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Colour-concept association formation for novel concepts

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ABSTRACT

Colour-concept associations influence fundamental processes in cognition and perception, including object recognition and visual reasoning. To understand these effects, it is necessary to understand how colour-concept associations are formed. It is assumed that colour-concept associations are learned through experiences, but questions remain concerning how association formation is influenced by properties of the input and cognitive factors. We addressed these questions by first exposing participants to colour-concept co-occurrences for novel concepts ("Filk" and "Slub" alien species) using a category learning task. We then assessed colour-concept associations using an association rating task. During alien category learning, colour was a noisy cue and shape was 100% diagnostic of category membership, so participants could ignore colour to complete the task. Nonetheless, participants learned systematic colour-concept associations for "seen" colours during alien category learning and generalized to "unseen" colours as a function of colour distance from the seen colours (Experiment 1). Association formation not only depended on colour-concept co-occurrences during alien category learning, but also on cognitive structure of colour categories (e.g., degree to which an observed red colour is typical of the colour category "red") (Experiment 2). Thus, environmental and cognitive factors combine to influence colour-concept associations formed from experiences in the world.

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Colour cognition; colour categories; associative learning; statistical learning

People have associations between colours and concepts, which influence a wide variety of judgments in visual cognition. Colour-concept associations affect object recognition (Macario, 1991; Nagai & Yokosawa, 2003; Ostergaard & Davidoff, 1985; Tanaka & Presnell, 1999; Wurm et al., 1993), colour perception (Delk & Fillenbaum, 1965; Hansen et al., 2006; Olkkonen et al., 2008; Witzel, 2016; see Valenti & Firestone, 2019 for contrary evidence), perceptual experiences in other modalities (e.g., flavour) (Piqueras-Fiszman & Spence, 2012; Velasco et al., 2014), colour preferences (Palmer & Schloss, 2010; Schloss & Palmer, 2017; Strauss et al., 2013; Taylor & Franklin, 2012), visual reasoning with information visualizations (Lin et al., 2013; Schloss et al., 2018; Schloss et al., 2019), and interpretations of other people's emotions (Thorstenson et al., 2018). Thus, to fully understand visual cognition, it is necessary to understand the nature of colour-concept associations. In the present study, we investigated factors that influence colour-concept association formation for novel concepts.

Motivation for studying colour-concept associations. Early work on the role of colour-concept associations in visual cognition primarily focused on effects of the single, most diagnostic colour of objects that are high in colour diagnosticity (e.g., red for fire trucks) (Bramão et al., 2010; Joseph & Proffitt, 1996; Nagai & Yokosawa, 2003; Ostergaard & Davidoff, 1985; Tanaka & Presnell, 1999). For example, Tanaka and Presnell (1999) found that participants were better at identifying objects when objects were presented in their most diagnostic colour versus presented in an atypical or achromatic colour.

However, recent work suggests that focusing on diagnostic colours for colour-diagnostic objects is

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insufficient for understanding effects of colour-concept associations for visual cognition. This limitation has been highlighted in studies on how people interpret the meanings of colours in information visualizations (e.g., graphs, maps, diagrams, and signs) (Mukherjee et al., 2022; Schloss, 2018; Schloss et al., 2018; Schloss et al., 2021). When inferring which colour maps to a particular concept, participants did not always choose the strongest associated colour. Instead, using a process called assignment inference, they inferred mappings that optimize overall colour-concept association strengths (Schloss et al., 2018). This process can lead to inferring that concepts map to weakly associated colours when there are more strongly associated candidate colours (see Schloss et al., 2018 for details). To perform assignment inference, observers cannot merely rely on their representations of diagnostic colours for particular objects; they must represent relative colour-concept associations extending over colour space.

Colour-concept associations can be represented as continuous distributions over perceptual colour space (Lindner, Bonnier, et al., 2012; Lindner, Li, et al., 2012; Mukherjee et al., 2022; Schloss, 2018; Schloss et al., 2018; Schloss et al., 2021). Figure 1 shows examples of *colour-concept association spaces*, which depict the degree to which a given concept is associated with each possible colour sampled from a continuous colour space (Rathore et al., 2020; Schloss, 2018). Some concepts, such as raspberry, have a single, most strongly associated colour, with decreasing association strength as distance from the strongest associate increases. Other concepts, such as watermelon in Figure 1 (right) have multiple strongly associated areas of colour space (reds and greens), with decreasing associations between peaks. If a concept is equally associated with all colours, whatever the association strength may be, that would manifest in a uniformly weighted colour-concept association space. Colour-concept association distributions can be quantified in various ways, including human judgments (Dael et al., 2016; Mukherjee et al., 2022; Ou et al., 2004; Schloss et al., 2018; Schloss et al., 2021; Tham et al., 2020), automated estimations from image statistics (Lin et al., 2013; Lindner, Bonnier, et al., 2012; Rathore et al., 2020; Setlur & Stone, 2015) and natural language (Havasi et al., 2010; Setlur & Stone, 2015). However, a fundamental question concerns how people form colour-concept associations that "populate" continuous colour concept association spaces.

Potential accounts of colour-concept association formation. Many have assumed that colour-concept associations are learned through experiences (Elliot et al., 2007; Mehta & Zhu, 2009; Rathore et al., 2020; Schloss, 2018; Tham et al., 2020; Velasco et al., 2014; Witzel et al., 2011). In the Colour Inference Framework, Schloss (2018) proposed that people continually learn and update colour-concept associations from colour-concept co-occurrences in their environment. Even associations between colours and abstract concepts might stem from associations with related

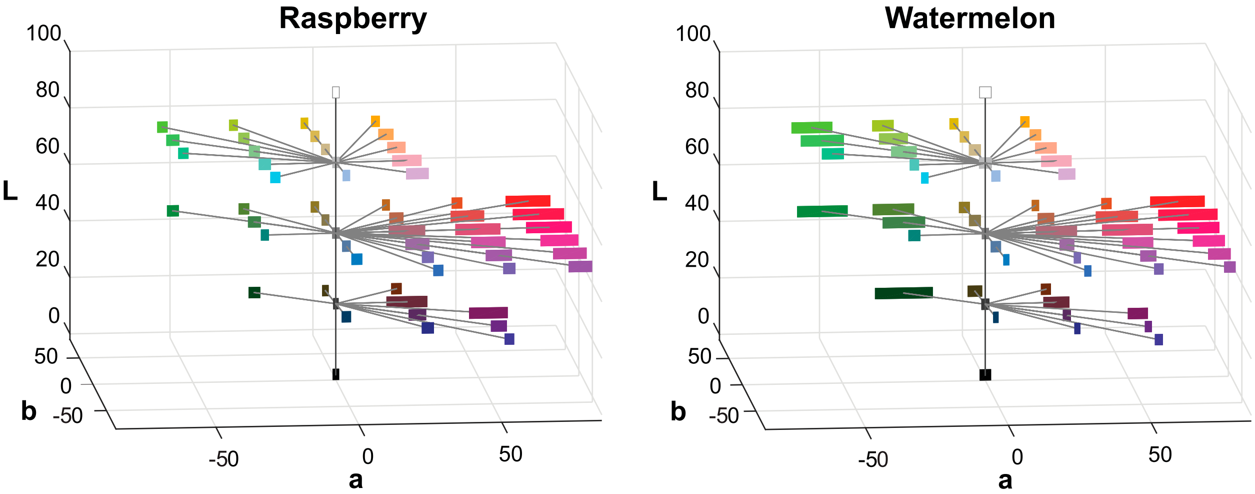

Figure 1. Example colour-concept association spaces for the concepts *raspberry* and *watermelon*. The data were obtained by asking participants to rate their association strength between each concept and each of 58 colours sampled uniformly in CIELAB space (Rathore et al., 2020). The centre of each bar indicates the colour coordinate in CIELAB space, and the width of the bar represents the colour-concept association strength. Figure adapted from Supplementary Material in Rathore et al. (2020).

concrete objects that have directly observable colours (Schloss, 2018; Soriano & Valenzuela, 2009). It may seem obvious that people would form and update colour-concept associations when using colour for particular activities, such as learning to use colour to discern between ripe and rotten fruit. But, what about activities where colour is not directly relevant?

If opportunities to form colour-concept associations are confined to experiences in which colour is central to a task, then opportunities to form these associations through daily experiences would be severely limited. When making inferences about the world, people tend to prioritize other factors over colour such as shape (Landau et al., 1988; Smith, 2000; Tek et al., 2012; Vlach, 2016) and functional relations (Gopnik & Sobel, 2000). An exception is for categorizing food-related objects, in which colour is prioritized over shape (Macario, 1991). During experiences when non-colour related factors are prioritized, people may not detect colour-related statistics needed to form and update colour-concept associations. This possibility is consistent with evidence that in the presence of more informative cues, less informative cues are used less (Kruschke & Johansen, 1999) and are harder to learn (McLaren et al., 2014).

Although colour often may be a less reliable cue than other cues like shape and motion, that does not necessarily mean that people are insensitive to colour statistics from the environment. For example, to cross a street safely, it is necessary to estimate the speed and distance of oncoming traffic, not attend to the colours of the cars, but that does not mean people are insensitive to car colour frequency. Extensive evidence suggests that people learn about properties and relations from statistical regularities in stimulus input (Austerweil & Griffiths, 2013; Fiser & Aslin, 2001, 2002; Park et al., 2018; Saffran et al., 1996; Turk-Browne et al., 2005; Turk-Browne et al., 2008; Yu & Zhao, 2018; Zhao & Yu, 2016). Perhaps most relevant to the present study, participants learn relations among cues that co-occur while completing tasks that do not require learning such relations, such as identifying when a shape repeats in a sequential stream of shapes (Turk-Browne et al., 2005). Even outside of awareness, participants are sensitive to co-occurrence frequencies in their environment (Hasher & Chromiak, 1977; Hasher & Zacks, 1979, 1984; Turk-Browne et al., 2005; Wattenmaker, 1991, 1993; Zacks & Hasher, 2002). If people are sensitive to colour-concept co-occurrences when using colour is nonessential, then associative learning could enable them to continually form and update colour-concept associations through daily activities that do not require using colour.

Moreover, such associative learning need not be confined to exact colours from the visual input. During associative learning, organisms tend to show tolerance around the input and generalize learned associations to similar stimuli (see Ghirlanda and Enquist (2003) for a review). Thus, learned associations through colour-concept co-occurrences may spread to nearby colours in colour space (Rathore et al., 2020). One possibility, is that the degree of generalization could simply depend on distance between the colours in colour space. However, generalization may also depend on perceived similarity. Rosch (1975a) found that judgments of colour similarity are *asymmetric*: non-prototypical colours (e.g., mauve) are more similar to colour prototypes (e.g., pure red) than prototypes are to non-prototypes. If generalization of colour-concept associations depends on colour similarity, and colour similarity is asymmetric, then generalization may also be asymmetric.

Present approach. In this study, we conducted two experiments investigating factors that influence colour-concept association formation for novel concepts. Both experiments used the same two-part experimental paradigm. First, we exposed participants to colour-concept co-occurrences during a task in which they could reach 100% accuracy by using only shape and ignoring colour. Second, we assessed colour-concept associations for colours "seen" during that initial task, plus additional "unseen" colours. Through the lens of several hypotheses, we tested whether participants learned and generalized colour-concept associations from the initial exposure task:

1. **Frequency hypothesis:** association strength will increase with increased co-occurrence frequency.
2. **Exposure hypothesis:** associations will be stronger for seen colours during colour-concept co-occurrences than for unseen colours.
3. **Frequency generalization hypothesis:** frequency effects for seen colours will extend to similar, unseen colours.
4. **Colour distance generalization hypothesis:** the degree to which associations for seen colours

generalize to unseen colours will decrease as colour distance from the seen colours increases

5. **Asymmetric generalization hypothesis:** the degree to which associations for seen colours generalize to unseen colours is asymmetric, depending on colour category typicality.

We tested the first two hypotheses in Experiments 1 and 2, the frequency generalization and colour distance generalization hypotheses in Experiment 1, and the asymmetric generalization hypothesis in Experiment 2. Experiment 2 was preregistered prior to data collection at osf.io/6cjkz, Experiment 1 was not preregistered.

In our study, support for these hypotheses suggests that people can form colour-concept associations during experiences when colour can be ignored while successfully completing the task at hand. Our results further suggest that continuous colour-concept association spaces can become "populated" through experiences in the world by the combination of (1) observed colour-concept co-occurrences from a sampling of colours, and (2) a generalization gradient away from the observed colours.

Experiment 1

Experiment 1 investigated whether participants would form colour-concept associations from co-occurrence frequencies during exposure to images of novel alien species. Our primary focus was on testing the frequency, exposure, frequency generalization, and colour distance generalization hypotheses. We also examined potential effects of noticing colour-related patterns during alien category learning on association formation. The Supplemental Material includes additional data on baseline associations and additional analyses testing for effects of goodness-of-fit among features (shape, colour, and name for each alien species) on category learning and learned colour-concept associations. All materials, data, and analysis code from both experiments are publicly available at github.com/SchlossVRL/ColorConceptAssociations.

Methods

Participants

Two hundred and twenty University of Wisconsin–Madison undergraduate students (134 women, 82 men, 4 no report; mean age = 18.6 years, 1 no report) participated in exchange for partial course credit in an Introductory Psychology course. We determined this sample based on a power analysis from a pilot study (see Supplemental Material). All participants had normal colour vision as assessed with the H.R.R. Pseudoisochromatic Plates (Hardy et al., 2002), and all had a categorization accuracy above the *a priori* criteria, see details below, thus no participants were excluded. All participants of this experiment and the following experiment gave informed consent, and all protocols were approved by the University of Wisconsin–Madison Institutional Review Board.

Design, displays, and procedure

The experiment included two tasks: (1) alien category learning task, followed by (2) association ratings task. For each task, participants also completed a post-task questionnaire: a strategy questionnaire after the category learning task, and a colour pattern noticing questionnaire after the ratings task. At the end of the experiment, participants were checked for typical colour vision using the H.R.R. Pseudoisochromatic Plates (Hardy et al., 2002). This check was completed last to avoid priming participants to think about colour before the alien category learning task. In the following sections, we describe the design, displays, and procedures separately for the category learning and association rating tasks.

Alien category learning task. In the alien category learning task, participants were presented with images of aliens from two novel alien species, Filk and Slub. These species names were selected from the artificial language Sillyspeak (Hudson Kam & Newport, 2005). These words were selected to be opposites phonetically and visually in regard to their "pointiness" (Aveyard, 2012; Gómez et al., 2013; Nielsen & Rendall, 2011; Westbury, 2005). The words "filk" and "slub" in Sillyspeak are verbs meaning "to be red" and "to be blue", respectively (Hudson Kam & Newport, 2005). The alien species differed on two dimensions: body shape and colour distribution.

Alien body shape. One species of aliens always had pointy bodies and the other species had curvy bodies (Figure 2(A)), such that body shape was 100% diagnostic of alien category membership. Within each body type (pointy and curvy) there were five different body shapes to add variety. Each body

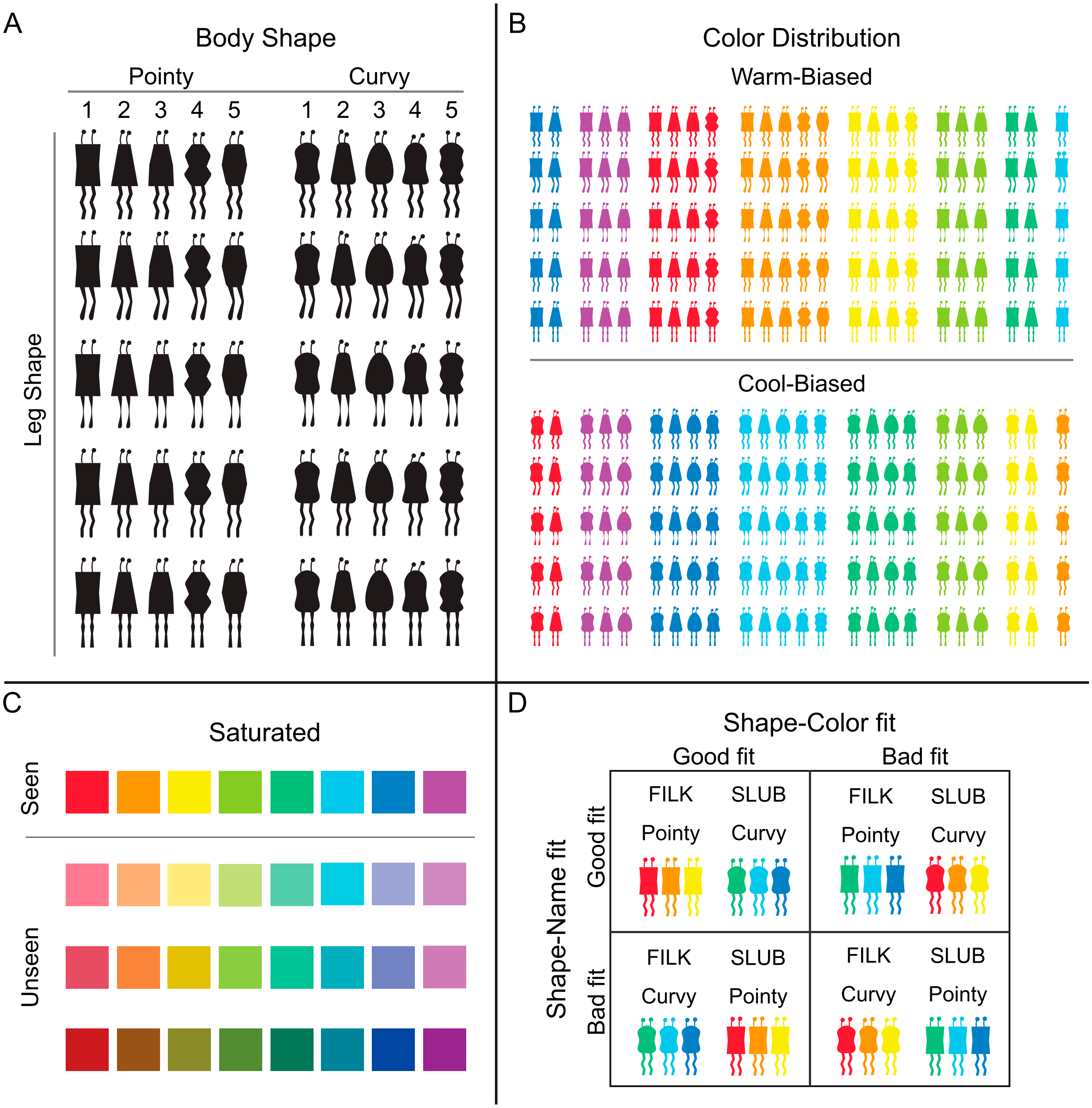

Figure 2. Stimuli for Experiment 1. (A) The two body shapes, pointy and curvy, each had 5 different body types that co-varied with 5 different leg types, resulting in 25 alien bodies per species. (B) Colour distributions when pointy aliens were warm-biased, and curvy aliens were cool-biased. (C) The BCP-32 colours (Palmer & Schloss, 2010) judged in the colour-concept association task of the present study. "Seen" colours were the colours of aliens seen during the alien category learning task. "Unseen" colours were the same hues but different lightness/saturation levels as the seen colours. (D) The four between-subject conditions, which crossed shape-colour fit with shape-name fit. Sets of three aliens in the figure represent the colour distributions (warm vs. cool) in B.

shape had unique antennae, such that antennae perfectly co-varied with body shape. Five different leg types appeared equally often with all bodies from both species, thus providing no helpful information for categorization.

Alien colour. One alien species had a "warm-biased" colour distribution and the other species had a "cool-biased" distribution (Figure 2(B)). However, the colour distributions overlapped, so colour was only partially diagnostic of species category membership. Each alien was a single colour, sampled from the eight saturated colours from the Berkeley Colour Project 32 (BCP-32) colours (Palmer & Schloss, 2010). These alien colours included eight hues: red, orange, yellow, chartreuse, green, cyan, blue, and purple. See Table A1 in the Appendix for

CIE xyY coordinates. The warm-biased species included 20 red, 25 orange, 20 yellow, 15 chartreuse, 10 green, 5 cyan, 10 blue and 15 purple aliens (Figure 2(B)). The cool-biased species was the opposite, including 10 red, 5 orange, 10 yellow, 15 chartreuse, 20 green, 25 cyan, 20 blue and 15 purple aliens.

Within each colour distribution, the most frequent hue (orange for warm-biased, cyan for cool-biased) was presented in all five body shapes for its respective category of bodies (pointy or curvy), see Figure 2(B). The second most frequent hues (red and yellow for warm-biased, green and blue for cool-biased) were presented in body shapes 1–4. The third most frequent hues (chartreuse and purple for both) were presented in shapes 1–3. The fourth most frequent hues (green and blue for warm-biased, red and yellow for cool-biased) were presented in shapes 1–2. The least frequent hue (cyan for warm-biased, orange for cool-biased) was only presented in shape 1. This method created distributions of 120 unique aliens for each species.

The species' names (Filk, Slub), body shapes (pointy, curvy), and colour distributions (warm, cool) were all counterbalanced across participants, creating four conditions ($n = 55$ per condition): warm-pointy-Filks/cool-curvy-Slubs, cool-pointy-Filks/warm-curvy-Slubs, warm-curvy-Filks/cool-pointy-Slubs, and cool-curvy-Filks/warm-pointy-Slubs (Figure 2(D)). See Supplemental Material for additional details testing the goodness-of-fit between these features and their effects on association formation and alien category learning (including Figures S2–S4 and Tables S7–S9).

Participants were presented with the distributions of aliens in a category learning task (Figure 3(A)), similar to the task in Lupyan and Casasanto (2014). On each trial, a single alien (approx. 100 × 250 px; 2.5 × 6.7 cm) appeared in the centre of the screen with the two species' names (FILK and SLUB) displayed above the alien to the left and right. Participants indicated the species to which they thought the alien belonged using the left/right arrow keys. They received feedback with text displaying "Yes. This is a FILK/SLUB" or "No. This is a FILK/SLUB", then after 1000-ms, the alien moved beneath the correct species name (1000-ms duration). Participants therefore guessed on the initial trials until they learned how to categorize the species based on the feedback. Each of the 240 aliens were presented once in a random order, separated by 500-ms inter-trial intervals, with breaks after every 40 trials.

Strategy questionnaire. After the alien category learning task, participants provided written responses to the following three questions: (1) Please describe what strategy you used for the previous task; (2) Were there any visual features that you paid particular attention to complete the previous task?; (3) If so, what features did you attend to? If not, please write "None".

Association ratings task. In the association ratings task, participants were presented with a series of trials, each containing a coloured square

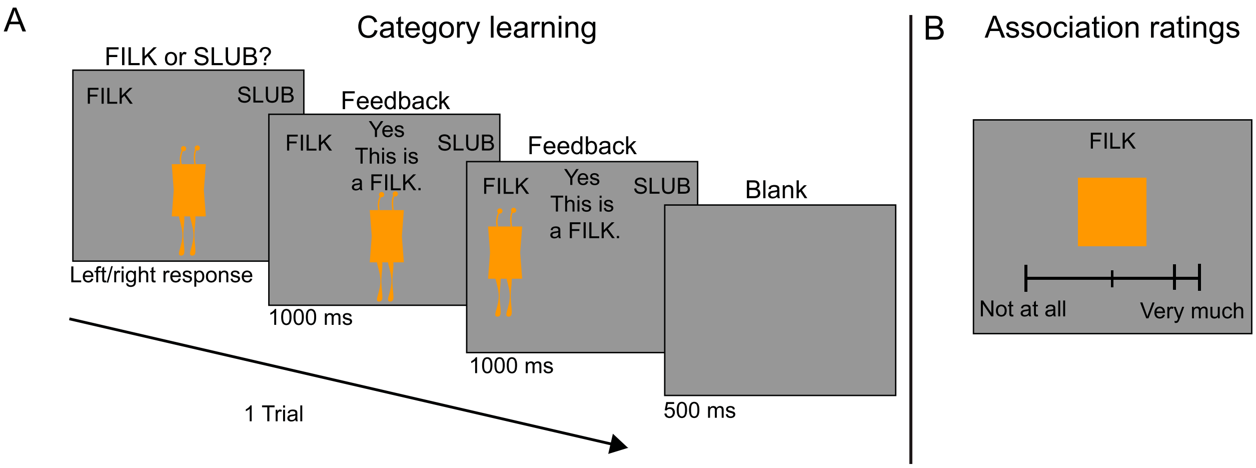

Figure 3. Experiment tasks. (A) Sequence for a trial during the alien category learning task. Participants saw a single alien and responded with an arrow press which species they believed it belonged to. Text and then motion feedback appeared, with the alien moving underneath the correct species. (B) Example association ratings trial in which saturated orange has been rated as strongly associated with the Filk species.

(100 × 100 px; 2.7 × 2.7 cm) centred on the screen and one species name displayed above. The colours were each of the BCP-32 colours (Palmer & Schloss, 2010), which included the eight saturated hues seen during alien category learning, which we refer to as the "seen" colours, plus three additional colours of each hue, varying in lightness and saturation. We refer to these as the "unseen" colours (Figure 2(C)) (see Table A1 in the Appendix for CIE xyY coordinates). Participants rated their association strength for the given colour and species using a line-mark slider, with endpoints labelled "Not at all" (−200) and "Very much" (200) (Figure 3(B)). Trials were blocked by species, and species order was randomized over participants. Within each species, each colour was presented twice using a blocked randomized design, such that all colours were judged once in a random order, before all colours were judged a second time in a new random order (total of 128 trials).

Before beginning the association ratings task, participants completed an anchoring exercise to promote full use of the rating scale (Palmer et al., 2013). Participants saw the 32 colours on the screen that they would later be asked to rate individually. For each species, participants were asked to point to the colours on the screen that they believed were "very much" and "not at all" associated with each species, and were told to rate these colours near the endpoints of the scale during the task.

We prepared the colour-concept association ratings for analysis for each participant by first averaging over their ratings across the two repetitions and dividing by 400 so the range was 0 (not at all) to 1 (very much).

Colour pattern noticing questionnaire. After completing the association ratings task, participants indicated if they noticed any patterns in the colours during the categorization task. They wrote responses to the following two questions: (1) Did you notice any patterns or regularities in the colours of either alien species during the first task?; (2) If so, what did you notice? If not, please write "None".

All displays in the two tasks were presented on a 24.1 in. ASUS ProArt PA249Q monitor (1920 × 1200 resolution). We used a Photo Research PR-655 SpectraScan® spectroradiometer to calibrate the monitor and verify accurate presentation of the colours. The deviance between the measured colours and target colours in CIE 1931 xyY coordinates was <0.01 for x and y and <1 cd/m^2 for Y. The background for all displays was a medium grey (CIE x = 0.312, y = 0.318, Y = 19.26) that approximated CIE Illuminant C. Participants sat approximately 60 in. from the screen in a dark room. Instructions for all tasks were read aloud while also presented visually on the computer screen. The experiment tasks were coded and implemented using Presentation (www.neurobs.com).

Results and discussion

This experiment assessed colour-concept associations formed after exposure to colour-concept co-occurrences during the alien category learning task. Our approach relied on participants quickly learning the alien categories so they would have ample exposure to the colour distributions of each species while knowing which aliens belonged to which species. Participants achieved high accuracy quickly (mean cumulative accuracy reached 88% by trial 50 out of 240; total accuracy was 96%[1]; see Figure S2 in the Supplemental Material). This high accuracy was likely facilitated by shape being a 100% diagnostic cue to alien category membership. Indeed, responses to the strategy questionnaire (administered after category learning, before colour-concept association ratings) indicated that only 10% of participants reported using colour, whereas all other participants reported using only shape. If participants formed colour-concept associations based on colour-concept co-occurrences, that will suggest people can develop colour-concept associations during experiences when colour is not central for successfully completing the task. We test this possibility through the lenses of the frequency, exposure, frequency generalization, and colour distance generalization hypotheses.

Effects of frequency for seen colours during category learning

According to the frequency hypothesis, participants will form stronger associations between a given colour and concept as colour-concept co-occurrence frequency increases. As shown in Figure 4, mean colour-concept association strengths for seen colours did indeed increase with increased co-occurrence frequency (warm-biased species: $r = .86$, $p = .006$; cool-biased species: $r = .74$, $p = .04$; data averaged over species' name and shape). This result was

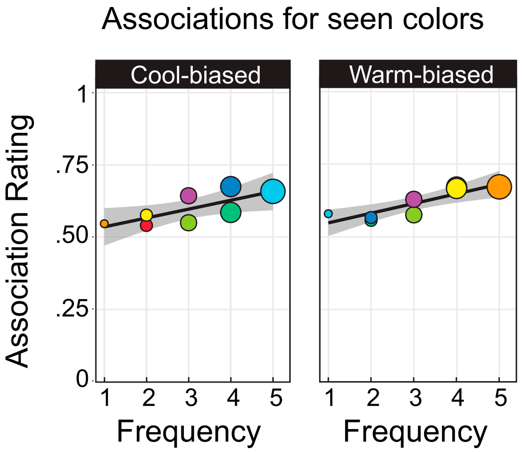

Figure 4. Colour-concept association ratings from Experiment 1. Mean association ratings for the seen colours as a function of co-occurrence frequency during alien category learning for the cool-biased species (left) and warm-biased species (right), averaged over species name and shape. Mark size represents co-occurrence frequency of the seen hue and error bands represent 95% confidence interval around the best fit line.

further supported by a linear mixed-effects model predicting association ratings for the seen colours from a fixed effect of co-occurrence frequency, a by-subject random intercept, and a by-subject random slope ($R^2 = .74$) (Bates et al., 2011; R-3.6.0, RStudio version 1.2.1335, lme4 1.1–21; versions used for all reported analyses). Frequency was a significant predictor of associations ($\beta = 0.03$, $F(1,218) = 26.784$, $p < .001$), indicating that association strength increased with co-occurrence frequency.

Exposure, frequency generalization, and colour distance generalization comparing seen and unseen colours

Figure 5(A) shows the mean colour-concept association ratings for seen and unseen colours as a function of frequency, averaged over the warm and cool-biased species (see Figure S1 in the Supplemental Material for figure separated by warm vs. cool-biased species). We used a linear mixed-effects model (LMEM) to test whether effects of frequency for seen colours generalize to unseen colours, while also testing for effects of exposure and colour distance generalization. The model predicted colour-concept associations for the full set of 32 colours from fixed effects for frequency, exposure (seen vs. unseen colours), and colour distance (ΔE) between the unseen colour and seen colour of the corresponding hue (seen colours were assigned $\Delta E = 0$), plus a by-subject random intercept and all relevant by-subject random slopes ($R^2 = .35$).

Although technically unseen colours had zero co-occurrence frequency, the frequency generalization hypothesis suggests that the frequency effect reported for seen colours could extend to similar, unseen colours. Thus, we coded frequency of the unseen colours with respect to the seen colours of the same hue. For example, if seen, saturated orange had a co-occurrence frequency of 5 for the warm-biased species and 1 for the cool-biased species, then the unseen oranges were coded as having a co-occurrence frequency of 5 for the warm-biased species and 1 for the cool-biased species.

As shown in Figure 5(A), associations were overall stronger for seen colours than unseen colours, supporting the exposure hypothesis ($\beta = 0.068$, $F(1,218) = 17.277$, $p < .001$). Overall, association strength increased with increased frequency ($\beta = 0.025$, $F(1,218) = 28.996$, $p < .001$), regardless of whether colours were seen or unseen (no frequency × exposure interaction; $\beta = 0.012$, $F(1,218) = 2.783$, $p = .096$). This result suggests that the frequency effect for seen colours generalized to unseen colours, but to directly test the frequency generalization hypothesis, we ran the above model for only the unseen colours (removing exposure—seen vs. unseen—as a factor). Frequency was still a significant predictor ($\beta = 0.019$, $F(1,218) = 15.533$, $p < .001$), suggesting effects of co-occurrence frequency extend to colours that share the same hue as the seen colours.

Figure 5(B) shows the mean colour-concept associations for each of the seen and unseen colours, plotted as a function of colour distance (ΔE; Euclidean distance in CIELAB space) from the seen colours (plotted at position 0 on the x-axis). Supporting the colour distance generalization hypothesis, association strength decreased as colour distance from the seen colours increased ($\beta = -0.004$, $F(1,218) = 135.779$, $p < .001$). Examining the model that only included unseen colours, colour distance still had an effect ($\beta = -0.004$, $F(1,218) = 135.819$, $p < .001$), suggesting generalization to unseen colours decreases with colour distance from the seen colours.

Effects of noticing colour patterns during alien category learning

We next examined if the effects reported above were modulated by whether participants reported noticing

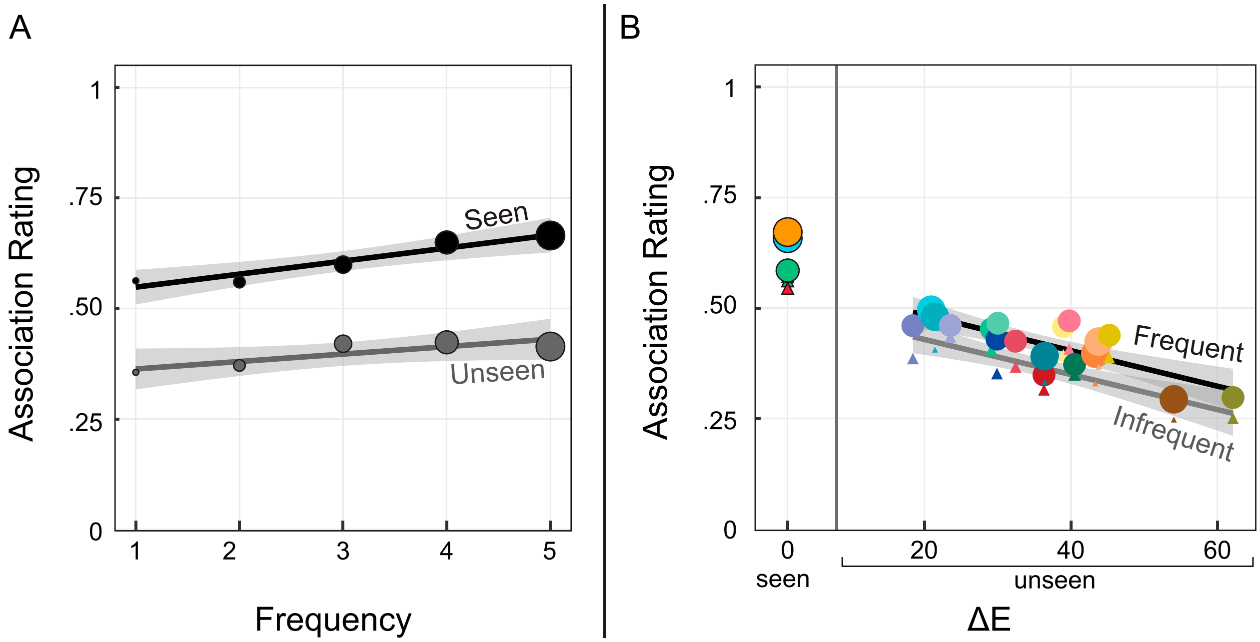

Figure 5. Colour-concept associations ratings from Experiment 1 averaged over warm vs. cool-biased species. (A) Mean association ratings for seen (black) and unseen (grey) colours as a function of co-occurrence frequency of the seen hue. (B). Mean ratings for frequent (circles; red, orange, yellow for warm-biased species and green, cyan, blue for cool-biased species) and infrequent (triangles; green, cyan, blue for warm-biased species and red, orange, yellow for cool-biased species) as a function of ΔE in CIELAB space from the seen colours. This figure excludes ratings for chartreuse and purple, which were seen equally often for both species, but all colours were included in the analysis (see Figure S1 in Supplemental Material for association ratings for all colours). For (A) and (B) mark size represents co-occurrence frequency of the seen hue and error bands represent 95% confidence interval around the best fit line.

colour-related patterns in the two alien species. We classified participants as "noticers" or "non-noticers" depending on their response to the noticing questionnaire at the end of the experiment, which asked if they self-reported noticing colour-related patterns during the first task. We coded participants as noticers if they identified at least one colour related to a species (e.g., "Filks were in more reds and Slubs were in more greens") or used colour comparison terms (e.g., "one species was warm and one was cool", "one dark, one light", etc.). We included anyone who reported they noticed anything about colour, even if their observation was inaccurate (e.g., reporting Filks were often cool colours when they were actually warm-biased). Based on this self-report measure of noticing, we cannot rule out the possibility that some non-noticers actually did detect colour-related patterns but did not report so on the noticing questionnaire. Thus, we interpret this measure as an assessment of whether colour-related patterns were salient enough for participants to report what they saw when asked if they noticed any patterns in the colours during the first task.

In total, 36% of participants were noticers and 64% were non-noticers. We tested whether participants who deliberately used colour during alien category learning (reported on the strategy questionnaire) were more likely to be noticers (reported on the noticing questionnaire), but found no significant difference ($X^2(1) = 1.149$, $p = .284$).

Figure 6 shows the mean association ratings from Figure 5, separated by whether participants were noticers. We tested for effects of noticing using a LMEM analysis predicting association ratings from co-occurrence frequency (determined by the seen colour of each hue; within-subject), exposure (seen vs. unseen; within-subject), colour distance (ΔE; within-subject), noticing (noticers vs. non-noticers; between-subject), and all interactions except those with both ΔE and exposure, and a by-subject random intercept and by-subject random slopes for all relevant within-subject fixed effects ($R^2 = .35$) (see Table S1 in Supplemental Material for full output).

As in the model without noticing, there were main effects of co-occurrence frequency ($\beta = 0.029$, $F(1,219.02) = 39.570$, $p < .001$), exposure ($\beta = 0.057$, $F(1,217.08) = 11.875$, $p < .001$), and colour distance ($\beta = -0.004$, $F(1,217.08) = 120.973$, $p < .001$). However, noticing interacted with multiple factors. To understand these interactions, we conducted the model

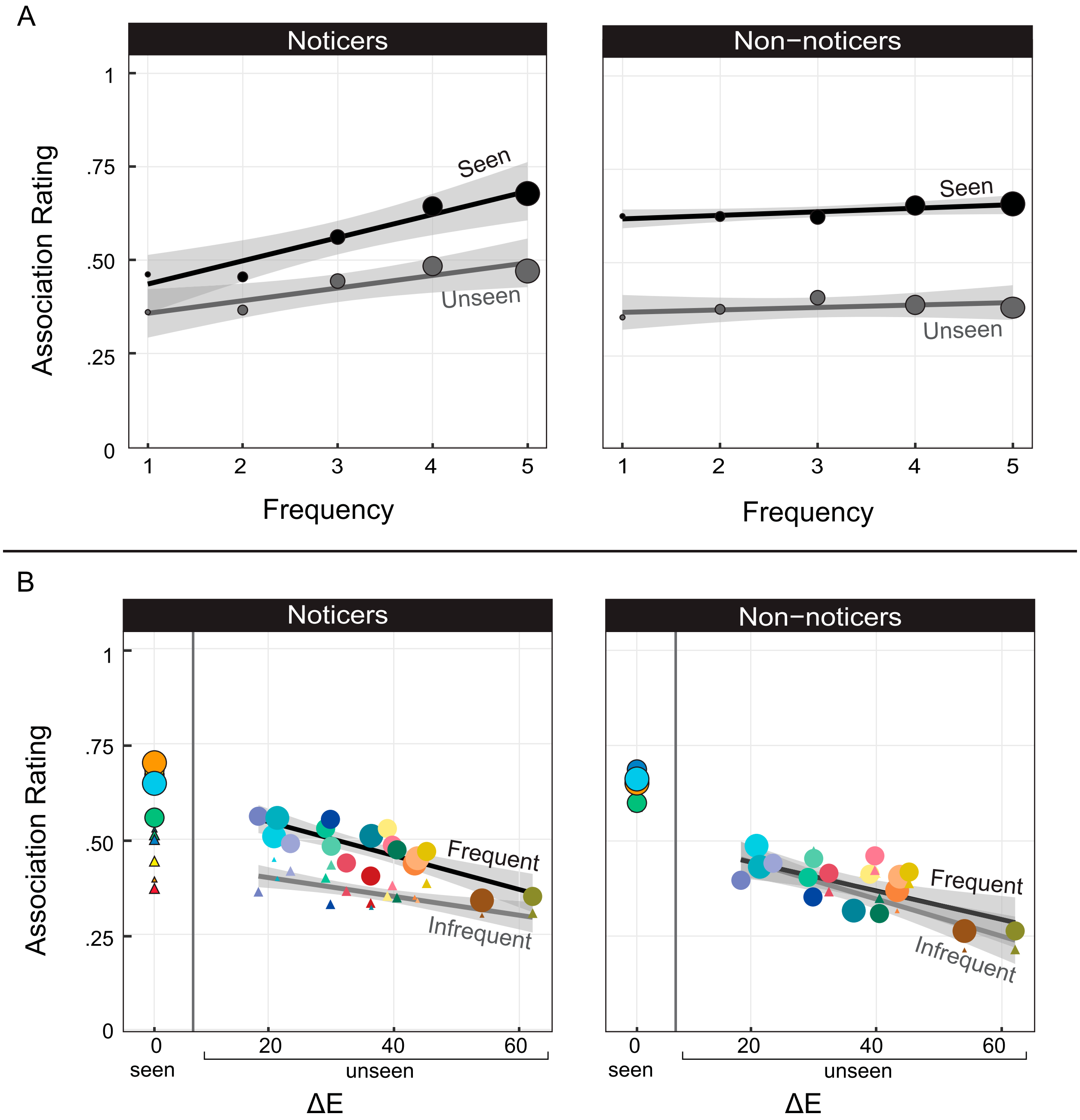

Figure 6. Mean association ratings separated by noticing. (A) Seen vs. unseen colours as a function of co-occurrence frequency, and (B) frequent and infrequent colours as a function of Δ*E*. The data are plotted in the same way as Figure 5, but are further separated by whether participants reported noticing colour-related patterns.

separately for noticers and non-noticers (see Table S2 in Supplemental Material for full output).

Interaction between noticing and frequency. Noticing interacted with frequency ($\beta = 0.035$, $F(1,219.02) = 14.153$, $p < .001$), such that the effect of frequency was stronger for noticers than non-noticers (steeper slope in Figure 6(A)). Still, both groups showed increased association strength with increased frequency (noticers: $\beta = 0.046$, $F(1,82) = 26.184$, $p < .001$; non-noticers: $\beta = 0.117$, $F(1,135) = 6.312$, $p = .013$). These results suggest that explicitly noticing colour related patterns is not required for forming associations based on co-occurrence frequencies, but it may lead to stronger effects of frequency.

Interaction between noticing and exposure. Noticing interacted with exposure ($\beta = -0.088$, $F(1,218.08) = 7.053$, $p = .009$), such that the effect of exposure was stronger for non-noticers than for noticers (Figure 6(B)). Tested separately, noticers showed no significant difference in association strength between seen and unseen colours ($\beta = 0.013$, $F(1,82) = 0.364$, $p = .548$), whereas non-noticers showed a robust difference, forming strong associations for all seen colours, and weak associations for all unseen colours ($\beta = 0.101$, $F(1,135) = 20.666$, $p < .001$). Although it may appear that there was a 3-way interaction between noticing, frequency, and exposure, it did not reach statistical significance ($\beta = -0.010$, $F(1,302.18) = 0.451$, $p = .502$).

No interaction between noticing and colour distance. Noticing did not significantly interact with colour distance ($\beta = 0.000$, $F(1,217.08) = 1.857$, $p = .174$). As shown Figure 6(B), association strength decreased with increased colour distance from the seen colours for both noticers ($\beta = -0.003$, $F(1,82) = 52.704$, $p < .001$) and non-noticers ($\beta = -0.004$, $F(1,135) = 85.632$, $p < .001$). Although there was a 3-way interaction between noticing, frequency, and colour distance ($\beta = -0.001$, $F(1,219.55) = 5.950$, $p = .016$), the 2-way interactions between frequency and colour distance were not significant among noticers ($\beta = -0.001$, $F(1,82) = 3.412$, $p = .068$) or non-noticers ($\beta = 0.000$, $F(1,135) = 2.103$, $p = .149$). Thus, this 3-way interaction should only be interpreted with caution.

What determines noticing? Although it is clear from these results that noticing colour-related patterns has an effect, the question remains of what determines whether a participant is a noticer. One possibility is that noticing depends on cognitive strategy during category learning. For example, Williams and Lombrozo (2010) found that participants were more likely to notice patterns in properties of aliens when they were asked to explain their approach to categorization than when they simply described what they saw. Thus, it is possible that our participants who were noticers had detected colour-related patterns by virtue of being spontaneous "explainers," but that is an open question for future work.

Summary. In summary, this experiment showed that participants formed colour-concept associations from exposure to co-occurrence frequencies during a task in which attending to colour was unnecessary for successful performance. Overall, association strength between a given colour and concept was stronger as colour-concept co-occurrence frequency increased (frequency hypothesis), but this effect was stronger for noticers than non-noticers. This effect of frequency for seen colours extended to unseen colours (frequency generalization hypothesis). Association strength was stronger for colours seen during category learning compared to unseen colours (exposure hypothesis), but this effect was driven primarily by non-noticers. Finally, associations decreased with increased colour distance from seen colours (colour distance generalization hypothesis), which was unaffected by noticing. These results suggest people can "populate" a continuous colour-concept association space for a given concept by tracking frequencies of co-occurrence and spreading associations learned from exposure to neighbouring colours in colour space.

Experiment 2

In Experiment 2 we aimed to replicate the effects of frequency and exposure observed in Experiment 1, and test a new generalization hypothesis: the asymmetric generalization hypothesis. The analyses used to test these hypotheses were preregistered (osf.io/6cjkz; Schoenlein & Schloss, 2020).

Although we introduced the asymmetric generalization hypothesis in the introduction, we explain it in greater detail here. The asymmetric generalization hypothesis suggests that patterns of colour-concept association generalization depend on colour typicality within the cognitive structure of colour categories. To avoid confusion, we emphasize that by "color categories", we refer to cognitive structure that carves continuous colour spaces into discrete categories (e.g., category of red, blue, yellow, etc.) (Berlin & Kay, 1969; Parraga & Akbarinia, 2016; Rosch, 1973, 1975b). We are not referring to alien categories (Filk, Slub) that participants learn during the alien category learning task in our paradigm. And, by "typicality," we refer to how typical the colour is for its respective *colour* category (i.e., whether a red colour is a prototype or non-prototype of the colour category "red") (Rosch, 1973, 1975b), not how typical the colour was for a given alien species during alien category learning (e.g., the typicality of the colour red for a Filk alien).

Colour typicality may influence generalization from seen to unseen colours because of asymmetries in colour similarity. Unlike distances in colour space, which are symmetric (the Euclidean distance between colour 1 and colour 2 is the same as the Euclidean distance between colour 2 and colour 1), Rosch (1975a) found that participants judged non-prototypes (e.g., mauve) as being more similar to prototypes (e.g., pure red) than prototypes were to non-prototypes (Rosch, 1975a). If generalization of colour-concept associations depends on judgments of colour similarity, and colour similarity is asymmetric, then generalization should also be asymmetric. That is, there should be greater generalization of learned associations from non-prototypes to prototypes (e.g., exposure to mauve generalizing to pure red) than from prototypes to non-prototypes (exposure to pure red generalizing to mauve).

To test the asymmetric generalization hypothesis we had to modify the colours of the experimental stimuli, but otherwise the general methods in Experiment 2 were analogous to Experiment 1.

Methods

Participants

One hundred and twenty-six participants completed the experiment (69 women, 56 men, 1 prefer to not respond; mean age = 25.79 years). Eighty-two University of Wisconsin–Madison undergraduate students participated online in exchange for partial course credit and 44 mTurk workers participated in exchange for monetary compensation. Given the experiment was conducted online, colour vision was assessed with two yes/no questions: (1) Do you consider yourself to be colorblind? and, (2) Do you have difficulty seeing colours or noticing differences between colours compared to the average person? Data from an additional 19 participants was excluded due to self-reported atypical colour vision (an answer of yes to either or both of these colour vision questions). Data from 10 additional participants was excluded for their categorization accuracy being lower than the *a priori* criterion of the upper bound of the 95% confidence interval (57.22%).

For this online experiment, we implemented an additional *a priori* exclusion criterion using the reliability during the association ratings task. We calculated the correlation between the association ratings for the two presentations of each colour with each species (30 pairs of ratings). Data from 28 participants were excluded for having an average correlation less than .4 for the 30 pairs. This cutoff was based on the smallest correlation needed for 30 pairs to achieve $p < .05$, which was $r = .365$. We rounded this to .4 to be more conservative. An additional 17 participants signed up but did not complete the entire experiment, therefore their data was not included.

Design, displays, and procedure

The design, displays, and procedure used in this experiment were similar to Experiment 1, except for the following changes.

Alien category learning task. For all participants, Filks were warm-biased, pointy aliens and Slubs were cool-biased, curvy aliens (given that goodness-of-fit had no effect on learned colour-concept associations in Experiment 1, see Supplemental Material). Each of the two colour distributions included three high frequency colours and three low frequency colours (Figure 7(A)). The Filk distribution consisted of 25 aliens in each of red, orange, and yellow, and five each of green, blue, and purple.[2] The Slub distribution had the opposite frequencies, creating a total of 180 aliens to judge in the alien category learning task.

Participants saw aliens in each of the six hues presented in one of two typicality conditions: colour category prototypes (Figure 7(A), left) or colour category non-prototypes, which were the same hue and value (lightness) in Munsell space as the prototypes but decreased in chroma (Figure 7(A), right). We adapted these colour sets from Rosch's (1975b) prototypes and non-prototypes such that the colours could be rendered on a standard computer monitor (Rosch's colours were selected from Munsell chips, some of which are outside a standard monitor gamut). To define coordinates for our prototypes, we started with Rosch's (1975b) prototypes and decreased the Munsell chroma of each colour until it could be rendered within the gamut of a standard computer monitor (sRGB) with a white point of CIE Illuminant C (CIE $x = .312$, $y = .318$, $Y = 116$). We then reduced the Munsell chroma of Rosch's (1975b) non-prototypes by the proportional amount of change made for the respective prototype of the same hue.[3] Thus, colours we call "prototypes" may not be the most typical possible colour for each colour category, but they should at least be more typical than the non-prototypes.

The chromaticity of the grey background approximated CIE Illuminant C for an sRGB display ($x = 0.312$, $y = 0.318$, $Y = 19.26$). See Table A2 in the Appendix for CIE 1931 xyY coordinates, which were

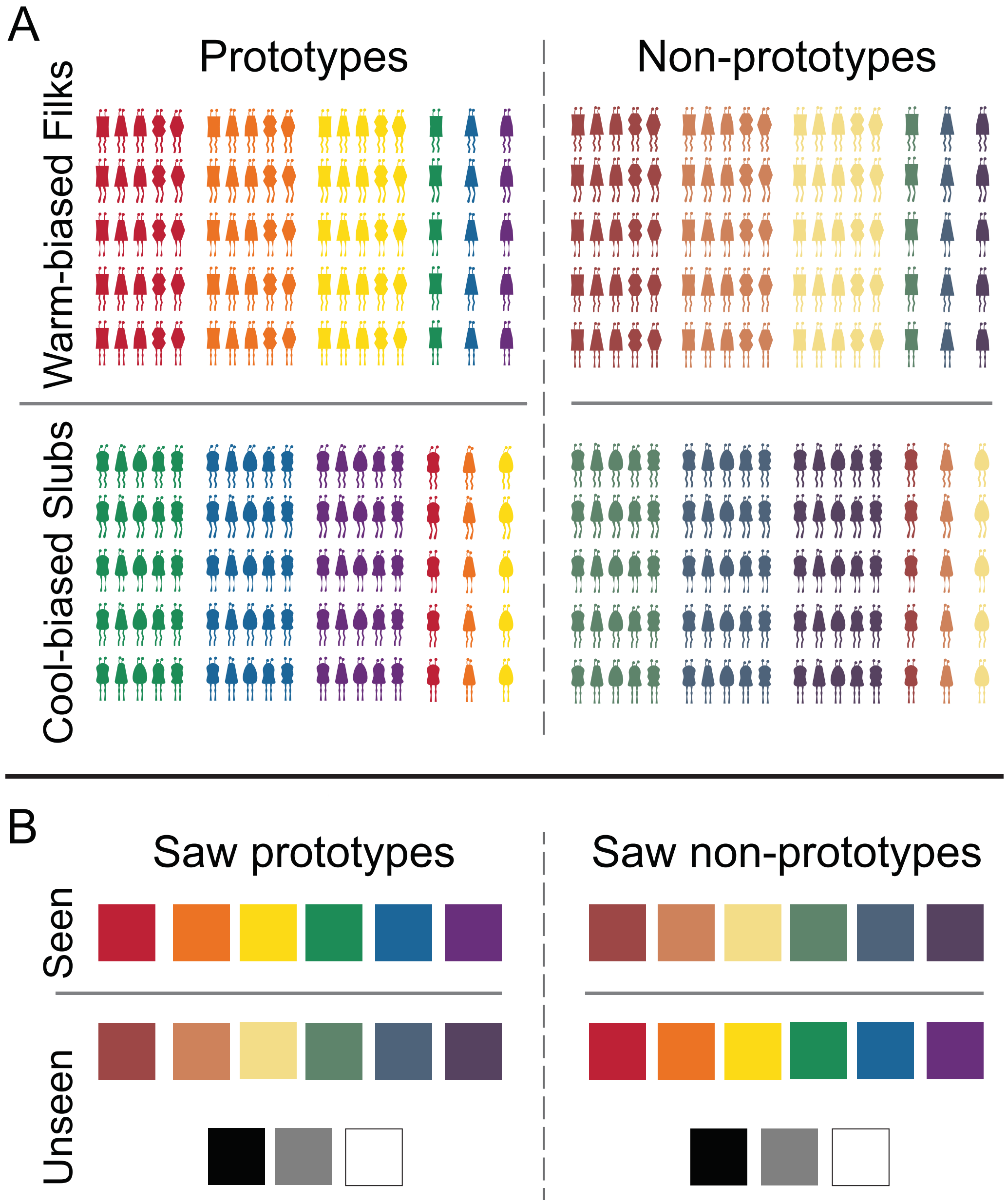

Figure 7. Stimuli for Experiment 2. (A) Warm and cool-biased distributions for participants who saw aliens in prototypical colours (left) and in non-prototypical colours (right). (B) Seen colours (alien colours during category learning) and unseen colours, depending on whether participants saw prototypes or non-prototypes.

converted from the Munsell coordinates using the Munsell Renotation table (Wyszecki & Stiles, 1982). RGB coordinates were obtained by converting the xyY coordinates to XYZ and then using MATLAB's xyz2rgb function with a specified white point of Illuminant C.

Unlike Experiment 1, Experiment 2 was completed online, on participants' own computers. Thus, the coordinates in Table A2 are approximations of the colours observed during the experiment, using assumptions about standard monitor specifications in MATLAB's xyz2rgb function. Although the exact colours each participant saw likely varied somewhat across devices, we found systematic results that replicated effects in Experiment 1, supporting the robustness of these effects. The tasks were coded in Javascript using jsPsych (de Leeuw, 2015).

Association ratings task. The colour-concept association ratings task was the same as Experiment 1, but with different colours. Participants judged the six prototypes and six non-prototypes from the alien category learning task in Experiment 2, plus three achromatic colours (15 colours total). During anchoring at the start of the procedure, participants evaluated all 15 colours presented as shown in Figure 7(B) (left), but without the horizontal grey line and labels. Within each group of participants, "seen" colours were colours seen during alien category learning (prototypes vs. non-prototypes, depending on the typicality condition), "unseen chromatic" colours were colours not seen during alien category learning but of the same colour categories as the seen colours (e.g., if participants saw prototypes during the alien category learning task, unseen chromatic colours were non-prototypes), and "unseen achromatic" colours were the black, grey, and white, which no participants saw during alien category learning. The achromatic colours were included to reduce potential floor effects that could have occurred for the unseen chromatic colours.[4]

Results and discussion

As in Experiment 1, participants quickly achieved high accuracy in the alien category learning task (mean overall accuracy was 94%[5]; mean cumulative accuracy reached 89% by trial 50 out of 180; see Figure S5 in the Supplemental Material). In the strategy questionnaire, only 9% of participants reported using colour to complete the task, and all other participants reported using shape. We classified participants as noticers or non-noticers using the same criteria as in Experiment 1 (37% were noticers, 63% were non-noticers). The mean colour-concept association ratings are shown in Figure 8, and we discuss the results corresponding to each hypothesis below.

Frequency hypothesis

The frequency hypothesis predicts that participants will associate the warm-biased concept Filk more strongly with warm colours and associate the cool-biased concept Slub more strongly with cool colours. This pattern can be seen in Figure 8(A), which shows mean association ratings for the seen colours separated by warm versus cool hues for each species, depending on whether participants saw prototypes or non-prototypes, and whether they were noticers or non-noticers.

We tested the frequency hypothesis using a preregistered LMEM analysis predicting association ratings from colour warmness [warm (red, orange, yellow) vs. cool (green, blue, purple); within-subject], species (warm-biased vs. cool-biased; within-subject), typicality of colours seen during alien category learning (prototypes vs. non-prototypes; between-subject), noticing (noticers vs. non-noticers; between-subject), all interactions, and relevant by-subject random effects ($R^2 = .47$). Here we focus on effects central to the frequency hypothesis, but see Table S3 of the Supplemental Material for the full model output.

Supporting the frequency hypothesis, colour warmness interacted with species ($\beta = 0.440$, $F(1,122) = 92.800$, $p < .001$): warm colours were more strongly associated with warm-biased Filks than cool-biased Slubs ($\beta = 0.218$, $F(1,122) = 79.597$, $p < .001$) and cool colours were more strongly associated with cool-biased Slubs than warm-biased Filks ($\beta = -0.222$, $F(1,122) = 76.592$, $p < .001$).[6] As shown in Figure 8(A), this interaction was larger for noticers than non-noticers (colour warmness × species × noticing interaction: $\beta = 0.603$, $F(1,122) = 43.691$, $p < .001$). This finding is a conceptual replication of Experiment 1, where noticers were more sensitive to frequency than non-noticers (Figure 6).

This model also revealed an unexpected effect of typicality, with stronger associations for prototypes than for non-prototypes ($\beta = 0.077$, $F(1,122) = 10.950$, $p = .001$). This difference might be explained by prototypical colours generally being easier to remember (Bae et al., 2015; Bartleson, 1960; Heider, 1972; Persaud et al., 2021).

Exposure hypothesis

The exposure hypothesis makes two predictions. First, associations for seen colours will be stronger than associations for unseen chromatic colours from the same colour category. Second, associations for both seen and unseen chromatic ratings will be stronger than associations for unseen achromatic colours because the seen and unseen colour share the same colour category. The results addressing the exposure hypothesis are shown in Figure 8(B). The association ratings for the seen colours in Figure 8(B) were computed as the mean over warm and cool colours within each frequency level from Figure 8(A) (averaged over species). As in Experiment 1, the unseen chromatic colours were assigned the same frequency value as the seen colours of the same hue (e.g., if pure red was a frequently seen colour for Filk, then mauve was also scored as frequent colour for Filk because they are the same hue). The mean associations for the unseen achromatic colours are plotted as

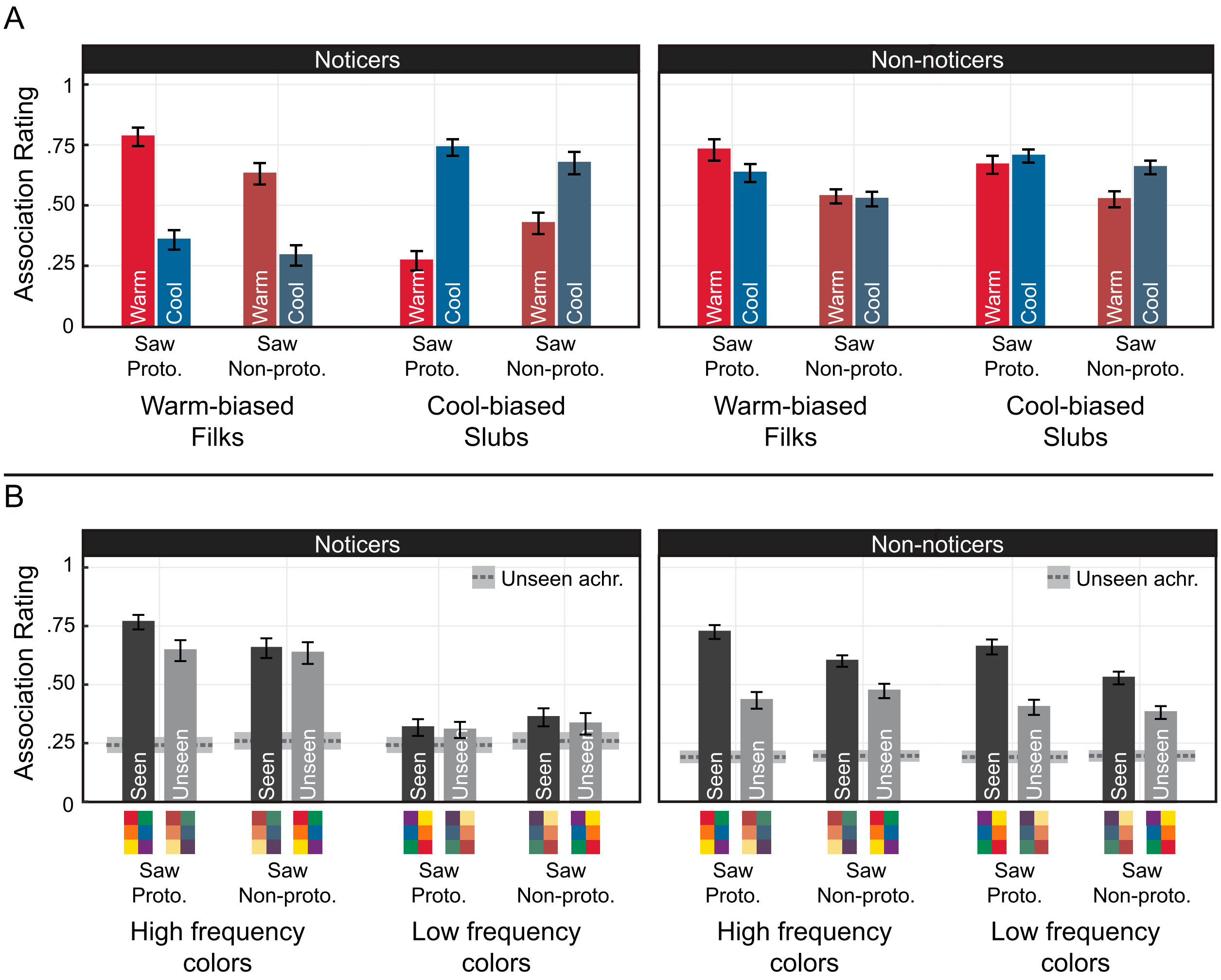

Figure 8. Colour-concept associations from Experiment 2. (A) Mean colour-concept association ratings for colours seen during alien category learning. Associations with the concepts Filk (warm-biased during category learning) and Slub (cool-biased during category learning) are shown separately for warm colours (red, orange, yellow; represented in red) and cool colours (green, blue, purple; represented in blue). Data are separated by typicality of seen colours during alien category learning (saw prototypes (proto.) vs. saw non-prototypes (non-proto.)) and noticing (noticers vs. non-noticers). (B) Mean ratings for seen (dark grey) and unseen chromatic (light grey) colours for high and low co-occurrence frequencies, separated by typicality and noticing. Colours beneath bars signify which colours were seen vs. unseen (i.e., for the saw proto. group, seen colours were prototypes and unseen colours were non-prototypes; for the saw non-proto. group, seen colours were non-prototypes and unseen colours were prototypes). The three achromatic colours (dashed line) for each typicality condition are redundantly shown behind the bars for both high and low frequency colours. Error bars and grey regions behind the dashed line for achromatic colours represent standard errors of the means (SEM).

horizontal lines behind the bars for both the high and low frequency colours for the corresponding group of participants.

We tested the exposure hypothesis using two pre-registered LMEM models, one for each co-occurrence frequency level, because the achromatic colours did not have corresponding high and low frequency colours. The high frequency model compared frequent seen colours, corresponding unseen chromatic colours, and unseen achromatic colours. The low frequency model compared infrequent seen colours, corresponding unseen chromatic colours, and unseen achromatic colours. For both models, the predictors included two within-subject contrasts: (i) seen vs. unseen chromatic contrast, coding seen colours as 1/2, unseen chromatic colours as −1/2, and unseen achromatic colours as 0 and (ii) chromatic vs. achromatic contrast, coding seen colours as 1/3, unseen chromatic colours as 1/3, and unseen achromatic colours as −2/3. The models also included between-subject fixed effects for typicality of the seen colours and noticing, plus all interactions, and by-subject random effects for each within-subject fixed factor (high frequency: $R^2 = .54$; low frequency: R^2

$= .45$). Here we focus on effects central to the exposure hypothesis, but see Table S5 of the Supplemental Material for the full model output.

The results support the exposure hypothesis for both high and low frequency colours: associations were stronger for seen chromatic colours than unseen chromatic colours (high frequency: $\beta = 0.07$, $F(1,122) = 47.042$, $p < .001$; low frequency: $\beta = 0.055$, $F(1,122) = 36.708$, $p < .001$), and associations were stronger for both sets of chromatic colours than unseen achromatic colours (high frequency: $\beta = 0.39$, $F(1,122) = 298.99$, $p < .001$; low frequency: $\beta = 0.186$, $F(1,122) = 66.710$, $p < .001$), see Figure 8(B).

Recall that in Experiment 1, non-noticers had stronger associations for seen than unseen colours (Figure 6 right), whereas noticers had similar associations for seen and unseen colours (Figure 6 left). Figure 8(B) in the present experiment shows an analogous effect; non-noticers showed greater differentiation between the seen versus unseen chromatic colours compared to noticers (noticing seen vs. unseen contrast interaction; high frequency: $\beta = -0.07$, $F(1,122) = 11.349$, $p = .001$; low frequency: $\beta = -0.091$, $F(1,122) = 25.090$, $p < .001$). Moreover, within the low frequency colours, non-noticers showed greater differentiation between the seen and unseen chromatic colours versus the unseen achromatic colours compared to noticers (noticing × chromatic vs. achromatic contrast interaction; $\beta = -0.207$, $F(1,122) = 20.562$, $p < .001$).

Asymmetric generalization hypothesis

The asymmetric generalization hypothesis suggests that generalization from seen to unseen chromatic colours is asymmetric: the difference between association ratings for seen versus unseen chromatic colours should be greater for those who saw prototypes than those who saw non-prototypes. This effect should result in an interaction between typicality of the seen colours (prototype vs. non-prototype) and exposure (seen vs. unseen chromatic colours) (Figure 8(B)). We tested the asymmetric generalization hypothesis in a preregistered LMEM analysis that predicted association ratings from co-occurrence frequency (determined by the seen colour of each colour category: low vs. high; within-subject), exposure (seen vs. unseen chromatic colours; within-subject), typicality of seen colours (prototypes vs. non-prototypes; between-subject), noticing (noticers vs. non-noticers; between-subject), all interactions, and relevant by-subject random effects ($R^2 = .45$). Here we focus on the results central to the asymmetric generalization hypothesis (see Table S6 in the Supplemental Material for the full model output).

As shown in Figure 8(B), participants who saw prototypes during alien category learning showed a larger difference between seen and unseen colours, compared with those who saw non-prototypes (typicality × exposure interaction; $\beta = 0.088$, $F(1,122) = 5.801$, $p = .018$). This pattern was more extreme for high frequency colours than low frequency colours (typicality × exposure × frequency interaction; $\beta = 0.084$, $F(1,122) = 8.239$, $p = .004$). If generalization is simply operationalized as the difference in association strength for seen and unseen colours, then these results support the asymmetric generalization hypothesis—those who saw prototypes generalized less than those who saw non-prototypes.

However, when formulating this hypothesis purely in terms of association difference, we assumed that the seen colours would have similar associations, regardless of whether they were prototypes or non-prototypes. Thus, the baseline for comparison (seen colours) would be the same for the two groups. However, as reported in the analysis of frequency effects within seen colours, participants who saw prototypes formed stronger associations for seen colours, than those who saw non-prototypes. This finding enables an alternative interpretation of the typicality × exposure interaction, which still depends on colour category structure, but does not point to asymmetric generalization. The interaction could be due to stronger associations for prototypes compared to non-prototypes, regardless of exposure (whether they were seen or unseen). Stronger associations for prototypes would lead to a larger difference between seen and unseen colours when seen colours were prototypes, and a smaller difference when seen colours were non-prototypes. Regardless, the results under both interpretations demonstrate that the cognitive structure of colour categories influences colour-concept associations.

Summary. In summary, the results of this experiment supported the frequency, exposure, and asymmetric generalization hypotheses. Participants learned stronger colour-concept associations from more frequent colour-concept co-occurrences (frequency hypothesis). This effect was largely driven by noticers, whose association strengths indicate they were more sensitive to frequency than non-noticers. Associations were stronger for seen colours than unseen chromatic colours, and associations for these two sets of chromatic colours were stronger than unseen achromatic colours (exposure hypothesis). These differences were more extreme among non-noticers, whose association strengths were more sensitive to what they saw versus did not see during alien category learning. Participants who saw non-prototypes during alien category learning generalized more to unseen colours compared to those who saw prototypes (asymmetric generalization hypothesis), but this result may have been driven by overall stronger associations for prototypes, regardless of whether they were seen during category learning. Taken together, these results indicate that when people form colour-concept associations they do not merely store observed statistics and generalize to nearby colours, they construct associations based on their cognitive representations of colour categories.

General discussion

In this study, we investigated whether participants were sensitive to colour-concept co-occurrences when using colour was nonessential for the task at hand. We addressed this question through the lens of the frequency hypothesis, exposure hypothesis, and multiple generalization hypotheses. Support for these hypotheses suggests that people can continually form and update associations between colours and concepts through experiences in the world, even if they do not explicitly think they are using colour to complete tasks.

The frequency hypothesis proposed that colour-concept associations formed during alien category learning would be influenced by colour-concept co-occurrence frequencies. Overall, participants formed stronger colour-concept associations as co-occurrence frequency increased, however this effect was stronger for participants who reported noticing colour related patterns during alien category learning. The frequency effect is consistent with evidence that people continually detect statistics from their environment (Austerweil & Griffiths, 2013; Fiser & Aslin, 2001, 2002; Hasher & Chromiak, 1977; Hasher & Zacks, 1984; Park et al., 2018; Saffran et al., 1996; Turk-Browne et al., 2005; Turk-Browne et al., 2008; Wattenmaker, 1991, 1993; Yu & Zhao, 2018; Zacks & Hasher, 2002; Zhao & Yu, 2016), even if those statistics are not essential to the task at hand.

The exposure hypothesis proposed that associations would be stronger for seen colours than for unseen colours. Both experiments supported this hypothesis, but the effect of exposure was stronger for non-noticers than noticers. That is, those who did not notice colour related patterns, and who were less sensitive to the frequency of seen colours during exposure, were more discerning between colours they saw versus those they did not see during alien category learning.

Taken together, these results suggest that both noticers and non-noticers "populated" their colour-concept association spaces for these novel concepts during exposure, but the way in which they populated them differed depending on whether they noticed colour-related patterns during exposure.

However, there are limitations to our measure of noticing. Given that our measure relied on self-reported observations, we cannot rule out the possibility that non-noticers did actually notice colour related patterns during the alien category learning task and forgot or chose not to report them at the end of the experiment. It is also possible that those classified as noticers had actually guessed about colour-related patterns without noticing them during the alien category learning task. Further research with more objective measures of noticing would be needed to fully understand effects of detecting colour-related patterns on association formation.

Moreover, we do not yet know why such individual differences in noticing arise. One possibility could be related to how participants thought about the features during alien category learning. Williams and Lombrozo (2010) showed that people learn regularities of object features better when they provide explanations of their thoughts while learning. In their study, participants who were instructed to explain while observing exemplars of two alien robot categories were more likely to notice a subtle, but 100% diagnostic feature rule (i.e., all glorps had pointy feet and all drents had flat feet), compared with participants who were instructed to describe during observation. In our study, participants may have become noticers if they were more likely to spontaneously try to explain colour variability in the alien distributions. Future studies designed specifically to study this noticing effect will be needed to understand the nature of these individual differences.

We examined multiple generalization hypotheses, proposing that learned associations from colour-concept co-occurrences will generalize to similar, unseen colours. Supporting frequency generalization, frequency effects observed for seen colours extended to unseen colours of corresponding hues. Supporting colour distance generalization, learned colour-concept associations generalized more strongly to colours that were closer in colour space. Supporting asymmetric generalization (if we take association strength for seen colours as baseline for assessing generalization), generalization from non-prototypes to prototypes was greater than generalization from prototypes to non-prototypes (Figure 9(A)).

The asymmetric generalization hypothesis directly follows from asymmetric similarity (Rosch, 1975a), if one assumes that generalization depends on similarity. However, this generalization pattern may seem counterintuitive given classic evidence in semantic cognition suggesting the opposite—greater generalization from prototypes to non-prototypes. As illustrated in Figure 9(B), Rips (1975) found that if participants are told that a new disease (a property) emerged in robins (prototypical birds), they rate the disease as highly likely to emerge in ducks (less typical birds), but if they are told the disease emerged in ducks, they rate it less likely to emerge in robins.

However, this type of scenario is distinct from the scenario in the present study. We studied generalization between different properties (pure red, mauve) of an object (e.g., Filk) depending on typicality of the properties of their property category (red) (Figure 9(A)). In contrast, Rips (1975) studied generalization of one property (disease) between multiple objects (robin, duck), depending on typicality of objects to their object category (bird) (Figure 9(B)). Thus, our results do not contradict earlier work on feature generalization in category membership (Rips, 1975). Instead, they suggest that effects of typicality on generalization may be more intricate than previously thought. Further work is needed to understand this distinction, and to understand why different patterns of generalizations may arise in these two cases.

We also considered an alternative interpretation of the results in Experiment 2 that does not involve asymmetric generalization. We found unexpected effects of colour typicality on learned associations for colours seen during alien category learning. From the perspective of mere statistical co-occurrence, one would

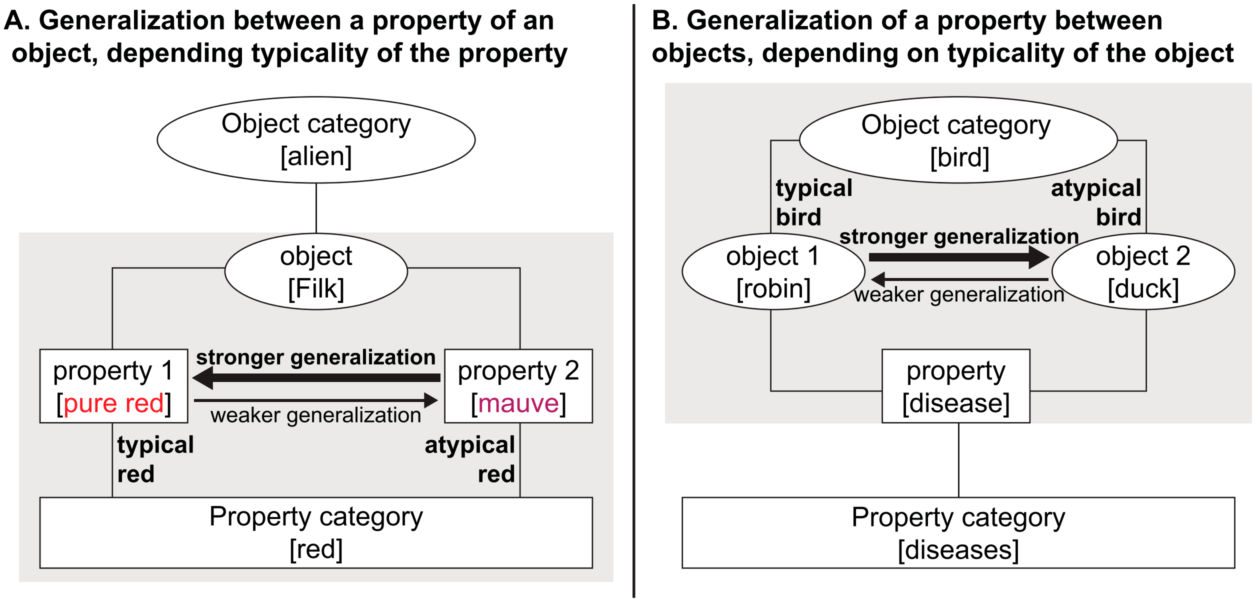

Figure 9. Potential patterns of generalization between (A) properties within objects and (B) properties across objects. (A) Predicted patterns of generalization for the present study, in which generalization is between properties that vary in typicality for a given object. Thicker arrows indicate stronger generalization. (B) Classic patterns of generalization in semantic cognition, as described by Rips (1975), in which generalization is of properties between two objects which vary in typicality.

expect that the strength of learned associations depends on frequencies of colours seen during category learning, but not on which exact colours were seen. Yet, participants formed stronger associations for seen colours if they saw prototypical colours ("good" examples of colour categories, such as a saturated red colour for the colour category *red*) during learning than if they saw less typical colours (worse examples of colour categories, such as a mauve colour for the colour category *red*). This finding is consistent with previous reports that people have better memory for colour category prototypes than for less typical category members (Bae et al., 2015; Heider, 1972). It is possible that participants form stronger associations for prototypes, regardless of whether they were seen or not. Such an effect could also produce the observed pattern of results in Experiment 2. Although further work is needed to disentangle these potential effects due to colour category structure, it is clear that colour category membership plays an important role in the formation of colour-concept associations.

In conclusion, our results suggest people form associations between colours and concepts through detecting co-occurrence frequencies, but people are not merely bottom-up statistic detectors. An individual's colour-concept associations are constructed depending on a combination of factors, including statistics in the colour input, whether they detect patterns in the colour input, and typicality of the colours in the input, as defined by the cognitive structure of colour categories. These results provide an initial step in explaining how people construct the rich representations of colour-concept associations that influence the way they interpret the meanings of colours in the world around them.

Notes

1. We set an *a priori* exclusion criterion of < 56.25% accuracy, but all participants exceeded this criterion, so none were excluded (the minimum accuracy was 59%). We determined this criterion by calculating the 95% confidence interval for chance performance and determined that the upper bound of the interval was 56.25%.
2. Purple can be considered on the border between "warm" vs. "cool" colours. For the purpose of this experiment, we classified it as a cool colour.
3. We also made an additional change to the yellows, shifting their hue from 2.5 to 5Y in Munsell space, based on more recent work suggesting that prototypical yellow is closer to 5Y in Munsell space (Olkkonen et al., 2010). After shifting in hue, we used the chromaticity (CIE x and y) if the value was 9, but adjusted the luminance to acquire a prototypical yellow with the highest possible chroma within the sRGB gamut. The non-prototypical yellow's chroma was set half-way between the prototype's chroma and achromatic.
4. The logic for introducing achromatic colours to reduce floor effects was as follows. Participants should have low association ratings for achromatic colours because those colours were so dissimilar from the seen colours for both groups. Given the anchoring of all colours was on the same rating scale, and achromatic colours were more different from the seen colours than the chromatic unseen colours, low ratings for achromatic colours should boost ratings for the unseen chromatic colours away from the bottom end point of the ratings scale.
5. We set an *a priori* exclusion criteria of < 57.22% accuracy. 10 participants were excluded, as described in the Participants section. Minimum accuracy after exclusions was 72%. We determined this criterion by calculating the 95% confidence interval for chance performance and determined that the upper bound of the interval was 57.22%.
6. These follow-up comparisons within species were not specified in the preregistration, but they follow directly from the preregistered predicted interaction in the frequency hypothesis (see Table S4 in the Supplemental Material for the full output of species-specific models).

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Appendix

Table A1. Colour coordinates for BCP-32 colours used in Experiment 1. The coordinates were modified to fit in the gamut of the monitors. The “seen” colours were saturated and the “unseen” colours were the light, muted, and dark variations of each hue.

Hue	Variation	x	y	Y	L	a	b
Red	Saturated	0.549	0.313	22.93	51.573	62.234	32.198
	Light	0.407	0.326	49.95	71.596	31.578	16.68
	Muted	0.441	0.324	22.93	51.573	33.58	16.981
	Dark	0.506	0.311	7.60	30.764	37.017	16.39
Orange	Saturated	0.513	0.412	49.95	71.6	31.215	69.647
	Light	0.399	0.366	68.56	81.35	15.001	30.172
	Muted	0.423	0.375	34.86	61.7	15.94	30.33
	Dark	0.481	0.388	10.76	36.51	18.354	30.597
Yellow	Saturated	0.446	0.472	91.25	91.08	−5.7506	86.678
	Light	0.391	0.413	91.25	91.08	−5.4588	47.705
	Muted	0.407	0.426	49.95	71.6	−3.3302	45.936
	Dark	0.437	0.45	18.43	46.83	−0.92513	43.35
Chartreuse	Saturated	0.387	0.504	68.56	81.35	−32.919	72.055
	Light	0.357	0.42	79.90	86.44	−20.62	40.644
	Muted	0.36	0.436	42.40	66.94	−19.975	37.45
	Dark	0.369	0.473	18.43	46.83	−19.923	36.863
Green	Saturated	0.254	0.449	42.40	66.94	−59.948	24.537
	Light	0.288	0.381	63.90	79.09	−34.126	15.212
	Muted	0.281	0.392	34.86	61.7	−33.267	14.065
	Dark	0.261	0.419	12.34	38.96	−33.292	12.408
Cyan	Saturated	0.226	0.335	49.95	71.6	−44.315	−6.1068
	Light	0.267	0.33	68.56	81.35	−26.118	−2.7294
	Muted	0.254	0.328	34.86	61.7	−25.402	−4.1266
	Dark	0.233	0.324	13.92	41.22	−24.26	−5.4518
Blue	Saturated	0.2	0.23	34.86	61.7	−13.209	−38.399
	Light	0.255	0.278	59.25	76.73	−8.8676	−20.82
	Muted	0.241	0.265	28.90	56.99	−7.8584	−21.411
	Dark	0.212	0.236	10.76	36.51	−6.5572	−23.727
Purple	Saturated	0.272	0.156	18.43	46.83	57.212	−50.49
	Light	0.29	0.242	49.95	71.6	26.028	−27.872
	Muted	0.287	0.222	22.93	51.57	28.052	−27.816
	Dark	0.28	0.181	7.60	30.76	33.038	−29.66

Table A2. Colour coordinates for prototypical and non-prototypical colours used in Experiment 2. Colours were based on Rosch’s (1975b) prototypes and non-prototypes in Munsell space, but adapted to fit in the standard gamut of a monitor. Yellow was shifted in hue as well due to colour category concerns (see main text).

Hue	Typicality	H	V	C	x	y	Y	L	a	b
Red	Prototype	5R	4	14	0.5734	0.3057	13.92	44.11798	62.5262	31.69846
	Non-prototype	5R	4	8	0.469	0.3209	13.92	44.11798	36.85677	18.5329
Orange	Prototype	2.5YR	6	14	0.5488	0.3947	34.858	65.63796	43.42444	71.12107
	Non-prototype	2.5YR	6	7.875	0.445	0.37	34.858	65.63796	24.76745	35.10147
Yellow	Prototype	5Y	9	12	0.4455	0.4719	83.52	93.24162	−5.94025	88.70761
	Non-prototype	5Y	9	6	0.3858	0.4071	83.52	93.24162	−5.3463	46.15292
Green	Prototype	2.5G	5	8	0.271	0.438	22.9332	55.00346	−43.5609	21.39649
	Non-prototype	2.5G	5	3.25	0.295	0.365	22.9332	55.00346	−19.1112	9.350688
Blue	Prototype	2.5PB	4	8	0.1995	0.2094	13.92	44.11798	−2.48853	−34.8861
	Non-prototype	2.5PB	4	3.8	0.255	0.265	13.92	44.11798	−1.63457	−15.8402
Purple	Prototype	5P	3	10	0.2772	0.1707	7.6038	33.14374	38.77706	−33.7731
	Non-prototype	5P	3	4	0.2928	0.2386	7.6038	33.14374	16.43582	−15.6187