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Sequence Position Affects Shape Categorization

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MS, Tufts University, 2020

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An abstract of
A thesis submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
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Abstract

Sequence Position Affects Shape Categorization

By Angelle Antoun

Language is an incredibly powerful ability that can be used to communicate a theoretically infinite range of ideas and concepts. This is possible because of the interaction of semantics, the meaning of words, and syntax, the rules that govern their organization and order. When presented with novel words, humans will use word order to determine which semantic category (noun, verb, etc.) the novel word belongs to. To determine whether this tendency to use sequence information to infer category membership exists outside of the domain of language, I examined the interaction of sequence and category using non-linguistic stimuli. I created three perceptual shape categories (rounded shapes, squared shapes, and pointed shapes), as well as a series of ambiguous intermediate shapes generated by morphing between those categories. Fifty participants first learned to categorize the shapes, and were then taught a simple sequence (rounded shape followed by squared shape, then pointed shape). When ambiguous morphs were inserted into the sequence, their position in the sequence radically shifted their categorization towards the shape whose position they occupied. This implies that the tendency to use sequence information to categorize stimuli may be a broad, generalizable ability, that occurs outside of the domain of language.

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Contents

Sequence Position Affects Shape Categorization

Language is an incredibly powerful tool, allowing humans to communicate a functionally limitless number of ideas and concepts. The ability to turn thought into communicable sentences allows for collaboration, innovation, and historical record. This allows for the rich communication of complex ideas, and is made possible through the interaction of syntax and semantics (Chomsky, 1965; Friederici et al., 2017). Syntax is the set of rules that govern word-order in sentences. For example, allowing us to determine who did what to whom. This gives language the potential to generate an infinite number of possible sentences with an unlimited variety of combinations. Semantics refers to the meanings of the words themselves, but it also includes the meaning of categories of words, such as nouns, verbs, and prepositions, word types that denote fundamentally different things, such as actions or objects (Palmer & Palmer, 1981). Syntax impacts semantics in two ways. First, word order impacts the meaning of individual words. For example, the same word can act as either a noun or a verb depending on where it occurs in a sentence. It also changes the meaning of the sentence holistically; taking the same words and rearranging them changes the meaning of the sentence as a whole. This interplay of semantics and syntax creates a unique system that is both incredibly expressive and powerful, and ubiquitous to all human cultures (Christiansen et al., 2009).

Part of what makes the interaction of syntax and semantics so powerful is that syntax not only acts on individual words, but entire categories of words (Chomsky, 1965). This allows a single sentence structure to apply in many contexts. For example, a simple sentence might have the structure determiner → noun → verb, and this could create sentences like "The man wrote," "A cat meows," or "an apple fell." This means that a limited number of grammatical rules can generate sentences to describe a vast range of situations. In addition to acting on entire categories, syntactic structure can impact how words are perceived, even changing their category membership based on word order. For example, in the sentence “I went on a run,” run is a noun, but in “Let’s run away,” it is a verb. In fact, humans often use word order to infer the category membership of novel words to aid word learning (Chierchia, 1994; Fisher et al., 2010; Naigles, 1990; Redington et al., 1998), as I will discuss below. This interaction of sequence with category is clearly involved in language learning and processing. But, it is unclear whether the tendency to categorize stimuli based on sequence position is a language specific ability, or if it is a domain general process that can apply outside of language contexts. Additionally, if this ability is domain general, it may still have evolved for linguistic purposes, but expanded since the evolution of language into a more general ability. Alternatively, it may be an ability that evolved for other reasons prior to language. Improving our understanding of the impact of sequence on categorization outside of a language context will help answer these questions, and it is the focus of my project.

Artificial Grammar Learning

The interaction of syntax and semantics makes it difficult to study natural language learning in either domain without interference from the other. One approach that allows for the study of syntax in isolation is the use of artificial grammar learning paradigms (Bahlmann et al., 2008; Franck et al., 2016; Gómez & Gerken, 1999; Petersson et al., 2012; Petkov & ten Cate, 2020; Uddén & Männel, 2018; Wilson et al., 2013, 2020). Artificial grammars are sets of rules that determine the order in which a set of stimuli (usually auditory or visual) occur in a sequence (Reber, 1967; Wilson et al., 2013). They are designed to mimic aspects of natural language syntax, and allow for a more controlled study of how language is learned. These paradigms vary in complexity, but do not involve symbolic or semantic learning, and instead map grammatical rules onto arbitrary, meaningless stimuli. Participants are exposed to these sequences of stimuli and, over time, notice regularities in the co-occurrence of the stimuli in the sequence. This statistical learning allows them to learn the structure of the grammar. In a subsequent testing phase, participants are presented with novel sequences, half of which are generated by the grammar and are therefore grammatical, and half of which are not, and are therefore ungrammatical. If participants neural or behavioral responses vary depending on the grammaticality of the sequences, this provides evidence that they have learned the structure of the artificial grammar (Gómez & Gerken, 1999; Petersson & Hagoort, 2012; Uddén & Männel, 2018).

Artificial grammar learning has been used successfully to explore the process of language acquisition in infants (Gómez & Gerken, 1999; Pelucchi et al., 2009; Saffran et al., 1996), language learning processes in adults (Petersson & Hagoort, 2012), and deficits associated with language such as aphasia (Cope et al., 2017; Grube et al., 2016) and dyslexia (Folia et al., 2008; Gabay et al., 2015). In humans, artificial grammar learning tasks engage overlapping brain networks compared to natural language syntax tasks (Friederici, 2011; Petersson et al., 2012), and have been shown to correlate with language ability (Conway & Pisoni, 2008), demonstrating their utility as tests of language-related syntactic rule learning. Artificial grammars need not be complex, and even simple sequences are useful for probing syntactic abilities (Clegg et al., 1998). One additional advantage of an artificial language approach is its lack of reliance on semantic or linguistic instruction. As such, these approaches have often proven useful in comparing human abilities to those of other species. Artificial grammar learning paradigms have identified both behavioral and neural homologies between humans and monkeys, suggesting that the core cognitive processes involving artificial grammar learning, and thus some aspects of language acquisition, might not be unique to humans or to language (Petkov & ten Cate, 2020; Wilson et al., 2017).

Interaction of Categories and Sequences in Language

One critical difference between many artificial grammar tasks and real-life grammar learning is the generalizability of grammars from acting on individual stimuli to categories of stimuli. The grammatical structure of a sentence is not only dependent on the specific words, but instead the categories of words. As mentioned in a previous example, determiner→noun→verb (D→N→V) is a grammatical structure, acting on word categories, that can apply across many specific words. “The dog ran,” “An airplane flew,” and “A pencil fell;” are grammatical sentences with the same structure but different meanings. This is possible because the D→N→V sequence does not act on the specific items themselves, but on the entire word categories (Chomsky, 1965). So, while artificial grammar studies have proven useful, many of these examples lack categories, and, as I will discuss, categories have important impacts on the learning and use of language.

One important interaction of sequence and category in language is the use of sequence in learning novel words. Children use grammatical category information, such as noun or verb, and flexibly apply grammatical rules to novel words within those categories. For example, the famous “wug test” shows children are able to pluralize nonsense nouns effectively, despite never hearing the nonsense words before (Berko, 1958). Children are presented with a picture of a nonexistent animal, and the sentence “This is a wug.” Further down on the page there is a picture with two of them, and the sentence “Now there are two of them. There are two ___.” Children will reliably fill in the blank with the word “wugs,” correctly pluralizing what they understand to be a noun. While the “wug test” is not explicitly a test of the interaction of sequence and category, the sentences in which the nonsense words were introduced did not explicitly state they were nouns. The membership of “wug” to the noun category was assumed from its position in the sentence, and pluralization rules were then applied accordingly.

Similar tasks have shown the ability to generalize past-tense endings to nonsense verbs (e.g. “blorp” is turned into “blorped”), and even demonstrated that nonsense nouns, verbs, and adjectives would be given different types of endings, despite all being nonsense exemplars (Prasada & Pinker, 1993). This varied application of ending types is based on the category membership of these nonsense words, with category membership determined by sentence position. Additionally, once an unknown word is determined to be a verb, toddlers can use the order of nouns in the sentence to determine who should be acting on whom, despite not knowing what action is being taken. This has been tested by inserting nonsense verbs into sentences to describe scenes where one agent acts on another (e.g. “look, the duck is blorping the bunny!”). Despite these novel verbs being unknown, when then asked to “find blorping,” children as young as 21 months will then look longer at the scene where the duck is acting on the bunny rather than where the bunny is acting on the duck. Again, this demonstrates that even young children use the order of words in the sentence to interpret which character should be acting on which, despite not knowing what the action actually is (Gertner et al., 2006).

In natural languages, people also make use of word order information to learn new words by using word position to infer which categories they fall into (e.g. noun or verb) (Redington et al., 1998). One example is in Lewis Carroll’s Jabberwocky poem (Carroll, 1871). Consider the first two lines of the poem: “'Twas brillig, and the slithy toves did gyre and gimble in the wabe.” Despite the words themselves being nonsense, the sentence is still decipherable. In fact, you can tell simply from the word order of the sentence that “gyre” is a verb. This highlights once more the importance of the interaction between sequence and category in language. Children regularly use sequence to infer category when learning language. Via a process called syntactic bootstrapping, children use the order and category membership of the words they know in a sentence to determine the category of a novel word they do not (Chierchia, 1994; Fisher et al., 2010; Naigles, 1990). All of this evidence suggests that this interaction of word order and category membership has the potential to affect how grammar is learned and utilized (Kako & Wagner, 2001). These studies tell us much about the ability to use sequence in categorization; it is clearly used in language, and present from an early age. This raises the question of whether this ability is language specific and operates only in linguistic contexts, or if it is a more general cognitive process with a more ancient evolutionary history. For example, if this ability were shared by nonhuman primates, it would suggest it was present in our most recent common ancestor, and thus predates the emergence of language. To test this, experiments must be developed that do not rely on semantic and linguistic information.

Categories in Artificial Grammar and Sequence Learning Studies

Most artificial grammar learning research has focused on how participants learn relationships between individual stimuli, similar to grammatical relations between individual words. However, as discussed above, language is rarely so simple, and acts on word categories rather than individual words. As such, some artificial grammar learning studies have included categories of stimuli rather than individual exemplars. These categories fall into two types; arbitrary, or perceptual.

In grammars that use arbitrary categories, unrelated stimuli are randomly assigned to each category. The category of each stimulus must be individually learned by participants. In these tasks, human infants were capable of learning grammars across category sets, even though the actual word items changed across tests (Gómez & Gerken, 2000; Saffran et al., 2008). This considerably increases the difficulty of the task, however, as participants must learn which categories stimuli correspond to in addition to the grammar. Additionally, items are not grouped based on any meaningful features, in the way that verbs, for example, are meaningfully similar in function. Despite not having common perceptual features, all verbs share the property of denoting actions. There is also some evidence for perceptual similarity playing a role in lexical categories (Onnis & Christiansen, 2008). As such, arbitrary categories in artificial grammar studies do not fully capture the meaningful relationship between language categories.

Grammars based on perceptual categories take a different strategy, creating categories based on perceptual links between the stimuli (Friederici et al., 2006). This allows categories to be immediately salient, and eliminates the need for memorization. Some have involved phonological similarities, such as using male voices for one category and female for another (Fitch & Hauser, 2004) or keeping vowel sounds consistent within each category (Bahlmann et al., 2008), while others have created a series of visual shapes with the same patterns for each category (Bahlmann et al., 2009). Using this method, novel stimuli can immediately be categorized by participants using perceptual features alone; a striped shape will automatically be categorized as belonging to the striped category, regardless of where it is presented in the sequence. As such, to study the impact of sequence information on stimulus categorization, perceptual categories alone are insufficient.

Outside of the artificial grammar literature, others have also assessed sequence learning based on categories of stimuli. For example, Terrace and colleagues have conducted many studies in which Rhesus macaques and humans learn to generate sequences from pictorial categories of images (e.g., cat → flower → human). Both humans and macaques are able to learn this task despite the specific images changing from trial to trial, demonstrating that they are capable of processing sequences based on perceptual categories of stimuli (Altschul et al., 2017). Humans and macaques can even use categories to infer order via transitive inference. That is, if they were taught to choose items from the first category over the second, and the second category over the third, they could transfer that knowledge to choose the first category over the third. This trained ordered set (essentially a sequence) reliably generalized to novel images. This demonstrated they could use the category membership of each picture to infer its position in that sequence (Tanner et al., 2017). However, it is unclear if the reverse, inferring category membership from sequence position, is possible, as with language.

Impact of Sequence on Categorization in Non-Linguistic Contexts

If people can use sequence order to infer the category membership of an uncategorizable item in a context outside of natural language learning, then it could indicate that the use of sequence to infer category is a broader, more general ability that was coopted for use in language. Alternatively, if sequence has no effect on categorization in a non-language context, then that may mean the impact of sequence on categorization is more language specific. Disentangling this would inform our understanding of how language skills evolved.

To better understand the impact of sequence position on category membership in a non-language context, I developed a novel paradigm. This required the creation of category groups that lacked semantic information. While it was tempting to use arbitrarily created categories, those categories are not generalizable to novel items. Additionally, as mentioned previously, they do not fully capture the meaningful properties of linguistic categories. Any arbitrary categories also require extensive memorization and limit the possible size of the stimulus set. With perceptual categories, however, novel items become instantly categorizable, eliminating any possibility of testing the effect of sequence position on this categorization. If you are presented with a repeating sequence (cat→dog→ rabbit) and are then presented with a new picture of a cat, you can still be confident that it is a cat, and it will be immediately categorizable. This will be true regardless of where it is presented in the sequence, even if it is in the position usually occupied by a rabbit. This is a different process than the categorization of a nonsense word, where there is no intrinsic indication of its noun membership, and order is informative. So, while perceptual categories are useful for the study of the interaction of sequence and category, testing the categorization of novel items require stimuli that mimic novel, uncategorizable words.

As such, to test the effect of sequence on category, I created category sets of perceptually similar shapes (rounded, squared, and pointed shapes). I then generated a spectrum of intermediate shapes that traverse the boundaries of those categories by morphing together shapes from each category (Destler et al., 2019). This created a series of increasingly ambiguous shapes that emulate uncategorizable novel words. This is a novel solution to examine how sequence impacts category membership in non-language contexts.

Participants first learned to categorize shape stimuli into three categories (rounded, squared, or pointed). They were then presented with ambiguous morphs, and I assessed how they categorized these ambiguous shapes. This provided my baseline. Next, participants were taught a simple, recurring sequence of categories: first rounded shapes, then squared, then pointed. The ambiguous morphs were then inserted into the sequence to assess how their sequence position changed how they were categorized. If participants use sequence information to categorize non-linguistic stimuli, then the threshold of shape categorization should shift based on the position of the ambiguous shape in the sequence. If this is the case, it demonstrates humans have the capacity to use sequence to infer category membership outside of language. It would also open up the possibility to study the interactions of sequence and category outside of a language context, with the potential for more controlled future comparisons between age groups and species.

Methods

Participants

51 Emory University Undergraduate students participated in this study. One was omitted for failing to complete the task due to technical difficulties, resulting in 50 participants. They were all 18-22 years old. 41 were female and 9 were male. All subjects had normal or corrected-to-normal vision. They were recruited through the Emory University SONA system, and each received 1 credit of introductory psychology research participation for taking part.

Stimuli

To study the impact of sequence on categorization, perceptually categorizable shapes were necessary, as were ambiguous stimuli that fall between those categories. To create perceptually different but well controlled shape categories, stimuli were generated in MATLAB R2021b. Images were white shapes on a black background, and 200x200 pixels. Three categories of shapes were generated, ‘rounded’, ‘squared’, and ‘pointed’, with between 4 and 10 limbs protruding from the center. Each shape category also had three variations in the width of the limbs, resulting in 21 distinct shapes per category, and 63 total shape stimuli (Fig. 1).

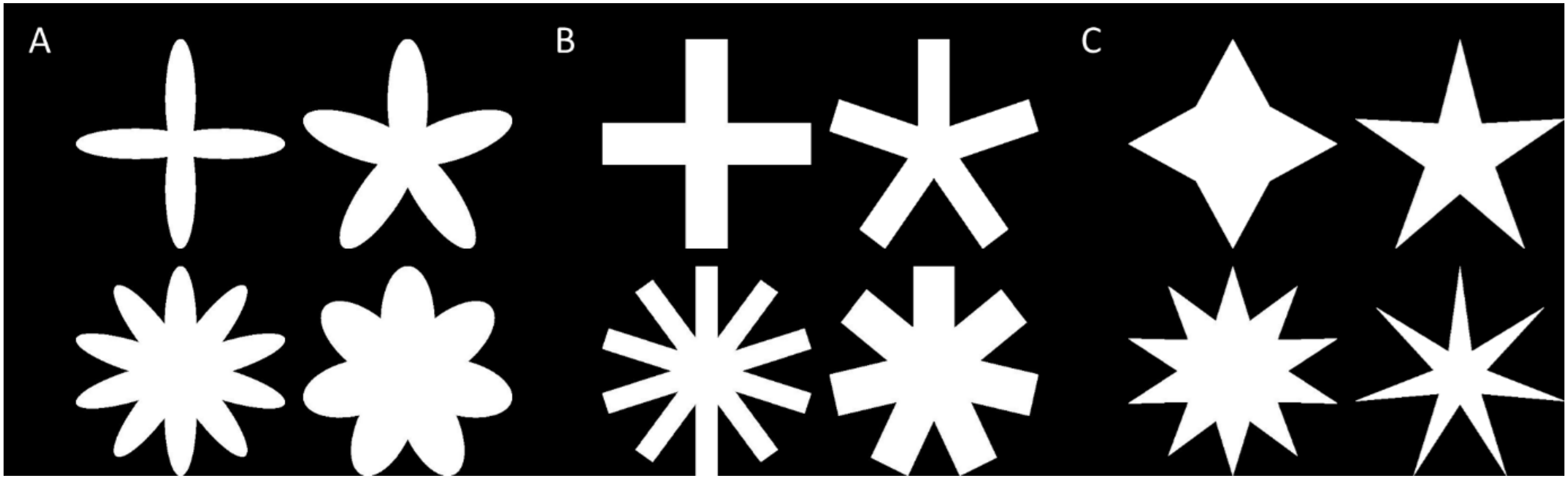

Fig. 1: Four exemplars from each category: A) Rounded, B) Squared, and C) Pointed. Each category included 21 items, ranging from 4 to 10 limbs, each with 3 variations of width and length.

Ambiguous shapes were generated in MATLAB R2021b, using a technique modified from Destler et al. (2019). “Morph spaces” were generated by selecting two distinct shape stimuli, and interpolating between the two anchor shapes, creating a range of ambiguous shapes. For testing purposes, 6 morph spaces were created: three exemplars of each category combination with 5 limbs, and three of each with 6. Each morph space generated 6 equidistant intermediate morph increments. The 4 morph increments in the center, which were the most ambiguous, were used for testing. This generated 24 individual morph stimuli for testing (Fig. 2).

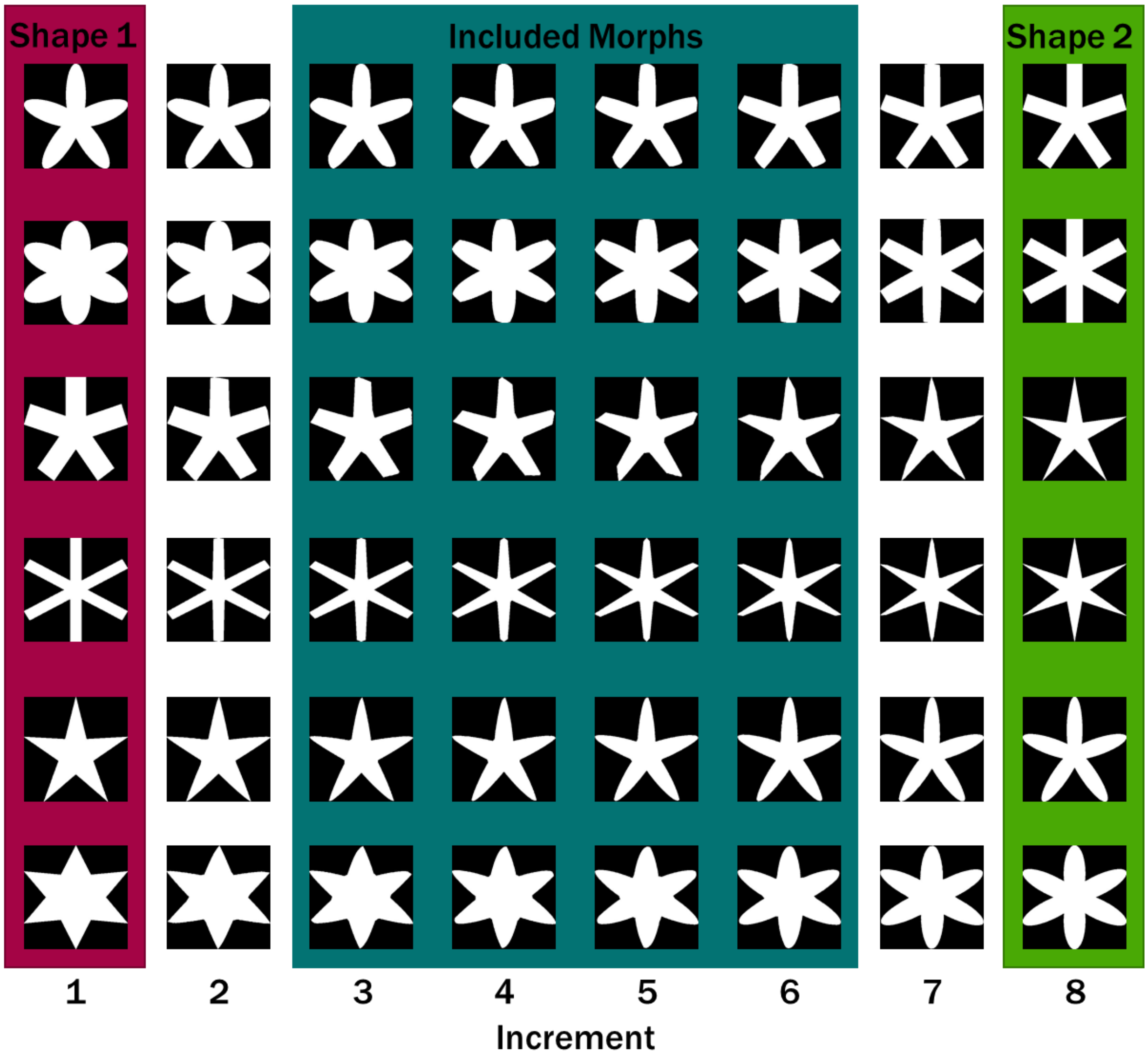

Fig. 2: The six morph spaces, generated in MATLAB. Only the center 4 increments of each were used as ambiguous test stimuli. Top to bottom these are rounded-squared 5 limbs, rounded-squared 6 limbs, squared-pointed 5 limbs, squared-pointed 6 limbs, pointed-rounded 5 limbs, and pointed-rounded 6 limbs. Red background indicates shape 1 anchors, green background indicates shape 2 anchors, and blue background indicates the morphs included in the trials.

Procedure

To determine how the position of an item in a sequence affects how that item is categorized, participants needed training on several tasks. This training occurred in four phases (Fig. 3A), and took place in a custom-designed, silent, well-lit testing room. Subjects were seated about 24 inches away from a 24-inch-wide touchscreen monitor that they could position comfortably via a movable mount. Across the four phases, stimuli were presented on the screen, and participants touched them to make choices. Feedback was given in the form of a green or red screen, and a positive or negative sound through the speakers. No other specific instructions were given, and participants learned the task via trial and error. They had the opportunity to take breaks between phases if they chose.

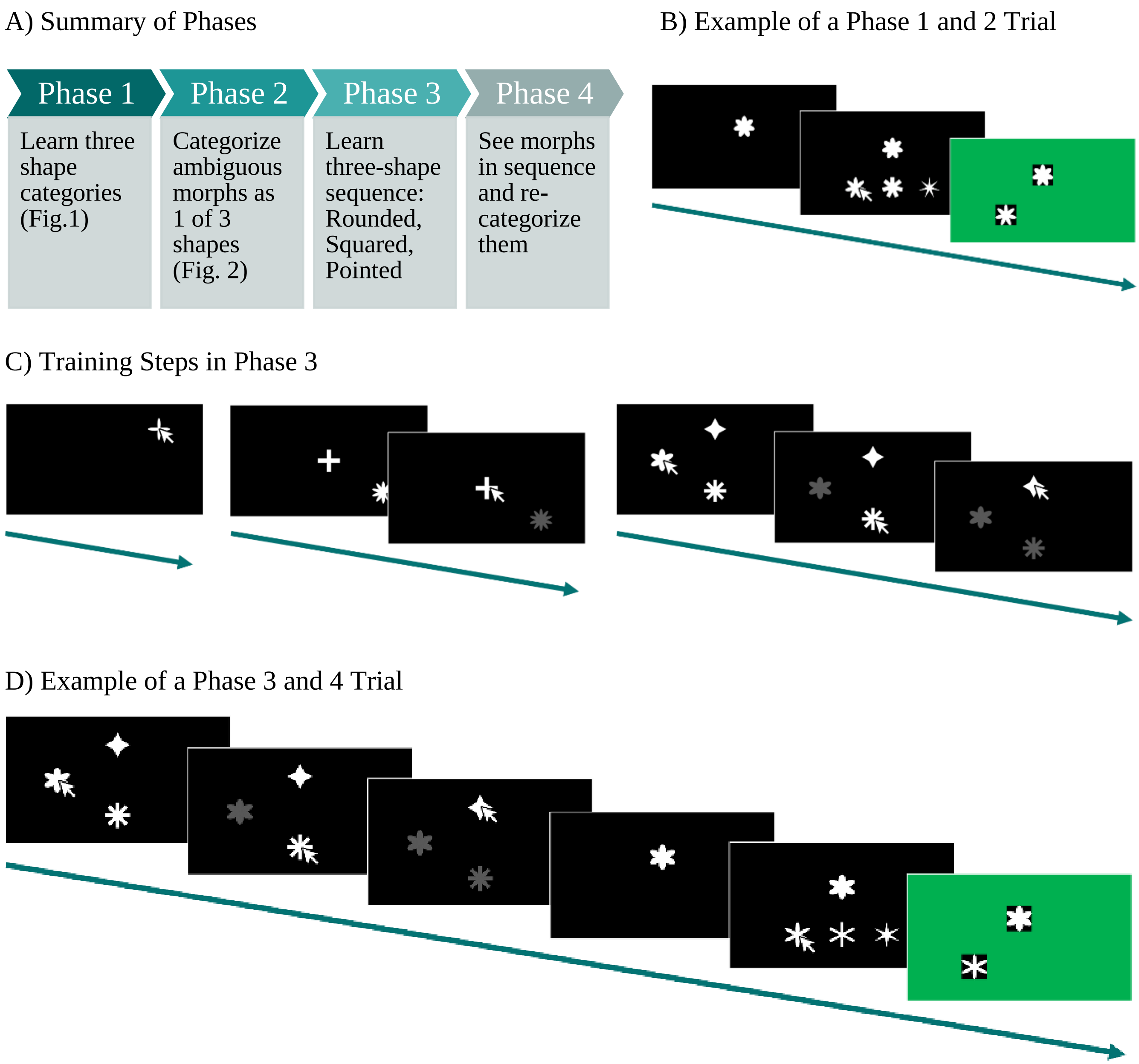

Fig. 3: A) A breakdown of the 4 experimental phases. B) An example of a categorization trial, in which participants were required to match the target stimulus to the correct category target at the bottom of the screen (Phase 1 and 2). C) The order of sequence training, with examples. Participants were given 5 trials where they touched a rounded shape appearing somewhere in a random position on a 3x3 grid on the screen. Then, they were given at least ten trials of both a rounded and squared shape and needed to touch rounded first then squared. Finally, they were given at least 15 trials with all three shapes appearing in random positions, and needed to select them in order: rounded, squared, pointed. D) An example trial of the final stage of phase 3, where participants were given the 3 item sequence to generate, and then immediately categorized an item from the sequence. Phase 4 used the same structure, but replaced one shape in the sequence with an ambiguous morph, and then presented that morph for categorization.

Phase 1: Category Training

To train participants on the three shape categories, participants were presented with a randomly selected shape stimulus (cue) in the center of the screen. When they touched the stimulus, one exemplar from each category appeared along the bottom of the screen (targets). Exemplars were randomly selected from those with the same number of limbs as the cue, but different width parameters (Fig. 3B). Participants then selected one of the target shapes. If they chose the correct shape, matching category, they were given positive feedback, otherwise they were given negative feedback. Each participant was given at least eleven trials, and testing continued until they reached 80% accuracy on the ten most recent trials. Most participants passed in the minimum number of trials, and all participants passed in less than 17 trials.

Phase 2: Baseline Categorization Threshold Testing

To determine each participant's baseline categorization boundary, the procedure from Phase 1 was repeated with the ambiguous morphs (Fig. 3B). All 21 morphs were presented in a random order as cue stimuli. The targets included the two anchor shapes from which the cue morph was generated, as well as one randomly selected exemplar with the same number of limbs from the third category. Selection of either anchor shape included in the morph was given positive feedback, while selection of the third shape was given negative feedback. This process was repeated 4 times, for a total of 84 trials.

Phase 3: Sequence Training

Participants were taught a simple sequence of rounded→squared→ pointed shapes in 3 steps (Fig. 3C). First, a randomly selected rounded shape appeared in a randomly selected position on the screen. Positions were generated by dividing the screen into a 3x3 grid, and randomly selecting one of the 9 possible options. Participants touched the rounded shape to move forward, and were reinforced with positive feedback. This was repeated 5 times.

In the following trial, both a rounded and a squared stimulus appeared in randomly generated positions on the screen, and participants were expected to learn to press the rounded shape first, then the squared shape. If participants selected the squared shape first, they were given negative feedback, and another trial began. If they selected the rounded shape, that shape became transparent and was no longer active, at which point they had the opportunity to select the squared shape to move forward. They were then given positive feedback, and another trial began. This procedure was repeated a minimum of 10 times, after which they continued until they reached 80% criterion on the ten most recent trials.

Finally, participants were presented with randomly selected exemplars from all three categories simultaneously, in randomly generated positions on the screen. They were rewarded for pressing rounded, then squared, then pointed, (again, with each shape turning transparent after selection), with any other combination resulting in negative feedback, and a new trial. After participants successfully generated each sequence of three shapes, they were given a follow-up categorization trial. This was to acclimate participants to continued categorization for the upcoming test phase. This categorization portion was identical to Phase 1. One shape that had appeared in the preceding sequence was selected as the cue stimulus for this categorization (Fig. 3D). Once participants touched the stimulus, three target shapes (exemplars from the three categories with the same number of limbs as the cue stimulus) were presented along the bottom of the screen. Incorrect categorization resulted in negative feedback, and successful categorization resulted in positive feedback. This process continued for a minimum of 15 trials, after which participants only moved forward once they achieved 80% accuracy on their 15 most recent sequence completion trials.

Phase 4: Sequence Effect on Categorization Testing

This final test examined how the categorization of ambiguous shapes changed after they appeared in the learned sequence. The procedure for the final stage of Phase 3 was repeated, with a trial made up of a three-item sequence generation followed by a categorization test (Fig. 3D). However, in these trials, one shape in the sequence was replaced by an ambiguous morph, and that same morph was the cue in the categorization test to assess the effect of sequence position on categorization. Each morph shape was included in two trials. In one trial, it was placed in the sequence where one of its shape anchors belonged, and in the second trial, it was placed where the other shape anchor belonged. For example, a ponted-rounded morph shape would be positioned in one trial as the rounded shape in the sequence (and thus should be selected first), and in another trial as the pointed shape in the sequence (and thus should be selected last). This process was repeated for each morph shape, resulting in 48 trials. The full set of 48 was repeated 4 times, with each set presented in a random order, and with random exemplars in the sequence and target positions. This resulted in 192 trials.

Data Analysis

All analyses were performed in RStudio, version 1.4.1103 (R Core Team, 2020). A baseline categorization curve was established for each morph shape in Phase 2. This was done by calculating the proportion of trials in which participants categorized the morph as the second shape in the morph space, and plotting that against the increment number (Fig. 4). In Phase 4, two more categorization curves were established. One for trials where the morph was presented in the anchor shape 1 position, and one for trials where the morph was presented in the anchor shape 2 position (Fig. 4). Data were analyzed via generalized linear mixed models using R package lme4 (Bates et al., 2015, p. 4) with binomial distributions. Model of best fit was selected via ICtab using package bbmle (Bolker & R Development Core Team, 2020), and factor effects were calculated via Anova using package car (Fox & Weisberg, 2019). To determine the direction of any effects, Tukey Post Hoc tests were run using package emmeans (Lenth, 2022).

Additionally, to investigate individual differences in the effect of sequence on categorization, differences in mean categorization proportions were compared for each participant. Trials where morphs were presented in the anchor shape 1 position were compared with trials where morphs were presented in the anchor shape 2 position for each participant. Pairwise t-tests were used via package rstatix (Kassambara, 2021) in this comparison to determine how many participants utilized sequence in their categorization strategy. Finally, Spearman's rank correlations were calculated to examine the relationship between this difference and performance and learning rates using package stats (R Core Team, 2020).

Results

Learning and attention checks

The goal of this task was to investigate the impact of sequence position on shape categorization. Shifts in categorization of ambiguous morphs based on where they were presented in a trained sequence of categories would be evidence for this. Phase 1 required the participants to learn to categorize shapes as rounded, squared, or pointed in a categorization task. Participants rapidly learned to categorize the three shape types in Phase 1. All participants reached criterion (80% correct in the previous 10 trials) within 17 trials, with the vast majority (47/50) needing only the minimum 11 trials.

When given ambiguous morphs to categorize, participants reliably (all above 90%, with 46/50 at 95% or higher) chose one of the two endpoint shapes in the morph over the third, unrelated shape. This indicates that the morphs shifted clearly from one shape to the other, never becoming so amorphous as to be confused for a different shape entirely. As expected, morph increment affected categorization (Fig. 4).

During sequence learning in Phase 3, most participants learned the three-item sequence quickly. Participants took 30 to 136 trials to complete the phase (*M* = 38.94, *SD* = 19.04), with the vast majority learning within 75 trials. One outlier took 136 trials to pass this phase. Subsequent analyses were performed both including and excluding this participant, but their removal did not impact the results. The reported results include all participants, for completeness.

In the final phase, participants were presented with ambiguous morph shapes within the sequence. Each morph was presented four times in the position of the first shape in the morph, and four times in the position of the second shape in the morph. Participants were then re-tested on categorization of the morph stimulus, to see if sequence position affected categorization. Trials where the sequence was produced incorrectly by participants were omitted, as the trial was aborted and they did not advance to the categorization phase of that trial. Those errors were recorded. All were well above chance.

Effects of Sequence Position on Categorization

I found that sequence position had a dramatic effect on shape categorization. I assessed how participants categorized morph shapes based on the position in which they appeared in the sequence. This morph position was compared for each morph when presented in the shape 1 position versus the shape 2 position, and each condition was also compared to baseline categorization from Phase 2. For example, comparing the categorization of a pointed-rounded shape when it was presented where the pointed shape belonged in the sequence versus where the rounded shape belonged in the sequence. For clarity, I am first displaying the overall results from the whole experiment (Fig. 4). The analysis included type of morph as a factor, so the data is subsequently broken down by morph type (Fig. 5).

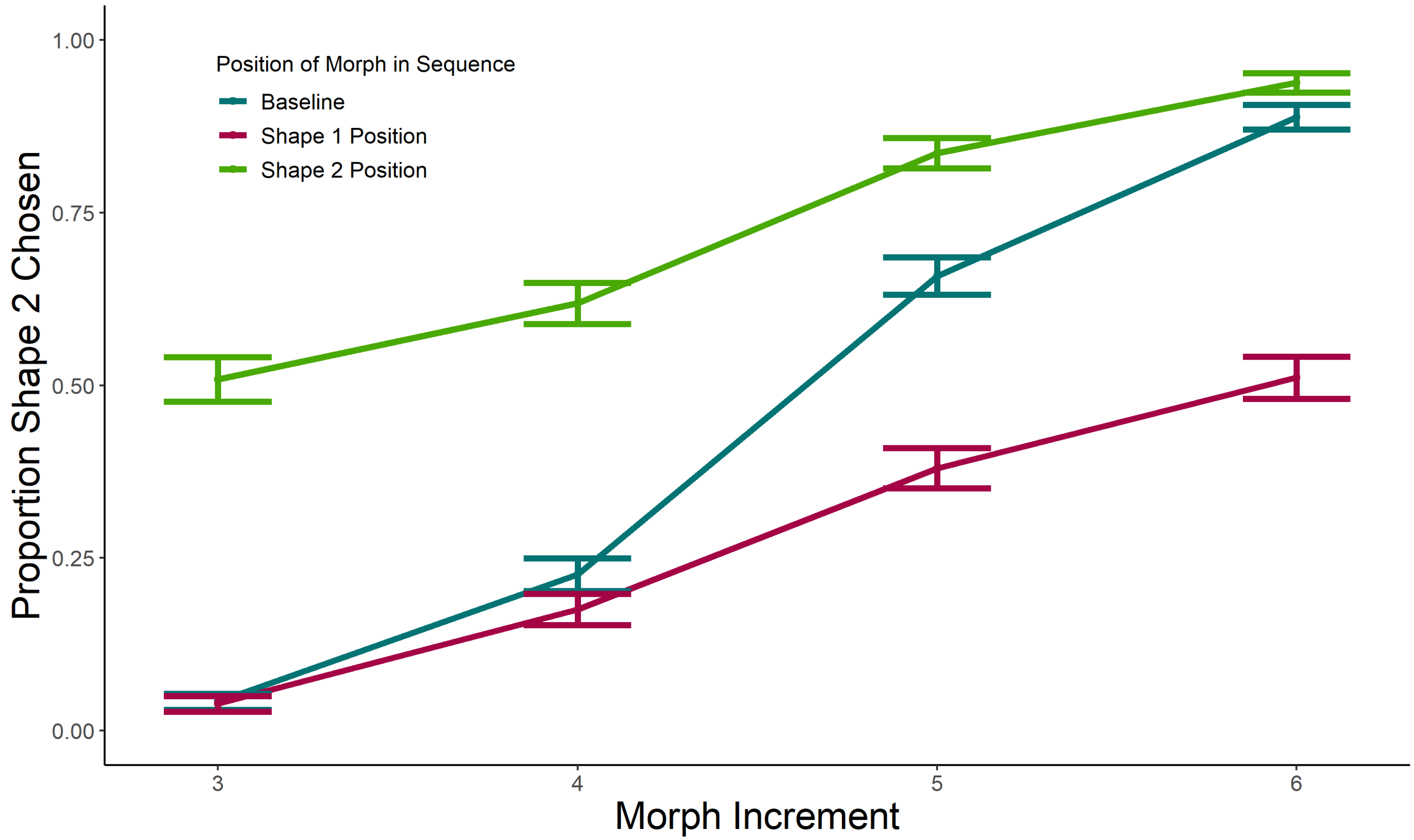

Fig. 4: Proportion of anchor shape 2 chosen is plotted on the y axis, where a value of 1 means anchor shape 2 was selected 100% of the time, and a value of 0 means anchor shape 1 was selected 100% of the time. This value was plotted against morph increment on the x axis for all morphs combined. Shape 2 categorization varied as a factor of where the morph was presented in the sequence, with shape 2 positions resulting in more shape 2 categorization, and vice versa. Proportion of shape 2 categorization also varied with increment, as increments closer to anchor shape 1 were less likely to be categorized as shape 2, and vise versal. The rate of change in categorization from one increment to another also varied with morph position. Error bars represent 95% confidence intervals.

To test for effects of sequence position, I ran a generalized linear mixed model (glmm). As morph categorization was recorded as a binary choice of either anchor shape 1 or anchor shape 2, I used a binomial distribution including participant as a random effect. The best fit model included the type of morph (rounded-squared versus squared-pointed versus pointed-rounded), the increment of the morph, and the position of the morph in the sequence as fixed effects, with participant as a random effect. This model was competed against relevant nested models, and selected as the model of best fit using Akaike information criterion using ICtab in package bbmle (Bolker & R Development Core Team, 2020). Factor effects were calculated via Anova using package car (Fox & Weisberg, 2019), and analysis was performed in RStudio, version 1.4.1103 (R Core Team, 2020).

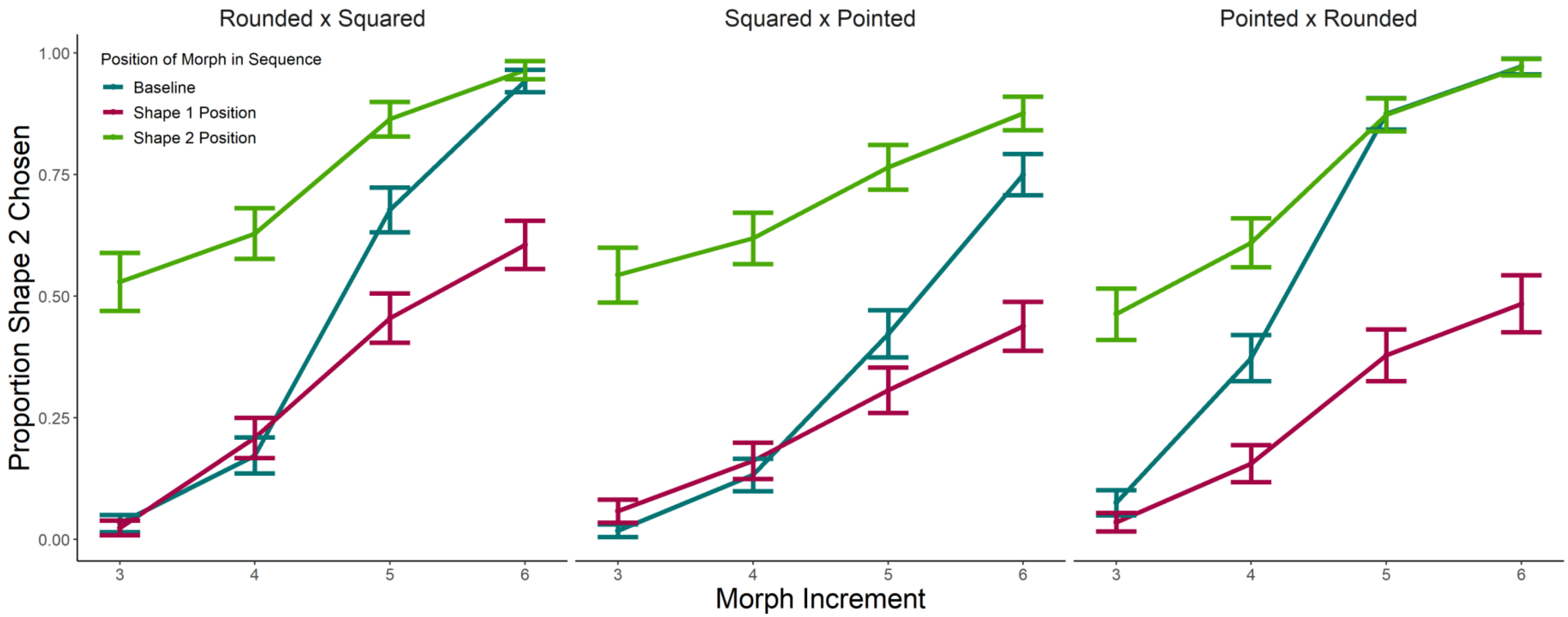

Fig. 5: Proportion of anchor shape 2 chosen is plotted on the y axis, and morph increment was plotted on the x axis for each type of morph. Shape 2 categorization varied as a factor of where the morph was presented in the sequence, with shape 2 positions resulting in more shape 2 categorization, and vice versa. Proportion of shape 2 categorization also varied with increment, as increments closer to anchor shape 1 were less likely to be categorized as shape 2, and vice versa. Shape categorization varied based on type of morph, with overall proportions of shape 2 selected varying based on the type of shape. The rate of change in categorization from one increment to another also varied with morph position. Finally, the rate of change in categorization from one increment to another also varied based on the type of morph, as categorization curves change at different rates depending on the type of morph. Error bars represent 95% confidence intervals.

The factor of interest, shape position, had a significant effect on categorization ($\chi^2(2) = 1800.20$, $p < 0.0001$). This demonstrated that the position of the morph in the sequence influenced how the morph was categorized. Morph type also significantly affected categorization ($\chi^2(2) = 156.67$, $p < 0.0001$), demonstrating categorization patterns were different depending on which shapes were being morphed. Increment also had a significant effect on categorization ($\chi^2(3) = 1956.52$, $p < 0.0001$), as increments closer to shape 1 were more likely to be categorized as shape 1, and vice versa. Similarly, there was a significant interaction effect of morph type and increment ($\chi^2(6) = 70.28$, $p < 0.0001$), as the increment categorization changed at different rates depending on which shapes were being morphed. In other words, the threshold for categorization occurred in different places in the morph space depending on which shapes were being morphed.

There was also an interaction of morph type and morph position ($\chi^2(4) = 183.145$, $p < 0.0001$), demonstrating that the effect of shape position varied based on the morph space. That is, the effect was stronger for some morph combinations than others. Additionally, there was an interaction of morph position and increment ($\chi^2(6) = 317.171$, $p < 0.0001$). So, categorization of individual increments shifted differently across the morph position groups. This is because morph increments closer to shape 1 were already reliably categorized as shape 1, and therefore did not change when presented in the shape 1 sequence position. Conversely, when presented in the shape 2 position, their categorization shifted drastically. The opposite pattern held for increments closer to shape 2, and increments in the center shifted more equally in each position condition.

To confirm the direction of the significant effect of morph position, Tukey HSD pot hoc comparisons were conducted. The results indicate that baseline shape categorization was significantly different from both the shape 1 position condition ($p < 0.0001$) and the shape 2 position condition ($p < 0.0001$), and both shape conditions were also significantly different from each other ($p < 0.0001$). This clearly demonstrates that the position of an ambiguous morph in a learned sequence significantly impacts how that ambiguous morph is subsequently categorized, with sequence information biasing respondents to categorize ambiguous shapes as the shapes that belong in that position.

Relationship Between Performance in Sequencing Phase and Categorization

To examine the factors that may have contributed to the impact of sequence position on categorization, I ran Spearman's rank correlations to establish which factors correlated with the morph position effect. To do this, I calculated the effect of sequence on categorization for each participant. This was done by taking the mean proportion of shape 2 choices when the morph was in the shape 2 position, and subtracting the mean proportion of shape 2 choices when the morph was in the shape 1 position. This provided an average difference based on sequence position for each participant. This effectively calculated the mean difference between the red and green lines in Figure 1 for each individual.

I next calculated how many trials it took participants to learn the sequence in phase 3 to determine if number of trials to criterion negatively correlated with the effect of sequence on categorization. There was a negative correlation between the length of phase 3 and the effect of sequence ($r(48) = -0.46$, $p = 0.0008$) (Fig. 6). This demonstrates that participants who struggled more learning the sequence showed less of an effect of sequence on their categorization in subsequent phases, possibly implying sequence was less of a salient factor overall for some individuals.

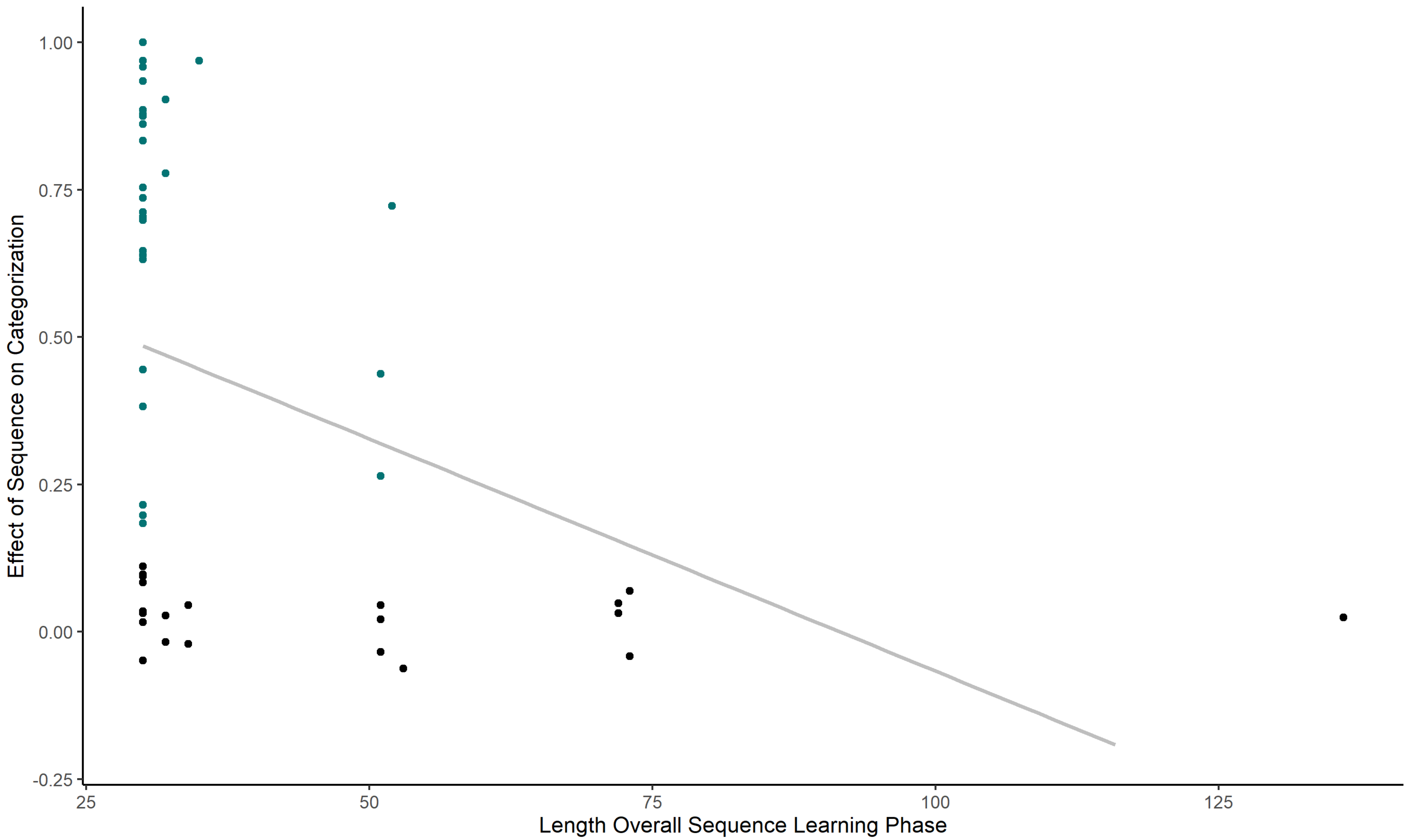

Fig. 6: Sequence position effect for each participant (calculated as mean proportion of shape 2 choices for trials where morph was in shape 2 position minus mean proportion of shape 2 choices for trials where morph was in shape 1 position) plotted against how many trials it took each participant to learn the sequence in Phase 3. Light blue dots signify participants who exhibited a significant sequence effect, and black dots signify those who did not.

To assess the relationship between sequence effect and performance in the final phase, I computed a Spearman's rank correlation. If the same individuals had low impact of sequence position on shape categorization, and low performance completing the sequence, it adds credence to the idea that some participants were less likely to attend to sequence position overall, and this impacted their shape categorization. Performance on Phase 4 was calculated as the proportion of trials where participants generated the sequence correctly, and chose one of the two possible correct morph anchors in the categorization portion. There was a positive correlation between performance and sequence effect ($r(48) = 0.53$, $p < 0.0001$), implying that successfully generating the sequence predicted sequence effect on categorization (Fig. 7).

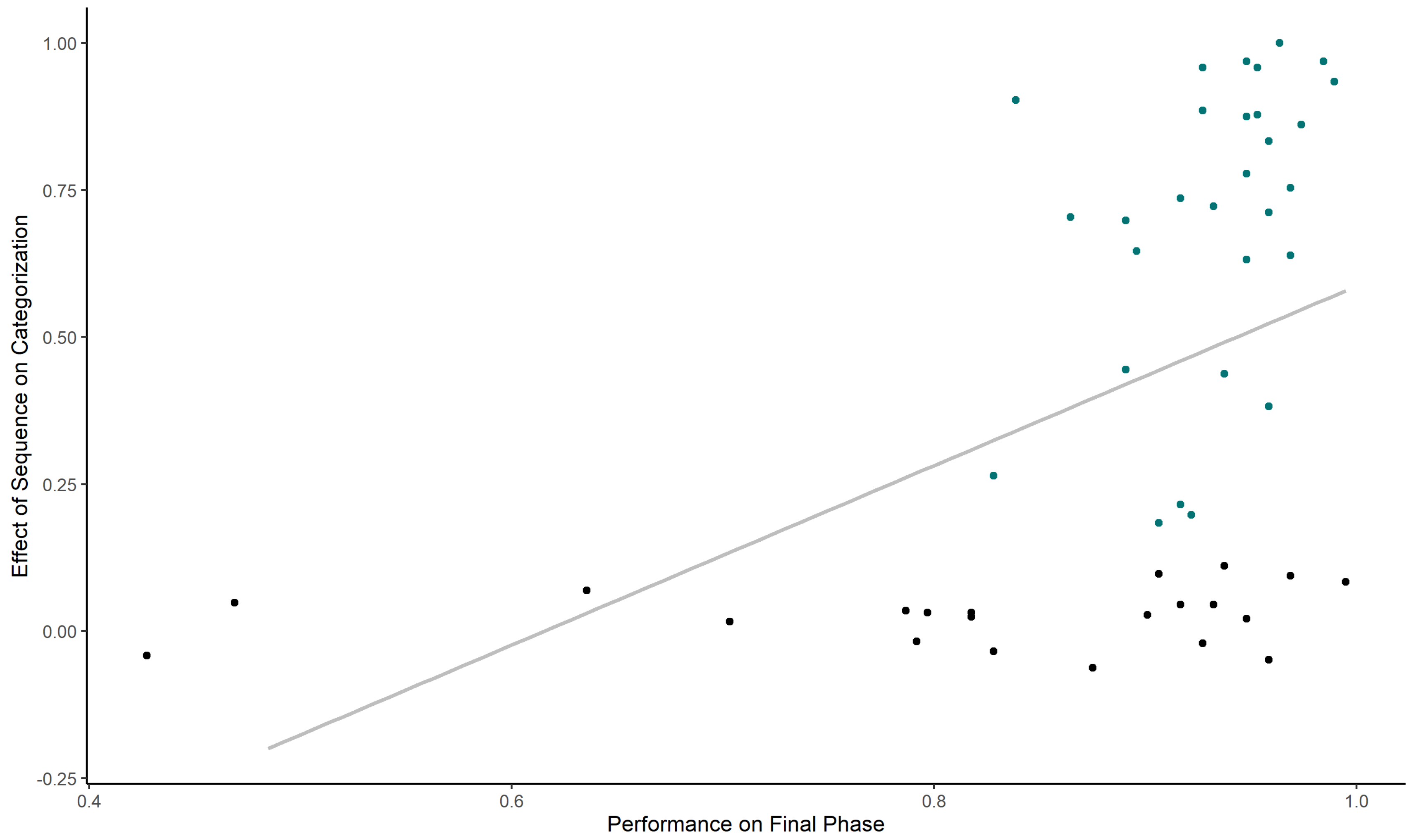

Fig. 7: Sequence position effect for each participant (calculated as mean proportion of shape 2 choices for trials where morph was in shape 2 position minus mean proportion of shape 2 choices for trials where morph was in shape 1 position) plotted against performance in Phase 4. Light blue dots signify participants who exhibited a significant sequence effect, and black dots signify those who did not.

Individual Differences in Categorization

When broken down by participant, there are some individuals who show strong sequence effects, and some who show no impacts at all. To further explore the breakdown of strategies among individuals, I compared how each participant categorized ambiguous morphs presented in the anchor shape 1 sequence position to the anchor shape 2 sequence position. I ran pairwise t-tests with Bonferroni corrections of sequence position (shape 1 vs shape 2) for each individual. 21 out of 50 participants did not show a significant sequence effect, demonstrating that there was variability in the ability to use sequence information to impact categorization (see participant distribution in Fig. 6 or Fig. 7).

Discussion

My results show that the position in a sequence in which a stimulus occurs can impact how that stimulus is subsequently categorized. By varying the position of an ambiguous shape in a learned sequence, I found its categorization shifted towards the shape that typically occupied that position. Sequence was not explicitly trained as being relevant, yet it had a drastic effect on categorization. In language, a similar phenomenon is observed in contexts such as syntactic bootstrapping (Naigles, 1990), or in the sorting of new words into word type categories based on their position in a sentence (Redington et al., 1998). While the use of sequence information for stimulus categorization in language was the basis for this study, its use to inform category membership outside of a linguistic context expands our understanding of human capabilities. My results provide evidence that this sequence-category interaction is a broad, domain general cognitive ability. This means the use of sequence for categorization may have evolved prior to language, and may be one of the general abilities on which language is built.

While this shape categorization task was designed to tap into language-related processes, the task itself did not involve meaningful language. While categorization within sequences does take place in language (Redington et al., 1998), my results suggest that this ability transcends those contexts. There are two possible explanations for this phenomenon. The first is that the ability to use sequence in categorization evolved along with language and has since been coopted for use in other contexts such as this task. The second is that the use of sequence in categorization was a more domain general ability that existed before language.

If the tendency to use sequence information in the categorization of stimuli evolved as part of language, then the effect of sequence information on shape categorization in this task could be explained two ways. First, the non-linguistic stimuli could have been re-coded using language. For example, shape categories could be converted into linguistic categories by giving them names. Doing this would turn the sequence into a repeating phrase of semantically meaningful information (i.e. "rounded, squared, pointed") onto which language processes could act. If the effect of sequence on shape categorization in this task is indeed based in language, I would predict that interfering with language (say with a linguistic interference task) would reduce the effect of sequence position. Linguistic interference tasks have successfully been used to disentangle the effect of language on other abilities, such as spatial reorientation (Ratliff & Newcombe, 2008), so this could be an useful addition in future research. Similarly, if this is a language specific process, I would not expect to find the effect of sequence on categorization in subjects without language, such as monkeys or apes.

Alternatively, participants may not be explicitly coding stimuli into linguistic categories, instead relying on domain general cognitive processes. The tendency to determine category from sequence may have evolved for language, but since developed into a more general ability. If this is the case, the impact of sequence on categorization would be a recent ability, evolving in tandem with language, but no longer relying on language exclusive processes. In this case, a linguistic distractor task would not derail this effect. However, non-human primates would not show an impact of sequence on shape categorization, as they diverged from human lineages prior to language evolution.

Alternatively, sequence categorization may be a domain general and ancient cognitive ability that was more recently co-opted for language. If this is the case, participants would not convert the trained sequence into linguistic labels, and thus linguistic interference would not impact the results. Additionally, if the impact of sequence on categorization is older than language and domain general, then non-human primates, who lack language, should also exhibit these sequence effects on categorization. It is possible that the tendency to use sequence in categorization could have been used in other contexts originally, such as sequences of actions in social displays (Cheney & Seyfarth, 1990; Seyfarth et al., 2005), tool use in food processing (Boesch et al., 2009), or other motor patterns. Demonstrating the effect of sequence on categorization in the non-language context presented in this study is initial experimental evidence for this view, and these questions form the basis for planned future studies.

The impact of sequence information on stimulus categorization in this data was very strong at a group level. There was some interesting variation among participants, however. While many showed very clear effects of sequence position on categorization, others did not, and there was a wide distribution in terms of the impact that sequence had. This may mean there were different possible strategies at play in this task, with some participants specifically attending to sequence information, some showing milder sequence effects, and some ignoring sequence position altogether and maintaining baseline patterns of categorization. This lack of attention to sequence may also have led to differences in how long it took individuals to learn the sequence in Phase 3 (as the number of trials to learn Phase 3 was negatively correlated with how strongly sequence position affected categorization), or conversely, more difficulty learning the sequence may have led to lower levels of attention to the sequence. There may also be differing levels of overall attention between individuals, though high performance on trials overall contradicts this possibility. Variation in the impact of sequence position on categorization may also be the result of more implicit processes. That is, participants may not be explicitly aware of how sequence impacted their decisions, and may rather be basing their decisions on less conscious shifts in perception. Either way, the impact of sequence was very strong, demonstrating that humans use sequence information readily and without prompting.

Because of the significance and scale of the effect of sequence on categorization in this experiment, there is reason to believe the effect will generalize. All participants were Emory Undergraduate Psychology students, however, making this a young, well-educated sample. As such, expanding to other populations would be a valuable future avenue for this work. Additionally, it is possible that sequence information was assumed to be meaningful to the task, despite no explicit indication that it was. If this is the case, participants trying to solve the task may have attended more to sequence than they would have in more naturalistic settings. That said, students assuming the relevance of sequence information is potentially strong evidence that sequence is a salient source of information. In either case, these results show very clear evidence that utilizing sequence in these contexts is possible, and even likely.

This study strongly supports the hypothesis that humans are capable of using sequence for categorization in non-linguistic contexts. The next step is to conduct comparative experiments on this task with primates to determine when the ability to use sequence to infer category evolved. Since the task presented in this study does not require the use of language, comparisons can be made to species that do not possess language abilities. Any capacity in non-human primates to complete the task is evidence that the use of sequence for categorization is pre-linguistic. If, however, non-human primates cannot use sequence for categorization, that supports the idea that the ability evolved alongside language and is potentially one of the critical changes that allowed for the evolution of language.

With continued human work, the complexity of sequences presented can be expanded to explore more complex interactions of sequence and category. Increasing grammatical variability and sequence difficulty would allow me to probe the limits of this interaction. I also aim to determine whether using sequence for categorization is generalizable to other modalities by expanding my protocol to include auditory stimuli. Additionally, the implementation of linguistic interference in future studies would make it clear if the ability to use sequence categorization is dissociated from language, or if language processing is necessary to observe this effect. All these expansions could inform our understanding of the generality of the sequence categorization effect.

This research provides exciting evidence that the impact of sequence on categorization in humans transfers to non-linguistic contexts. This demonstrates that the ability to use sequence for categorization may be a broad, non-linguistic process. Determining which language associated abilities are language specific, versus which can be generalized to other tasks, will help us determine how language evolved. Continuing to explore the extent of language associated abilities will provide insight into how language arose, and what changes allowed for the evolution of such a powerful ability.

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