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RESEARCH

Procedural and declarative knowledge simultaneously contribute to category response selection

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Abstract
Skilled behaviour in real-world contexts often relies on a combination of both declarative and procedural learning. However, precisely how declarative and procedural knowledge interact is not yet fully understood. Previous findings have shown that procedural and declarative learning may interact or compete at the systems level during encoding, consolidation, and retrieval, but beyond this, it is not known whether declarative and procedural representations themselves interact. The goal of the current study is to investigate whether procedural and declarative knowledge can contribute simultaneously to categorization response selection behavior. We designed a stimulus set in which information learned by each system sometimes supports different responses, and created trials in the test phase that are designed to maximize such divergence. Participants were instructed to use a completely diagnostic, verbalizable, shape-based rule to categorize exemplars, receiving feedback after each trial. However, unbeknownst to participants, the categories also differed probabilistically in their color distributions. Participants used both color (learned procedurally) and shape (learned declaratively) to categorize exemplars, responding more quickly when both sources indicated the same category judgement, and more slowly when they conflicted. Debriefing confirmed that most participants were unaware of the color distributions. These results show simultaneous trial-level contributions from both declarative and procedural memory systems. Our findings represent a novel form of interaction between the two systems and have implications for domains beyond the laboratory, such as decision-making and classroom instruction.

Introduction

The last century has seen great strides in our understanding of human learning and memory. Compelling evidence indicates that there are multiple dissociable memory systems with different characteristics and instantiated in different neural substrates (Gabrieli, 1998). One of the best-characterized systems is referred to as the declarative memory system, which requires intact medial temporal lobe structures and can yield verbalizable knowledge, which can be acquired within a single trial (Eichenbaum & Cohen, 2001; Graf & Schacter, 1985; Cohen & Squire, 1980). Within the multiple forms of memory that are not available to awareness and do not require the medial temporal lobe (Reber, 2013), another well-characterized system is the procedural memory system, which relies on a fronto-striatal network and is characterized by gradual learning across multiple learning episodes, yielding non-verbalizable knowledge that is more easily expressed through performance (Squire & Zola-Morgan, 1988; Squire, 1992, 2004, Reber & Squire, 1994).

The last few decades have moved beyond establishing the dissociable systems to examining ways that they may interact, since both are available in healthy adults. Many of these investigations have focused on competition (Poldrack & Packard, 2003), or possible collaboration (Freedberg et al., 2020) between systems during the learning process (encoding). What has not been examined as closely is whether and how information from both systems may contribute to downstream processes such as decision making and response selection.

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As we review below, much existing evidence suggests that information from only a single system at a time contributes to these downstream processes. However, outside of the laboratory, we observe scenarios in which information from both systems appears to be used simultaneously. For example, when making diagnoses, medical experts seem to use a combination of both conditional reasoning based on declarative knowledge as well as probabilistic reasoning based on experience (Norman & Brooks, 1997). Similarly, professional musicians performing from memory seem to simultaneously draw on both a non-verbalizable representation of motor sequences as well as a verbalizable understanding of the structure, form, and meaning of a musical piece (Chaffin et al., 2009 cited in Reber, 2013). Increasing evidence also suggests that procedural and declarative knowledge interact in language learning (Ullman, 2004, 2016; Pili-Moss, 2022) and tool use (Roy & Park, 2010; Roy et al., 2015).

Procedural and declarative category learning

Like tool use and language learning, category learning—learning that stimuli (such as objects) belong to categories, and that members of a category can often be treated in the same way —can be accomplished through either declarative or procedural learning, depending on task demands and category structure. In a typical category-learning experiment, a participant is shown an example stimulus (e.g., a face, butterfly, or abstract shape) and asked to classify it into one of two categories, with feedback given after each trial. Evidence of learning in these tasks is seen in increasingly accurate responses as training progresses, and can be measured against chance responding, which is usually 50% accuracy given the two-alternative forced-choice format.

When the category structure is simple and verbalizable (such as a unidimensional aka "Rule-Based" category boundary), declarative, verbally-mediated methods for learning are most efficient, and tend to be used more by participants. Declarative/verbalizable category learning has been mapped to the declarative or explicit long-term memory system in the human brain (Ashby & O'Brien, 2005), which depends on structures in the medial temporal lobe (MTL), including the hippocampus (Gabrieli, 1998 *inter alia).*

However, when the category structure is complex (such as in multidimensional or "Information-Integration" categories), or the relationship between items and category membership is probabilistic, then declarative strategies are inefficient. Under such circumstances, successful learning usually occurs through a non-declarative category learning mechanism. Specifically, one type of non-declarative long-term memory, sometimes referred to as "skill and habit learning" or "procedural learning", depends on the striatum of the basal ganglia and can be used to learn complex or probabilistic categories (Foerde et al., 2007; Knowlton et al., 1994, 1996a, b; Ashby & O'Brien, 2005; Ashby & Ell, 2001; Ashby & Ennis, 2006; Seger & Cincotta, 2006; Ashby et al., 1998; Foerde, 2018; Foerde & Poldrack, 2008; Knowlton et al., 1996a; Salmon & Butters, 1995; Seger, 2006). Importantly, the term "procedural" in the cognitive neuroscience long-term memory taxonomy (see e.g. Squire & Zola-Morgan, 1996, Fig. 1) is not used to mean "knowledge of procedures" or to mean only stimulus-response associations or condition-action rules, as it may be used in other areas of cognitive psychology. Specifically, this usage of "procedural" refers to skill and habit learning that depends on the basal ganglia and leads to abstract, long-term knowledge (Reber, 1989; Seger, 1994). Importantly, procedural learning is not limited to motor skill acquisition, but also includes cognitive skill acquisition (Poldrack et al., 1999; VanLehn, 1996; Wan et al., 2012).

Existing research on interactions between memory systems in category learning

Existing research on interactions between memory systems in category learning has emphasized competition, either at encoding or retrieval. Inspired by findings in rodent models that lesioning one system seemed to improve function of the other system (McDonald et al., 2004; Mcdonald & Hong, 2013; McDonald & White, 1995), early models of interaction between declarative and procedural memory in humans emphasized competition for resources during encoding (learning) [1]. Supporting this view, Poldrack et al. (2001) examined fMRI data from participants performing either a probabilistic classification task or a paired associate (declarative memory) task with the same stimuli and found an inverse relationship between MTL and striatal activity while participants performed a probabilistic classification task. They interpreted the results as evidence for competition between the systems during learning.

However, several subsequent studies suggested that simultaneous encoding—without interference or competition—could take place. For example, Foerde et al. (2006) found that activity in striatal regions was similar in both a single task condition and a dual-task condition (which is known to impair declarative category learning: Waldron & Ashby, 2001), suggesting that procedural learning occurred regardless of declarative learning. Several studies by Crossley and colleagues have also demonstrated simultaneous encoding of category information by procedural and

[1] Competition during consolidation has been observed in sequence learning, but to our knowledge not in category learning. (Brown et al., 2009; Brown & Robertson, 2007; Galea et al., 2010)

declarative systems (Ashby & Crossley, 2010; Crossley & Ashby, 2015; Turner et al., 2017).

To our knowledge, few studies have examined potential cooperation between declarative and procedural systems in categorization. One exception is an event-related fMRI study of probabilistic classification, by Dickerson et al. (2011), which found that both the medial temporal lobe and striatum showed a greater BOLD response to difficult cues than easy cues. Furthermore, they observed significant correlation in the time course of BOLD responses between the two areas, demonstrating functional connectivity. The authors interpret these results to mean that not only could both systems work in parallel without interfering with each other, but speculate that they may even collaborate to enhance overall learning[2].

Without contradicting the possibility of simultaneous encoding, some studies suggested that competition between the systems might take place later, when knowledge is retrieved and applied **(**Poldrack, & Rodriguez, 2004**)**, rather than at initial encoding. For example, rodents who had shifted from medial-temporal based representations to striatal based representations to navigate a maze reinstated the previously-learned medial temporal-based representations when their striata were inactivated with lidocaine (Packard & McGaugh, 1996). Similarly, while the studies by Crossley and colleagues mentioned above support the idea of simultaneous encoding, they also supported the idea of competition at retrieval or application.

Finally, some evidence suggests that if provided with an explicit cue, participants can flexibly switch between rule-based and information-integration categorization strategies on different trials within the same session (Turner et al., 2017). This finding demonstrates that coordination between the two systems is possible and may be managed by a third, coordinating system or mechanism[3]. However, intentional trial-by-trial switching appears to be rare or difficult in the absence of explicit cueing (Erickson, 2008; Turner et al., 2017).

Evidence for possible within-trial interaction

To our knowledge, no study has been *specifically* designed to test whether information from both systems simultaneously contributes to a response within a single trial. However, some studies have hinted at this possibility.

For example, Allen and Brooks (1991) observed that even though participants were given a perfectly predictive classification rule, their responses on a transfer task were nevertheless affected by similarity to previously seen exemplars along irrelevant dimensions—almost as if the similarity information were “contaminating” the rule-based classification. However, this study was originally designed to contrast rule-based and exemplar-based learning, not declarative and procedural learning, so it is possible that that the generalization based on exemplars could have been mediated by either procedural or declarative mechanisms[4]. Similarly, Schoenlein and Schloss (2022) trained participants to classify stimuli based on a completely diagnostic shape difference, but using a cool-biased color distribution for one category and a warm-biased color difference for the other category. Participants were able to use the shape rule effectively, and in a set of debriefing questions, they did not report color as a feature used to classify the stimuli. However, after training, participants were asked to rate how associated different colors were with each category (using the category names) on a continuous scale labeled from “not at all” to “very much.” The participants rated cool colors as more associated with the cool-biased category and warm colors as more associated with the warm-biased category, even generalizing to warm and cool colors that had not been included in the training set. These findings demonstrate that participants were able to form a color-category association with out any explicit instructions or cues to attend to color, even while they were simultaneously using a fully diagnostic non-color rule. However, since the color-category associations were assessed outside of the categorization task, this study could not test whether this probabilistic color information directly influenced category decisions during online classification performance. In addition, the degree to which the color-category association was available to declarative and explicit processes was unclear: participants did not report use of color to categorize stimuli in a verbal

[2] Cooperation between systems in the form of increased functional connectivity has also been observed for non-categorization tasks, including sequence learning (Albouy et al., 2013; Freedberg et al., 2020).

[3] The idea of a “third party” mediating the balance of function between procedural and declarative memory has been introduced in other discussions of interactions between procedural and declarative memory, but not in the context of category learning specifically. (Cabeza & Moscovitch, 2013; McDonald et al., 2004; Mcdonald & Hong, 2013)

[4] Allen and Brooks hypothesized that similarity to training items would affect test responses through the mechanism of episodic retrieval, i.e. explicitly remembering specific training phase exemplars and comparing the current test phase stimulus to them. Because of this theoretical framing, the feedback given to participants in the training phase of the Allen & Brooks study was not [optimized] for implicit learning; the feedback was somewhat indirect (an image showing the “animals” either “digging” or “building” their nests, thus revealing their membership in either the “digger” or “builder” category). In the current study, simple “correct” or “incorrect” feedback is given immediately after each trial, and a consistent response-stimulus-interval separates trials. Another important difference is that in the test phase of Allen & Brooks, most of the test items (32/40, 80%) were repeated from training, whereas in the current study, no training items are repeated in the test phase.

debrief, but were able to rate the association between each color and category.

More closely, Batterink and colleagues (Berger & Batterink, 2024; Batterink et al., 2014) taught participants an explicit rule (near/far objects) governing the use of novel artificial words in a word-object matching task. However, unbeknownst to the participants, the words also differed along a covert, second dimension (animate/inanimate objects). Participants showed greater reaction-time and lower accuracy on trials in which the word-animacy contingency was violated, even though they were unaware of the article-animacy contingency. This finding shows that information acquired without awareness can affect intentional response decisions that are made on the basis of a deterministic rule, delaying response times when the two forms of information conflict. These results suggest that both information that the participant is aware of, as well as information that the participant is not aware of, are interacting at the point of response selection.

However, the results of the studies by Batterink et al. leave room for explanations other than an interaction of procedural and declarative knowledge. For example, in any case of language or language-like learning, there is the possibility that language-specific learning mechanisms may be engaged, rather than (or in addition to) domain-general learning mechanisms. Moreover, although Batterink et al.'s study included violation trials throughout, other aspects of the task, such as the cue-outcome probabilities, and in particular the mapping to a semantically available construct (animacy), differ from classic probabilistic classification tasks that are known to engage procedural learning mechanisms (see e.g. Knowlton, 1994, 1996).

Inspired by, and borrowing elements from, the studies mentioned above, we have designed a paradigm specifically to examine the interaction of declarative and procedural learning mechanisms in visual category learning.

The current study

The goal of the current study is to observe whether procedural and declarative knowledge contribute simultaneously to categorization response selection behavior, after initial encoding has occurred. It can be difficult to disentangle the contributions of multiple learning systems in a single task because the systems typically converge on common responses. Here, we have designed a stimulus set in which information learned by each system sometimes supports *different* responses, and we have created trials in the test phase that are designed to maximize such divergence.

For the declarative system, we provide—explicitly, verbally, and with examples—a deterministic, verbalizable category rule based on feature combinations. In theory, this rule can be learned based on a single verbal presentation. For example, Category A is defined by one combination of features, and Category B is defined by another set.

For the procedural system, our training items follow a distribution of colors that differs probabilistically between the two categories (as defined by the feature combination rule). As in the Schoenlien and Schloss (2022) study, one category is presented in a warm-biased color distribution, and the other in a cool-biased color distribution (for example, training exemplars from Category A might appear in cool colors more often than in warm colors, and vice versa). Importantly, the relationship between colors and category is probabilistic: exemplars from each category appear in each of the possible colors, but for one category, the probability of an exemplar appearing as a warm color will be low (and vice versa) (see Fig. 1). If a color-category association is to be learned, it must be learned gradually, with feedback, via the procedural category learning system. The structure and task demands of probabilistic color-category association learning are very much like the probabilistic classification task, which has been reliably demonstrated to use the striatal procedural system (Foerde & Shohamy, 2011b; Knowlton et al., 1994; Knowlton et al., 1996a, b; Shohamy et al., 2004; Squire et al., 1994).

The experiment presented here includes a training phase and a test phase. The biased color distributions are used in the training phase to establish a color-category association. However, a non-biased color distribution is used in the test phase, so that many of the trials present a color-category combination that violates the expected color-category association established in the training phase (for example, if Category A was presented as warm-biased in the training phase, then the violation/incongruent trials in the test phase would include Category A stimuli presented in cool colors).

We also include measures of whether the color-category knowledge is available to awareness or not. If it is learned gradually, based on feedback, and without awareness, we may infer that this learning is mediated by the striatal procedural system. During the test phase, if we see a difference between trials in which procedural and declarative learning point to the same response (congruent) compared to those trials in which they point to different responses (incongruent), we will conclude that both sources of information contribute to response selection within a given trial. If we do not observe such a difference, we will conclude that information from both systems is not used simultaneously in response selection, at least in the current paradigm.

We initially explored these questions in a preliminary study that was presented as conference proceedings paper (Kalra et al., 2024). The current study improves on the original by including a post-test for color-category knowledge, as well as pre-registration of the analysis plan. The findings

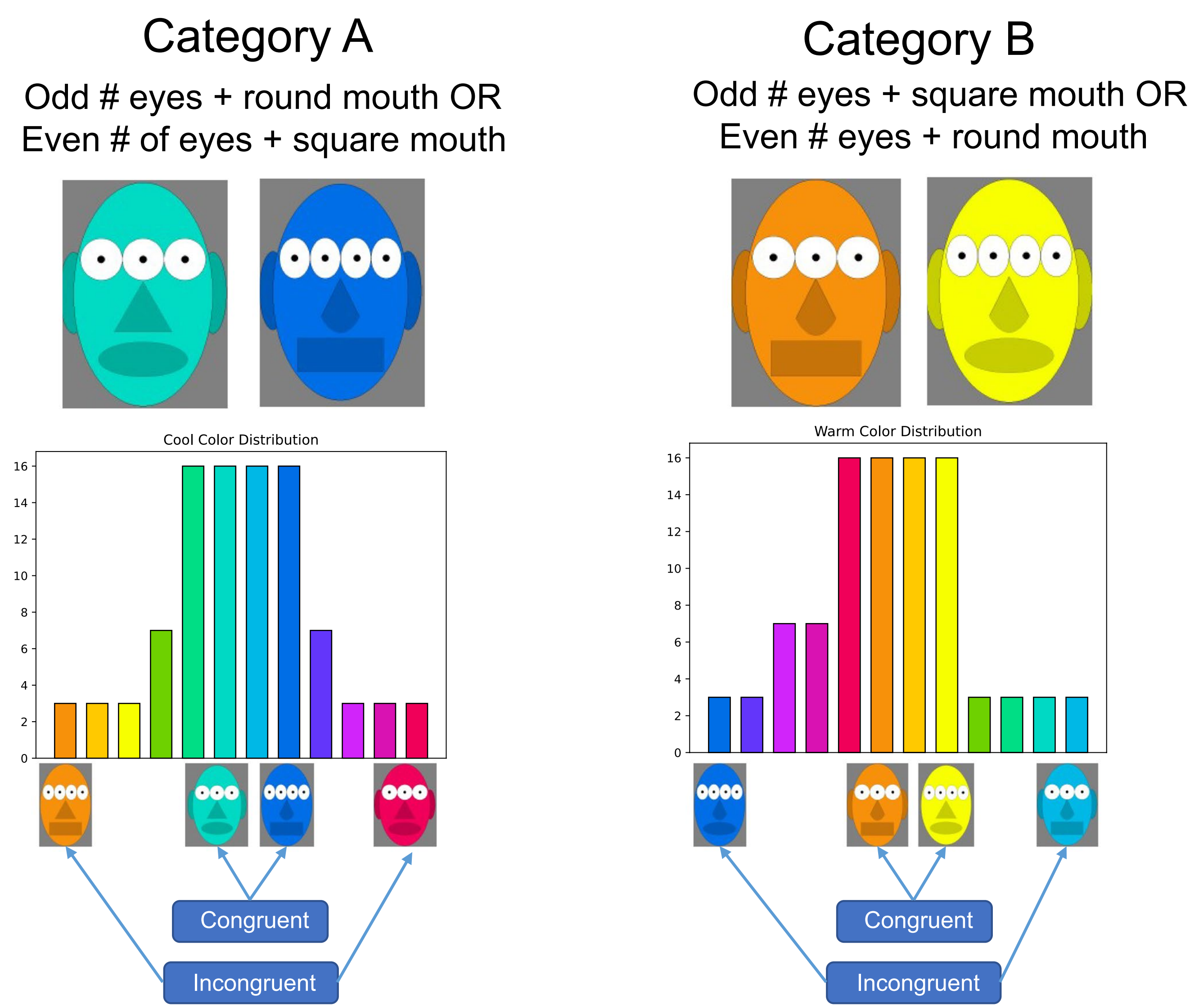

Fig. 1 Experiment design. Participants were told the complex disjunctive eye/mouth rule for classifying alien stimuli. In the training phase, items for each category were presented across a biased color distribution, either cool-biased (Category A) or warm-biased (Category B), creating a probabilistic color-category association. In the test phase, an even distribution of congruent and incongruent items from each category were presented

of the current study are consistent with the findings of the original study, so the current study may be considered a successful pre-registered replication (and expansion) of that study.

Methods

Participants

A total of 235 participants were recruited using the Connect Cloud Research platform (Hartman et al., 2023) following an approved ethics protocol (ages 19–71; mean age 36.69 years; 50% Male, 50% Female by self-report). Participants were compensated US$4.50 for completing the task. To encourage engagement with the task, participants were told that bonuses were possible for performance over 90% (the bonus given was $0.50). An accuracy performance criterion (70% accuracy on training and test phases) was instituted to detect and eliminate online participants who did not follow directions; participants were told that 70% accuracy was necessary to "win" the game, and mean accuracy was displayed on screen during the training phase. Of the 235 participants who completed all parts of the study, 204 met the minimum performance criterion and were included in further analyses.

This protocol for this study, including performance criteria for exclusion, was preregistered[5]. The preregistered protocol can be found at https://osf.io/atj5q.

Materials

Alien Stimuli

"Alien" images were created using custom code and Python's PIL package to combine geometric figures (ovals, rectangles, etc.). Each alien stimulus consisted of a large oval with some configuration of the following features: number of eyes (1–4), mouth type (round or angular), nose type (round or angular), ears (present or absent). All thirty-two possible combinations of these features were generated and used in the experiment (see Fig. 1A for example images).

Categorization features and explicit rule Alien stimuli were divided into two categories based on a disjunctive (exclusive "or"/XOR) rule over the eye and mouth dimensions (Fig. 1). Stimuli in Category A had either a round mouth and odd number of eyes OR a square mouth and even number of eyes. Conversely, stimuli in Category B had either a square mouth and odd number of eyes OR a round mouth and even number of eyes. Thus, each category included 16 possible configurations of features (including both the diagnostic [eyes, mouth] and nondiagnostic [nose and ears] feature dimensions). Because of the disjunctive nature of the rule, each category could be further divided into two subcategories based on which part of the rule applied (e.g., for each category, odd number of eyes and even number of eyes belonged to different subcategories). The complex disjunctive rule was chosen for two reasons. First, a disjunctive rule is difficult or impossible to learn from feedback alone (see e.g., Shepard et al., 1961; Feldman, 2000, 2003), so any use of the eyes/mouth rule could be assumed to be via the declarative system. Second, the complexity of the complex disjunctive rule requires considerable working memory and attention resource allocation, so it was unlikely that participants could attend to and become aware of the biased color distributions.

Color selection and distribution Each configuration of features was then generated in a variety of colors (Fig. 1). Colors were divided into warm and cool colors based on their hue angle. Even hue-angle spacing was used to choose hue angles of 0, 30, 60, 90, 120, 150, 180, 210, 240, 270, 300, 330 (where 0 corresponds to red and 180 to cyan). Warm colors were defined as those within 90 degrees (+/-) of 0; cool colors were defined as those greater than 90 degrees (+/-) from 0. For each hue angle position, saturation (chroma) was adjusted to minimize differences in saturation across hue angles and between warm and cool color groups. Given the inherent asymmetry of the visual color space, it was not possible to equalize luminance (brightness) between warm and cool colors; cool colors were systematically lower in luminance than warm colors (see Supplemental Figure 1). The COLORMATH package for Python (Taylor, 2018) was used to select colors in CIELCh$_{uv}$ color space (CIE, 1986) and to calculate the distances between colors in that color space (delta e). Degree of warmness and differences in warmness between colors were calculated based on hue angle and distance from 0. LHC and RGB values can be found in Table 1 of the Supplemental Materials. Note that because participants completed the tasks on their own computers via the online platform, actual displayed colors may have varied from our original specifications. However, the relative differences between colors would likely have been largely preserved.

Training phase color distributions Unbeknownst to participants, stimuli in the training condition followed biased color distributions. Two color distributions were created: one warm-biased and one cool-biased, and each was assigned to a category in counterbalanced fashion (i.e., for half of participants, Category A followed the warm-biased distribution and Category B the cool-biased distribution, and vice versa for the other half; see Fig. 1). Each color distribution included a total of 92 alien stimuli distributed across all 12 hue values. Each distribution contained 74 congruent (e.g., warm colors in the warm-biased category) alien stimuli and 18 incongruent (e.g., cool colors in the warm-biased category) alien stimuli. Within each category, each color was also distributed evenly across subcategory and number of eyes. The distribution of non-diagnostic features (nose type and ears/no ears) was also matched between the two categories. This balancing of color across subcategory, number of eyes, and non-diagnostic features was done to reduce or eliminate the possible formation of color-feature associations other than the intended color-category association.

Procedure

Overview

Participants completed the task on their personal computers (option to complete the task on tablet or phone was disabled). After giving informed consent, participants viewed an explanation of the explicit rule on a screen with visual

[5] Note that the current, preregistered study is a replication of a previous, non-preregistered study. The results reported here are consistent with the results of the previous study, which can be found in Kalra et al., 2024.

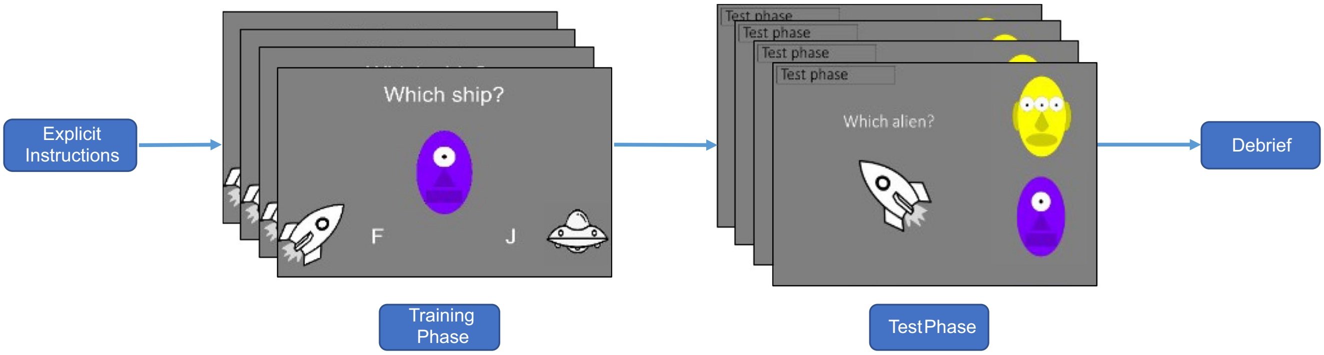

Fig. 2 Schematic illustration of experiment procedure. Feedback was given during the training phase but not the test phase

examples. Participants then progressed through the training phase, followed by the test phase. Finally, participants answered demographic and debriefing questions and completed a brief test of color-blindness using Ishihara plates. All instructions were provided in text form on the computer screen. Consent, demographic, debriefing, and colorblindness items were administered through Qualtrics (Qualtrics Software Company, 2024 Provo UT). Training and test phase categorization tasks were programmed in PsychoPy (Pierce et al., 2019), uploaded to the Pavlovia online experiment platform (www.pavlovia.org), and embedded in Qualtrics.

Training phase

Participants were given a cover story in which they were asked to match alien stimuli to their appropriate vehicles—aliens of one category used rockets, while the other category used saucers (no verbal labels were given for vehicle type). Participants were instructed on the explicit rule through slides that explained the rule (e.g. "Group 1[6] aliens have square mouths and an odd number of eyes") and provided examples. The training task then began. A short practice block of 12 trials preceded the four training blocks. The stimuli in the practice block were sequenced to highlight the diagnostic features differentiating the categories (e.g., Category A stimulus with one eye followed by Category B stimulus with one eye). In all other ways practice trials were identical to training trials.

On each trial, participants were shown an alien stimulus and two images of spaceships—one rocket, one saucer-shaped. The rocket was always on the left side of the screen and the saucer on the right (see Fig. 2). Participants categorized each alien stimulus by choosing rocket or saucer (left/right) with a key press (f/j). Participants received feedback in the form of the words "correct" or "incorrect" displayed on the screen. Feedback was based solely on the explicitly instructed mouth/eyes rule. Category-ship combination was counterbalanced across participants, so for half the participants Category A stimuli used the rocket and Category B stimuli used the saucer, and vice versa for the other half. To encourage accurate performance, incorrect responses were followed by a 3-second delay with countdown, serving as a penalty for errors. The task screen also included a "power bar" showing cumulative accuracy; in the pre-task instructions, participants were told that cumulative accuracy above 70% was necessary "to win the game."

Although participants were incentivized with regard to accuracy, they were not given any instructions regarding speed of response (i.e., they were not specifically instructed to respond as quickly as possible while being accurate). In addition, there was no response deadline; stimuli persisted on each trial until terminated by participant response. One reason we chose not to impose a response deadline on participants was to decrease stress, which is known to impair performance on complex cognitive tasks (e.g., Sussman & Sekuler, 2022, Caviola et al., 2017). We also assumed that participants were internally motivated to complete their participation as quickly as possible; this is why the 3-second delay was thought to be an effective deterrent for attempting to speed through the task without regard to accuracy. While a few highly accurate participants had long average responses times, across participants we did not observe a reaction time-accuracy trade-off (Supplemental Figure 5).

An inter-trial interval of 500ms separated the feedback screen and the subsequent alien stimulus presentation; during the ITI, only the background elements of the trial (such as the ships) appeared. Stimuli were presented in 4 blocks of 44 trials (plus one initial practice block of 12 trials); each block was roughly even in terms of category, color, subcategory, and non-diagnostic features. Stimulus order was pseudorandom such that no more than 3 trials from the same category appeared consecutively and consecutive same-color or same-eye-number trials were similarly limited.

[6] We attempted to limit verbal labeling of each category by referring to "Group 1" and "Group 2" in participant instructions. What the participants were told were Group 1 and Group 2 map to our internal division between Category A and Category B.

Trial order within a block was fixed, but block order was random across participants.

Test phase

The format of the test phase trials was deliberately differentiated from the training phase trials in order to probe for the effects of abstract category knowledge acquired by the procedural system rather than simply stimulus-response associations. Participants were shown two alien stimuli, one from Category A and one from Category B, and one ship, and were instructed to choose which alien corresponded to the presented ship. We manipulated the color congruency of both stimuli as a pair. Specifically, in half the trials, the colors of both stimuli were congruent with the training color distribution (e.g., A-warm/B-cool); in the other half of trials, both stimuli were presented in incongruent colors. All stimuli presented were novel (i.e., not previously seen in the training task). However, note that the colors used in the test phase were the same as the colors used in the training phase. The stimuli were novel in the sense that particular combinations of facial features and colors had not been seen in the training phase, but both the facial configurations and the colors (taken separately), had been seen in the training phase. To avoid confusion with the training left/right configuration of the ships, the stimuli were stacked vertically and response keys were u/n (upper or lower). Participants were presented with a total of two blocks of 36 trials each (one saucer block, one rocket block). As in the training phase, there was no response deadline and participants were not explicitly instructed to respond quickly.

Pairs in the congruent and incongruent conditions were balanced for total shared features, shared diagnostic features, shared non-diagnostic features, binned hue warmness difference, and mean distance between colors in color space (delta e).

Post-tests and survey questions

Colorblindness items Participants were asked to type the numbers visible to them in a set of 5 Ishihara plates selected to probe for deficiencies in color vision. Before any exclusions, about 1% of participants responded to the Ishihara plates in ways consistent with some form of colorblindness. However, performance for these participants was comparable to that of other participants and the main RT difference between congruent and incongruent trials at test was similar in colorblind and non-colorblind participants. It is likely the case that colorblind participants were able to perceive the differences in color distributions based on brightness differences even though they may not have been able to perceive all hue differences. For this reason, we did not exclude participants on the basis of their Ishihara plate responses or self-reports of colorblindness.

Strategy use and color awareness questions Participants were also asked to complete the following open-ended questions:

1. Describe the rule you used to classify the aliens (in your own words, to the best of your ability).
2. Other than the rule you were instructed to use, did you use any strategy or rule of thumb to decide which aliens went with which ships? (if yes, please describe briefly if you can)
3. Did you notice anything about the colors of the aliens? If yes, please describe below.
4. Describe what (if anything) you noticed about the colors of the aliens.
5. Did you use the colors to help the aliens find their ships? (yes/no)

As we were primarily interested in effects of implicit sensitivity to the color distribution on categorization performance, responses to any of these questions that suggested a use of color to classify stimuli, or awareness of the biased color distributions resulted in the participant being labeled as “qualitatively aware.” As stated in our preregistered protocol, data from qualitatively aware participants were analyzed separately and not included in the main analysis of reaction time and accuracy in the test phase. Complete participant responses and scoring can be found in the Supplemental Table 2.

Explicit color knowledge task A final test for explicit knowledge of the color-category associations was given in the form of a classification task like the training task, but with the cover story that now the aliens were viewed from behind, i.e. their “facial features” were not visible, only colors. Participants completed 16 trials (one trial for each color plus 4 additional trials using peak colors), and then after each classification trial, to rate their confidence in their decision on a scale from 1 to 4 (1 = guessing, 4 = completely confident).

Analysis

Participant awareness

The analysis of interaction between declarative and procedural memory depends on an assumption that the color information was learned procedurally only, i.e. that participants did not develop declarative knowledge of the color-category associations. In order to satisfy this assumption, we used two methods to identify participants who were aware of the color-category association (i.e., "aware participants"). The main analysis below consists of data from only "unaware" participants.

Survey responses Participants whose responses to survey questions indicated knowledge of the color-category association ($n=23$) and/or who answered "Yes" to "did you use color to categorize the aliens" ($n=31$) were excluded from further analysis (total $n=38$).

Explicit color knowledge accuracy In the "from behind" post-test, participants were asked to classify stimuli based on their color only. Unaware participants are expected to be at or near chance performance on this task (EV=8/16 correct responses; SE=2). Nine participants with performance statistically greater than chance (12/16=0.75) on this task were identified as "quantitative aware" and were not included in the main analysis. After these exclusions, 178 "unaware" participants were included in the main analysis.

Training phase

Accuracy analysis Mean accuracy was computed for each participant and each block. Mean accuracy was analyzed using a one-way repeated measures ANOVA with blocks (1–4) as a within-subjects factor.

Reaction time analysis Mean reaction time was computed for each participant and each block. Mean reaction time was analyzed using a one-way repeated measures ANOVA with blocks (1–4) as a within-subjects factor.

Test phase

Accuracy analysis Each participant's mean accuracy by condition (congruent/incongruent) was calculated separately. A paired t-test was performed between conditions.

Reaction time data cleaning and analysis All reaction time analyses were conducted on correct trials only. In addition, we took several measures to mitigate the effects of outliers on our main analysis of reaction times, as outlined in our preregistered protocol. First, outliers at the trial-level were identified by calculating each participant's mean and SD for reaction time and dropping trials that were 3 participant-SDs above or below each participant's mean RT; this step was preregistered. We routinely exclude trials with RTs less than 200ms in RT analyses because these were assumed to be mistakes, as the required decision could not be made in such a short interval (see e.g. Whalen et al., 1999); however, this step was not preregistered.

Next, participant outliers were identified in two ways. The first way, which was preregistered, was to drop participants who had unusually long or variable reaction times using cutoff values based on pilot data RT distributions (participant-mean RT>4.5s or participant SD RT>5s). However, it also occurred to us that a rational alternative would have been to use the criterion of participant mean RTs +/- 3SDs from the group mean RTs; since this step was not preregistered, we analyzed the data both ways. The direction, significance, and effect size did not differ substantially, regardless of whether only the preregistered steps were used for RT data cleaning or if additional or alternative steps were included.

Below, we report the results of the preregistered protocol, but results of the alternate analyses can be found in Appendix A. After these exclusions, 173 participants were included in the reaction time analysis.

After data were cleaned as described above, each participant's mean reaction time by condition (congruent/incongruent) was calculated and a paired t-test was performed between conditions.

Stimuli, code for creating stimuli, analysis scripts, and de-identified data (including full survey responses) can be found at:

https://osf.io/cb3zu/.

This study was pre registered. The preregistered protocol can be found at https://osf.io/atj5q.

Results

Task performance

Training phase

Mean accuracy ($M=0.90$ $SD=0.29$) and mean reaction time ($M=2.53$s. $SD=5.83$s)[7] on the training task improved over training blocks, as seen in significant effects of block on accuracy (F (3, 540)=20.73, $p<.001$) and reaction time (F (3, 540)=32.07, $p<.001$).

Test phase

Overall performance Mean accuracy was high ($M=0.967$ SD=0.180). After reaction time data cleaning (see above), mean response times were longer than in the training phase

[7] These results are from analysis of the final set of 178 participants. However, with no exclusions Accuracy $M=0.88$ SD=0.33; RT M=2.40s, SD=5.83s).

(M=3.45s SD=3.51s) reflecting the greater difficulty of the task.

Congruent/Incongruent accuracy analysis Accuracy for congruent and incongruent trials was nearly identical (($M_{CONGRUENT}$ = 0.967, $M_{INCONGRUENT}$ = 0.965; t (185)=0.63, p=.53).

Congruent/Incongruent reaction time analysis Participants' RTs were significantly slower for incongruent than congruent trials: ($M_{INCONGRUENT}$ =3.274s (SD=2.484s), $M_{CONGRUENT}$ = 3.063s (SD=2.29s); M_{RTDIFF} =.209s (SD=.481s); t (185)=5.93, p<.0001; effect size (Cohen's d)=0.18). Figure 3 shows the comparison of RTs across condition, within participant. Figure 4 shows individual participant differences for mean incongruent RT – mean congruent RT. While the majority of participants have a positive difference (incongruent RT > congruent RT), some do have a negative difference, and the size of the difference varies across participants.

Post-tests and survey

Strategy use (self-report)

87% of participants gave some response to the question "Describe the rule you used to classify the aliens (in your own words, to the best of your ability)." Of these, 85% gave a response that referred generally to the eyes and mouth or to the parity of the eyes and the shape of the mouth. An additional 3% referred to using a rule but did not describe the rule. While use of the declarative knowledge rule was inferred from categorization accuracy, these responses provide additional support for our interpretation

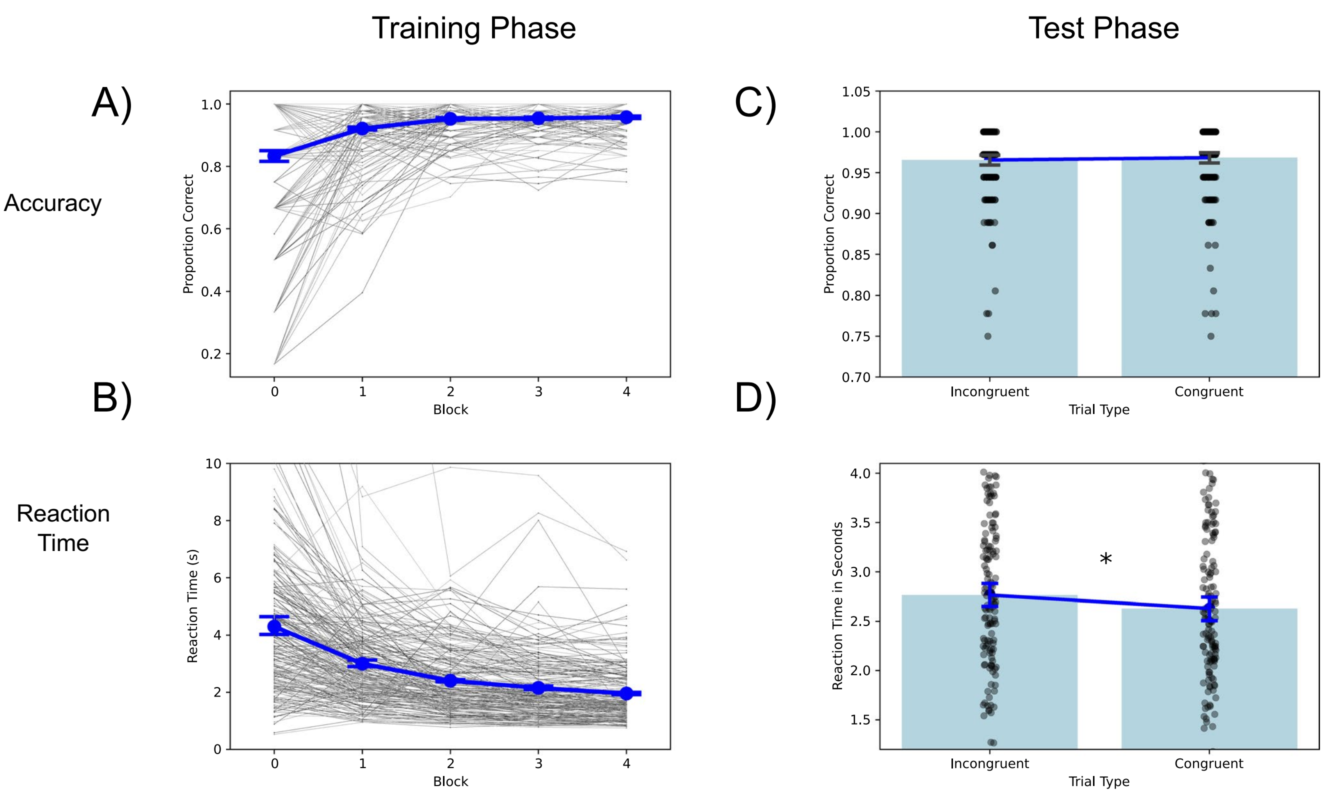

Fig. 3 Results (**A**) Training accuracy by block; high initial accuracy demonstrates use of the shape rule. Block 0 refers to the 12-item practice block before the four main training blocks. **B** Training reaction time decreased over successive blocks. **C** Test accuracy by condition: responses to color congruent trials were more accurate than incongruent trials, but the difference was not significant. **D** Test reaction time by condition: Trials in which color and shape information conflicted (incongruent) were significantly slower than trials in which they converged (congruent). ($M_{INCONGRUENT}$ =2.862s, $M_{CONGRUENT}$ = 2.719s; M_{RTDIFF} =.143s, t (172)=4.68, p<.0001)

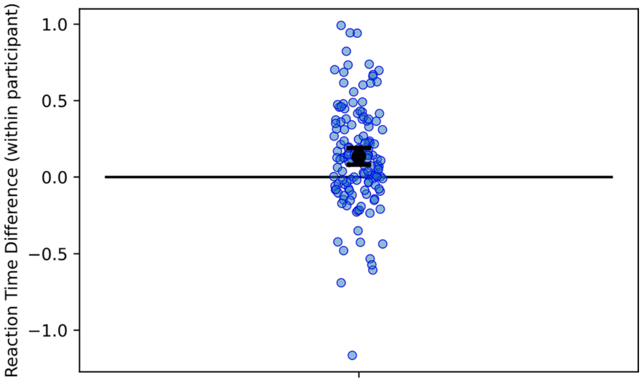

Fig. 4 Individual differences in knowledge interaction effect. Each point represents the difference in mean RT between incongruent and congruent trials for a single participant. A black marker with error bars representing the standard error of the mean shows the overall mean difference across all participants (M_{RTDIFF} =.143s, t (172) = 4.68, p <.0001)

that shape-based classification in these participants was supported by declarative knowledge of the complex disjunctive rule.

Explicit color knowledge post-test

On average, participants scored at chance on the explicit knowledge post-test (where categorization accuracy was based solely on stimulus color, in the absence of facial feature information; $M = 0.493$, $SD = 0.50$, $t\ (182) = 0.74$, p =. 461)[8]. Participants reported low confidence in their categorization decisions on the task: the mean slider response was 1.48 ($SD = 0.63$) (on a range where 1 = guessing to 4 = completely confident). Furthermore, there was no significant difference in confidence ratings for correct versus incorrect trials ($M_{correct}$ = 1.48; $M_{incorrect}$ = 1.49; SD = 0.78, $t\ (182) = 0.236$, p =.813), and no correlation between participant mean confidence and participant mean accuracy (r =.044, p =.556)[9] (see Supplemental Figure 4).

[8] This was true regardless of whether "qualitatively aware" participants were included or excluded. The mean accuracy for "aware" participants ($n = 27$) was also near chance $M = 0.504$, $SD = 0.595$ and not significantly different from the mean accuracy for unaware participants ($M_{unaware}$ = 0.498; M_{aware} = 0.504; Welch's $t = 0.169$, p =.866). However, participant mean confidence was higher for the aware participants ($M_{unaware}$ =. 1.397; M_{aware} = 1.858; Welch's $t = 3.755$, p <.001.) In addition, aware participants' mean confidence rating for correct trials is significantly higher than incorrect trials ($M_{correct}$ =1.942; $M_{incorrect}$ = 1.1.77; $t = 2.17$, p =.03).

[9] Nine participants scored above chance (> 75% accuracy), and these participants were labeled "quantitative aware" (analysis excluding "quantitative aware" participants was not preregistered but can be found in Appendix A). Only 3 participants were identified as both "qualitatively aware" and "quantitatively aware."

Discussion

Participants were explicitly taught a difficult disjunctive rule for categorization of stimuli ("aliens") based on a combination of eye and mouth characteristics, and successfully applied this rule during a training phase with feedback. During training, stimuli in each category were presented according to a biased color distribution, in effect creating a probabilistic color-category association (for a precedent, see Schoenlein & Schloss, 2022). Critically, in a subsequent test phase without feedback, participants showed faster categorization performance for trials in which the color-category associations were preserved ("congruent" trials) than on trials in which the association was violated ("incongruent" trials). This reaction time effect occurred in the absence of participants' conscious awareness of color differences between the categories, as assessed through questionnaire responses and performance on a color-category task. These results provide initial evidence that declarative and procedural learning systems can contribute to category selection within a single trial. On correct incongruent trials, participants correctly applied the explicit categorization rule, while their performance was simultaneously slowed by the atypical colour associated with the stimulus. Participants reported little or no knowledge of the color information, demonstrating that the color information was learned unconsciously and used automatically, meeting part of the definition for procedural learning. These results cannot be explained by current models of winner-take-all competition between procedural and declarative learning at encoding (McDonald et al., 2004; Mcdonald & Hong, 2013), consolidation (Brown & Robertson, 2007; Galea et al., 2010), or retrieval (Crossley & Ashby, 2015). In addition, the finding of a reaction time difference between congruent and incongruent trials in the test phase in the absence of declarative color-category association knowledge replicates the result of our earlier similar experiment (Kalra et al., 2024), reducing the probability that the current results are a form of Type I error. In addition, the effect size found here[10] is slightly larger than that found in the preliminary study.

There are at least two forms of evidence that the explicitly-instructed rule was learned and implemented by a declarative form of learning. In their short debrief responses, a majority (> 85%) of participants explicitly referred to the eyes and mouth (diagnostic features), or to "the rule that was given," and sometimes reported verbalizable heuristics based on the eyes/mouth rule. Furthermore, performance accuracy in the first block of training trials was near ceiling (Figs. 2a and 3a), suggesting that participants immediately applied the explicitly-instructed rule from the instruction

[10] In the pre-registered analysis, but see Appendix A.

phase, rather than searching for a rule or gradually accumulating information about the shape-category relation. In addition, as all stimuli shown in the test phase were novel (i.e. not shown in the training phase), participants could not use memory for specific exemplars to categorize the test stimuli (that is, the specific combinations of color and facial features were novel in the test phase. All individual colors and legal facial feature configurations had previously been seen in the training phase.)

In addition, there are also multiple forms of evidence that the color distribution information was learned procedurally (and not declaratively). In their short debrief responses, very few participants (< 10%) reported any explicit knowledge of the biased color distributions; those who did were excluded from the analysis intended to show interaction between declarative and procedural information. Additionally, we found that participants were at chance when asked to classify stimuli based on color alone, and their confidence ratings did not significantly differ between correctly and incorrectly classified colors (meeting the zero-correlation criterion; Dienes & Berry, 1997). Thus, taken together, participants in our final sample demonstrated little or no awareness of the hidden color distribution, but nevertheless were slower on incongruent trials. For these reasons, we infer that the color distribution was learned procedurally. Despite the fact that the reversed form of the test phase could potentially disadvantage a procedural learning system (Anderson & Fincham, 1994; Vaquero et al., 2020), we interpret the maintenance of the effect across this reversal as evidence of abstract learning beyond stimulus-response association (Reber, 1993; Seger, 1994), such as the formation of a probabilistic color-category stimulus space.

Our findings are consistent with previous research showing that procedural encoding can take place simultaneously and "covertly" during declarative encoding (Foerde et al., 2006; Packard & McGaugh, 1996; Song et al., 2007). However, other previous research has demonstrated competition at consolidation (Brown & Robertson, 2007; Galea et al., 2010) and/or retrieval (Crossley & Ashby, 2015; Packard & McGaugh, 1996). The results of the current study demonstrate that, at least in some situations, the competition at retrieval is not a zero-sum game: the output from one system is not completely disregarded or discarded in the process of decision-making. It may be the case that responses are either facilitated when procedural knowledge and declarative knowledge converge on a categorization decision, or hindered when they diverge.

Many of the previous studies on interaction between procedural and declarative learning have focused on whether both systems are active during encoding or retrieval, and whether one system's activity inhibits or facilitates activity in the other (see e.g., Freedberg, 2020; for exceptions see Robertson, 2022). However, the current study involves interactions between the representations or knowledge formed by each system, not just their relative activity. In doing so, it presents a challenge for computational models such as COVIS that consider only the confidence and bias of each module's decision, but do not consider whether the modules' responses converge or diverge for downstream response selection (Ashby, Paul, & Maddox, 2011).

Conceptually, the current study employs a form of Jacoby's Process Dissociation Procedure (1991). In the original form, the PDP was used to consider the relative contributions of two processes, recall and familiarity, to recognition performance. In our case, we are considering the contributions of procedural and declarative learning to categorization performance. Importantly, such an approach starts with the assumption that the two processes both contribute to performance, an assumption that may not have been made in previous studies. In the PDP, two conditions are contrasted: when the two processes converge on the same response (facilitation condition, A + B) and when the two processes diverge (interference condition, A-B). In our case, it may be the case that either facilitation is seen in the congruent trials, when procedural and declarative systems indicate the same category response, or that interference is seen in incongruent trials, when the two systems indicate different category responses. If only one process contributed to performance, there would be no difference between conditions. However, we observed a difference between congruent and incongruent trials, indicating that both processes contribute to categorization behavior. The design of the current study does not allow us to distinguish whether either facilitation, interference, or both facilitation and interference are occurring, but it strongly suggests that at least one of these forms of interactions does occur. Future studies could include a "baseline" condition for comparison, which would allow clarification on whether facilitation or interference drives the difference between conditions.

Potential implications for basic science and directions for future research

One potential implication of the current findings is an update to the COVIS model of interaction between category learning systems. The current specification of COVIS implements "winner-take-all" decision-making through its gating mechanism (Ashby et al., 2011). The gating mechanism allows the input of only one module (verbal or implicit) to feed forward to decision-making. Borrowing a "mixture of experts" type gating mechanism from the ATRIUM model (Kruschke, 1990, 2011), the COVIS model could be altered to make it compatible with the current results. Briefly, the gating mechanism would need to take into account the relative direction (sign) of each module's decision (e.g. Category A positive, Category B negative) in addition to the existing confidence and bias parameters, and sum the inputs from each module rather than selecting only one.

Another area for consideration is the developmental trajectory of interaction between procedural and declarative learning. We know that procedural and declarative learning have different developmental trajectories, with procedural learning maturing sooner (Finn et al., 2016). For this reason, we might predict that interactions between procedural and declarative learning in young children might show a different pattern than that observed in healthy, young adults, with stronger contributions from the procedural system. However, several studies of category learning with children have suggested that children perseverate in using simple rule-based strategies based on declarative learning (Huang-Pollock et al., 2011; Rabi et al., 2015; Rabi & Minda, 2014). The explanation proposed by these studies is that the children are unable to inhibit the output of the declarative system, which is consistent with the relative immaturity of prefrontal areas responsible for inhibition as well as other means of adjudicating between different response options (Gogtay et al., 2004; Lenroot & Giedd, 2006; Shaw et al., 2006). However, these studies contrasted category induction for rule-based (declarative) and information-integration (procedural) category structures; the children had to infer the rule rather than being told a rule before the task started. Pure induction reflects the way naturalistic categories are learned, but is not necessarily how categories and concepts are typically learned in formal instructional contexts, like classrooms. In these contexts, instruction often emphasizes declarative knowledge without considering the role that covertly learned procedural knowledge may play. Future studies, such as those that adapt the current paradigm for use with children, will be needed to fully address the issue of developmental differences in interactions between declarative and procedural learning, particularly when considering instructional implications.

Perhaps because of the emphasis on establishing the separateness of multiple category learning systems, little research has investigated whether and how the representations of category information formed by each system might interact. In the current study, we have demonstrated that although two separate mechanisms may contribute to the acquisition of category information, they can both influence response selection. This finding raises the question of whether each system creates a distinct representation of the category structure, and both of these contribute to response selection, or whether both systems contribute to the creation of a shared knowledge base. This "shared knowledge base" could in fact be what is thought of as semantic memory, but because semantic memory is grouped as "declarative" in most memory system taxonomies, there has been little work connecting procedural or implicit category learning with the acquisition and development of semantic memory. There is sadly even relatively little work connecting even declarative category learning and semantic memory formation.

Although the current behavioural results cannot speak to this issue, we are currently conducting a fMRI-representational similarity analysis (RSA) study to address this question. Because the category structures learned by each system are slightly different, different theoretical similarity matrices can be constructed which will then reflect the contribution of each system. These theoretical matrices can then be compared to empirical similarity matrices derived from brain activity (Kriegeskorte et al., 2008). If the areas of the brain in which patterns of activity (empirical similarity matrices) correlate with the theoretical matrices for procedural and declarative learning do not overlap, we can infer that the representations formed by each form of learning are distinct.

Finally, looking backward, rather than forward, it may be possible to reinterpret some traditionally puzzling findings (such as Allen & Brooks, 1991; Armstrong et al., 1983) in the context of interaction between rule-based and similarity-based representations of a stimulus space. Allen and Brooks (1991) found that participant categorization decisions were skewed by similarity along non-diagnostic (but partially predictive) dimensions; it could be the case that this interaction between rule-based and similarity-based reasoning was an interaction between declarative and procedural knowledge, as in our study, but to an extent that influenced accuracy as well as response times. Armstrong et al. (1983) demonstrated that participants would, when prompted, gave responses that suggested a graded representation even for categories with strict criteria (such as odd numbers). These apparently paradoxical findings could potentially be explained in terms of task demands that preferentially recruit procedural or declarative knowledge for decision making. Future research could include replications of these classic studies with specific controls and measures in place to monitor the relative contributions of procedural and declarative knowledge.

Potential implications beyond basic science

One practical implication of the current findings is that in complex, real-world situations, both declarative and procedural decision-making processes may interact. For example, in formal instruction, students are often given rules or necessary and sufficient criteria for category membership (e.g., mammals have hair and produce milk to feed offspring). However, even when students are given such a rule or criteria, if they experience only a biased selection from the space of possible category members (e.g. only dogs and cats as mammals), they may have difficulty transferring their knowledge of mammals in general to unfamiliar exemplars (whales, armadillos). Our main finding is consistent with an emerging body of evidence that supports the idea of sampling broadly from the example space during instruction to facilitate later transfer (Carvalho et al., 2021; Nosofsky et al., 2018). However, other studies have suggested that more narrow sampling, particularly focused on a category's central tendency may be beneficial for learners (Bowman & Zeithamova, 2020, 2023; Homa & Vosburgh, 1976; Homa & Cultice, 1984). Further research will be required to determine when and why narrow versus broad sampling is beneficial for robust learning and transfer. Considering interactions between procedural and declarative knowledge may clarify the conditions under which broad versus narrow sampling is beneficial in instruction.

Furthermore, our results suggest that individuals may vary in the degree of interaction between procedural and declarative knowledge in decision making (Fig. 4). In addition to being an interesting contribution to basic science, this finding may also have applications in educational settings. It may be the case that for some students, for example those with atypical executive function (e.g., low working memory, ADD/ADHD), strategic instructional domain space sampling may play an especially important role in facilitating their abilities to apply rules and recognize category members. We are currently investigating the role of such individual-level variables in predicting the knowledge interaction effect.

Our results also provide insights into the formation of stereotypes and potential ways to counteract learned negative associations. Similar to many studies using the Implicit Association Test (Greenwald & Banaji, 2017), the current findings provide further experimental evidence that behavior is often influenced by a combination of implicit representations based on accumulated experiences and explicit understandings or beliefs. Generally, the IAT reveals reaction time differences whereby pairing a social group with traits that are stereotypically associated with that group (e.g., male – engineer) results in faster reaction times than pairing with traits that are stereotypically not associated (e.g., male – nurse) (Banaji & Hardin, 1996). Importantly, these reaction time differences are found even when individuals hold explicit beliefs that contradict the stereotypes (Greenwald & Banaji, 1995; Greenwald et al., 1998); somehow, exposure to stereotypes in the environment (for example through media portrayals) creates an implicit bias that can operate despite an individual's best intentions to hold unbiased attitudes towards particular social groups. Our findings are consistent with this general model of interaction between implicit and explicit representations. While many successful interventions for counteracting implicit bias recruit explicit reasoning and declarative knowledge (Devine et al., 2012; Forscher et al., 2019), our findings support suggestions that interventions that recruit procedural learning mechanisms, such as the presentation of counter-stereotypical exemplars, may be an important complement (FitzGerald et al., 2019; Forscher et al., 2019), since both procedural and declarative knowledge can contribute to real-time decision making.

Limitations

On that note, one important limitation of the current study is low ecological validity. Although we have suggested practical implications, we hasten to point out that the paradigm used in this study bears only a faint resemblance to learning in a classroom setting or making decisions that may be affected by social bias. In particular, fewer exemplars can be presented in a classroom or other real-world situations, and they are usually distributed more widely across time and without immediate feedback. It is possible that the selection of examples from the space creates an implicit representation that could conflict with a rule-based category definition in real-world learning settings, just as in our laboratory paradigm, but this must be confirmed empirically in studies with greater ecological validity.

Another limitation is related to precise interpretation of the results. Although we successfully demonstrated that reaction times were faster when the responses of each system converged, the design of the current study does not allow us to infer whether this is due to facilitation in congruent trials or interference in incongruent trials. Future studies could be designed to include a baseline condition for comparison to aid in distinguishing these possibilities.

Finally, while we have taken several steps to ensure that the color-category association was not learned by a declarative mechanism, future studies could go further to establish affirmatively that it was in fact learned by a procedural mechanism. One way to do this would be to use a delayed or deferred feedback condition during training; this should "block" procedural learning (see e.g. Maddox et al., 2003; 2004 Maddox & Ing, 2005; Foerde & Shohamy, 2011a; Smith et al., 2014, 2018), thereby supporting the interpretation that in the immediate feedback condition, it is indeed a procedural process that allows learning of the color-category association.

Conclusion

In the study presented here, we have demonstrated a novel form of interaction between procedurally-learned and declaratively-learned category information in decision-making.

This form of interaction is not predicted by previous studied or accepted models of interaction between memory systems. While much future work is required to determine precisely when and how such interaction takes place, we have at least provided a plausible example of procedural and declarative knowledge being used simultaneously to complete a task. Future studies may reveal the extent to which such interaction underlies phenomena such as expert performance, language learning and use, and tool use, among others.

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Data availability Data is available on OSF.

Code availability Code for stimulus creation and data analysis are available on an OSF repository.

Declarations

Ethics approval This study was approved by the Western Health Sciences Research Ethics Board, protocol #11628.

Consent to participate and to publications All participants gave informed consent to participate, including consent for their data to be used in publications.

Competing interests The authors declare no competing interests.

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