting conditions. We hypothesized that higher working memory capacity would be associated with better category learning performance and may be affected by the complexity of the visual distractors. Specifically, we measured participants' visual working memory capacity based on their score on an operation span task.

To understand if working memory was related to category learning ability, we first used a simple linear regression to test if working memory score significantly correlated with final

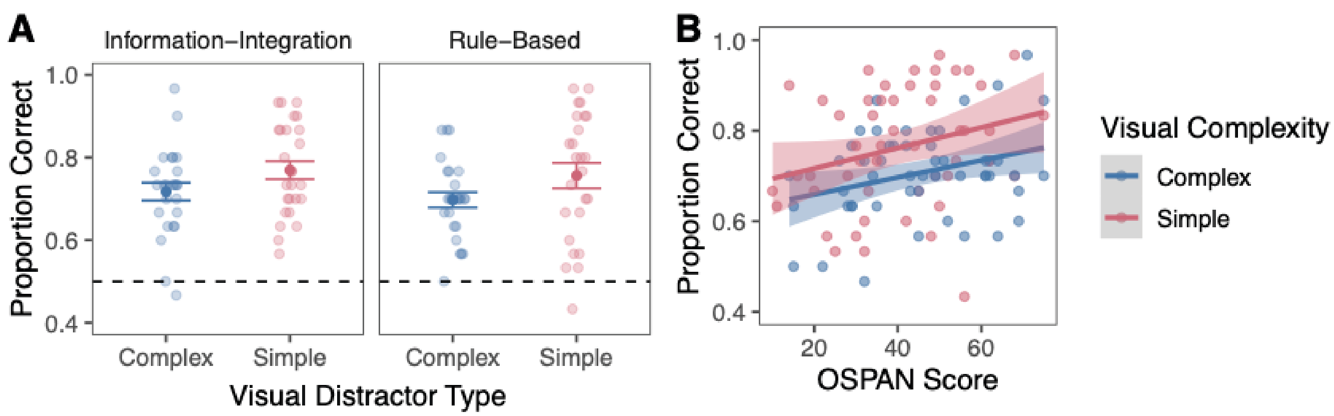

Figure 4: Visual distractor performance and relation with working memory. A. Mean proportion of correct answers on visual distractor same-different questions. Error bars reflect SEM and the dashed line reflects chance performance (50%). Lighter dots represent individual participants. **B.** Regression results of relationship between working memory and visual distractor questions separately by complexity of the visual distractors and averaged across both categories.

Fixed effect	Estimate	SE	*p*	sig
Intercept	68.857	4.785	<.001	***
OSPAN (working memory score)	0.150	0.111	.178	ns
Complex	-5.674	6.990	.419	ns
OSPAN (working memory score) x Complex	0.089	0.153	.563	ns

Table 1: Linear regression model results for effect of working memory on categorization based on condition. Table depicts the Estimate from the regression model, SE (Standard Error), and *p*-value of the linear regression model for the fixed effects of intercept, OSPAN score, complex stimuli, and the interaction between OSPAN score and Complex stimuli (OSPAN x Complex).

block accuracy **(Figure 3B)**. Overall, we found that working memory score was significantly related to categorization accuracy (R^2 = 0.049, *p* = .014). As working memory score increased by one, final block accuracy increased by 0.19% (β = 0.19, SE = 0.075).

We then tested whether working memory score significantly predicted final block accuracy differently in the simple or complex visual distraction conditions using a multiple linear regression model **(Figure 3B, Table 1)**. The overall regression was not statistically significant (R^2 = 0.039, *p* = .075). We did not observe a statistically significant difference in the relationship between working memory and final block accuracy for the simple and complex distraction conditions.

Finally, we examined if working memory score significantly predicted final block accuracy based on the interaction of category and visual complexity condition using multiple linear regression **(Table 2)**. The overall regression was not statistically significant (R^2 = 0.061, *p* = .073). We did not observe a statistically significant difference in the relationship between working memory and final block accuracy across different combinations of types of category participants learned (RB, II) and the complexity of visual distractors (simple, complex).

Working Memory and Visual Distractor Accuracy

We tested whether working memory ability significantly predicted performance on the visual distractor questions using a simple linear regression model. The overall regression was statistically significant (R^2 = 0.043, *p* = .020). The higher one's working memory capacity, the better they performed on the visual distractor questions (β = 0.17, SE = 0.073), and as working memory score increased by one, accuracy on the visual distractor questions increased by 0.17%.

We also assessed whether working memory predicted performance on the visual distractor questions differently based on whether the visual distractors were simple or complex using a multiple linear regression model **(Figure 4B)**. We defined the regression model with final block accuracy as the predictor variable and visual distractor type (simple, complex) and working memory score as fixed effects. The overall regression was statistically significant (R^2 = 0.10, *p* = .0038). Working memory score significantly predicted accuracy on the visual distractor questions for the simple condition, and as working memory score increased by one unit, accuracy on the visual distractor questions for the simple condition increased by 0.23% (β = 0.23, SE = 0.10, *p* = .032). This was not significantly different from the complex condition (β = -0.038, SE = 0.14, *p* = .79). The relationship between working memory and accuracy was not significantly different in the simple and complex conditions. Together, these results

Fixed effect	Estimate	SE	*p*	sig
Intercept	69.868	6.128	<.001	***
Rule-Based	-4.509	9.704	.643	ns
Complex	-14.436	9.374	.127	ns
OSPAN (working memory score)	0.065	0.139	.640	ns
Rule-Based x Complex	20.631	14.008	.144	ns
Rule-Based x OSPAN (working memory score)	0.236	0.226	.297	ns
Complex x OSPAN (working memory score)	0.307	0.205	.137	ns
Rule-Based x Complex x OSPAN (working memory score)	-0.510	0.308	.100	ns

Table 2: Multiple linear regression model results for working memory and categorization based on interaction between condition and category. Table depicts the Estimate, SE (Standard Error), and p-value of the linear regression model for the fixed effects of intercept, Rule-Based category, Complex stimuli, OSPAN score, interaction between Rule-Based and Complex stimuli, interaction between Rule-Based and OSPAN score, interaction between Complex stimuli and OSPAN. Score, and interaction between Rule-Based, Complex stimuli, and OSPAN score.

indicate that higher working memory capacity is associated with better performance on the visual distractor questions, regardless of whether the visual distractors were simple or complex.

DISCUSSION

This study tested the relationship between working memory capacity and auditory category learning in the presence of competing visual stimuli. We hypothesized that higher working memory would be better for learning overall, but that working memory ability might have a stronger influence on learning when distractors were simple as opposed to complex. Our results support the first hypothesis. We found that working memory was positively associated with auditory category learning and retention of information about the visual distractors regardless of the kind of distractor. These results support a view of working memory capacity as being related to the ability to simultaneously attend to auditory and visual information.

We also found that in block 3, task accuracy in the II category was significantly higher than RB task accuracy. This was not seen in any other block, and it was likely due to the sampling of the stimuli from the II category in that block. That is, due to random chance, the stimuli presented in block 3 may have been harder for participants to categorize. There were no other differences between RB and II categories across other blocks, so we do not believe that the difference in block 3 reflects any meaningful difference between the learnability of the two types of categories.

On average, we saw a 0.19% increase in accuracy on the category learning task, for every increase of 1 unit in working memory. Working memory score varied from 5 to 80 for participants in this study, meaning that a 0.19% increase in task accuracy can have important effects as the working memory capacity of participants increases. Although a 0.19% increase in accuracy for every increase in working memory score may seem like a very minute increment, it can be rather impactful for large changes in working memory capacity. For example, a working memory score of 10, the lower end of the spectrum, yields a percent accuracy of around 68.3%, while a working memory score of 60, the higher end of the spectrum, yields a percent accuracy of around 77.8%. This is a difference of 9.5%, and for students, this is almost the difference between a whole letter grade, which can greatly affect their academic performance. Therefore, this study could have implications for understanding how students learn and process information in the classroom.

According to load theory, the processing of visual distractors likely diminished the resources available to the auditory modality, especially because the brain requires more resources to process visual stimuli (23). This may have caused the participants' task performance to be lower in accuracy, although this effect likely did not depend on the complexity of the visual distractor. Future work should directly compare learning with no visual distractors to learning with simple or complex visual distractors. A different effect may be observed if the distractors were composed of auditory instead of visual stimuli, and thus this work may also be expanded into understanding the impact of auditory distractors on auditory or visual category learning.

One limitation of this study is the inability to completely control participants' learning environments. Specifically, because participants completed the study on their own, we could not control for the distractions in their environments. For example, participants may have had various forms of auditory, visual, or other sensory distractions around them while completing the tasks. It is possible that any additional distractions may have diminished the cognitive resources available for the tasks assigned. Non-experimental distractors may have impacted participants' performance on the category learning task or the working memory task. Furthermore, when considering the complexity of the visual distractors, we did not observe a statistically significant relationship between working memory and category learning performance. It is possible that this relationship exists, but we were not able to detect it here due to the possible presence of additional distractors. This may indicate the necessity to examine this relationship in a larger sample with increased power to see any potential relationship. Future work may address the interaction between experimental and non-experimental distractors on learning, limiting any additional distractors that participants may have had, and therefore decreasing the effects of any other variables. Future work may also delve deeper into the learnability of RB tasks compared to II tasks, adding to the current body of research on the topic.

In our daily lives, we can learn and categorize stimuli in complex, multimodal environments with a large amount of irrelevant information. In the lab, category learning is often studied in simple conditions without any distractions. In this study, we explored the association between working memory capacity and auditory category learning in the presence of visual distractor stimuli. We found that individuals with higher working memory capacity were better at learning, regardless of the type of category they learned or the type of visual distractors they had to process. This research suggests that based on working memory ability, students may fare differently in the presence of distracting stimuli. For example, students often have background music or the television on while studying. These results uncover more information about the ways in which students learn and process information in the presence of distracting stimuli, for example in the classroom. Furthermore, the results of this study may also be able to be extended to helping children with learning disabilities, as disorders such as autism and ADHD have been linked to difficulty in filtering out distractions (31). Regardless of the complexity of these stimuli, higher working memory capacity may bolster learning in the face of irrelevant information.

MATERIALS AND METHODS

Participants

Participants were 102 individuals (37 male, 65 female), ages 18-35, recruited from Prolific (32), an online tool that allows access to a global population of participants. Participants completed this experiment on Gorilla Experiment Builder, an online experimental platform (33). Participants were randomly assigned to conditions and the number of participants in each condition are as follows: 26 II-Simple (15 male, 11 female, mean age = 22.7 years), 25 II-Complex (16 male, 9 female, mean age = 23.8 years), 25 RB-Simple (19 male, 6 female, mean age = 22.5 years), and 26 RB-Complex (15 male, 11 female, mean age = 21.8 years). II-Simple stands for participants assigned to the II category learning task with simple visual distractors; II-Complex stands for participants assigned to the II category learning task with complex visual distractors; RB-Simple stands for participants assigned to the RB category learning task with simple visual distractors; and RB-Complex stands for participants assigned to the RB category learning task with complex visual distractors A power analysis was conducted using the WebPower package in R and indicated that 23 participants per condition would be needed to achieve an effect size of $F = 0.3$ with power of 0.8 at alpha = 0.05 (32). The effect size was chosen based on prior work (35). Participants were compensated $10/hour for participation. Research protocols were approved by the Institutional Review Board at the University of Pittsburgh. The de-identified data is publicly available through the Open Science Framework (36).

Procedure

Participants first completed a category learning task, and then a working memory task.

Category learning task. During the category learning task, participants were told to learn two different categories of sounds. At the same time as they heard the sound, they saw visual objects appear on the screen. They were told to pay attention to both the sounds and the visual objects as they would be periodically asked about the visual objects. Participants completed six blocks of training with 50 trials per block.

For each trial, participants heard a category sound while four visual objects appeared on the screen for one second, after which the participants identified what category (category 1 or category 2) the sounds belonged to using the 1 or 2 keys on the keyboard. If the category was RB, then there was a simple way to differentiate between categories: category 1 had a higher temporal modulation, in Hz, while category 2 had a lower temporal modulation. If the category was II, it was harder to differentiate between categories: a stimulus from category 1 would have higher spectral modulation than a stimulus from category 2 with the same temporal modulation. There was not a set amount of time to complete each trial or task. Assignment of category to keyboard key was counterbalanced across participants, meaning that some participants pressed “1” for Category 1, while some pressed “2” for Category 1. Participants then received feedback about whether they were correct, by way of the word “Correct” or “Incorrect” appearing on their screen for one second. For 10% of the trials, after receiving category feedback, participants also completed a visual check to ensure that they were attending to the visual stimuli. For the visual checks, participants were presented with an image on the screen that was either identical or different from the image that they had previously seen during the trial. Participants responded whether the second image was the same as or different from the first image **(Figure 2)**. After each trial, there was a one second inter-trial interval.

Working memory task. We recorded participants' operation span (OSPAN) scores as a measure of their working memory capacity (36, 37). The OSPAN test used consists of a series of trials in which the participants were shown simple arithmetic problems (e.g., (9 + 5) x 1 = 15) and reported whether the solutions shown were correct or incorrect. Participants had a maximum of 5 seconds to respond, followed by a 0.5 second delay. Participants were then shown individual letters for 0.8 seconds (Figure 2). Participants were shown 15 equation-letter sequences that spanned from three to seven letters. At the end of a sequence, participants were asked to recall the letters in the order they were presented. The OSPAN score was calculated as the sum of the length of completely correct sequences, with one point being awarded for every correct letter. For example, if a participant correctly reported all three letters in a sequence, three points would be added to their score.

Data Analysis and Statistics

Data analysis was done in R, version 4.1.0 (38). Statistical significance was defined based on frequentist thresholds with an alpha of 0.05. We compared categorization accuracy across conditions using a mixed-model ANOVA with the complexity of the irrelevant visual distractors (simple, complex) and category type (RB, II) as between-subjects factors and block of 50 trials (1-6) as a within-subjects factor. We compared performance on the visual distractor questions across categories and visual distractor conditions using a two-way ANOVA with visual distractor complexity (simple, complex) and category (RB, II) as factors.

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