Building Conceptual Filters: Forming Clean Representations Through Early Categorization

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In rule-contingent tasks (e.g., mathematics or physics), the correct rule depends on the type of scenario that is encountered. In such instances, it can be useful to partition knowledge into corresponding categories for each type of scenario. Moreover, the category representations that are acquired at the outset of learning may be difficult to restructure and may affect subsequent learning; this can be particularly important when the knowledge that is acquired is incorrect or incomplete. Thus, it may be critical that people form the correct category representations at the outset of learning. It is proposed that learning can be improved if such categories are acquired at the outset of a task, as opposed to later stages. A series of experiments are reported in which one group learned to classify different types of scenarios first, and then learned each category's corresponding rule; the other group learned the rules for each scenario first, and then learned to classify each type of scenario. Experiments 1-5 used feature-based stimuli and Experiment 6 used relation-based stimuli. The results provide moderate support for the predicted hypothesis, but further research is required to better understand the learning mechanism(s) that drive this effect.

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CHAPTER I

Introduction

Rule-contingent learning plays a critical role in a variety of everyday tasks, such as problem solving and decision-making (Rips, 2001; Sloman, 1996). Learning the correct set of rules on a *rule-contingent task* – a task that contains problems or scenarios that can be solved by using a specific type of rule, which depends on the type of scenario (i.e., category) that is encountered – is often viewed as the most critical aspect of the task. This view is exemplified in various areas of instruction, such as mathematics, where an extensive amount of time is devoted to teaching students the correct set of rules for problem solving (Mayer, 1982; Owen & Sweller, 1985).

Although learning the correct set of rules on a rule-contingent task is important, it is equally important to know when to apply those rules. This is particularly important when the correct rule differs based on the category that a problem or scenario is a member of, such as in mathematics and physics, where the correct set of rules (i.e., formula) depends on the type of problem that is encountered. For example, the solution strategy (i.e., formula) that is used to solve a work-rate problem is different from the solution strategy that is used to solve a percent problem. In this example, the two problem types (e.g., work-rate and percent problem) are members of different categories because they consist of different relational structures and thus require a different solution strategy.

Importantly, there are three critical steps to successfully completing a rule-contingent task (e.g., mathematics): (1) learning the different types of categories for the task, (2) learning the different types of rules for the task, and (3) mapping the correct rule to its corresponding category. These types of tasks are often difficult because people must learn all three steps simultaneously. It has been found that although people do not struggle in learning solution strategies in mathematics (i.e., the rules to the task), they nonetheless have a difficult time knowing when to apply those strategies during problem solving (Mayer, 1998). This finding suggests that people either struggle to recognize or learn the different types of mathematical categories or have not adequately mapped the appropriate category to its corresponding rule.

Findings have shown that performance on rule-contingent tasks can be significantly improved by learning to categorize the different types of problems or scenarios that are contained in the task (Mayer, 1982; Sweller, Mawer, & Ward, 1983). Learning the different categories in a rule-contingent task may help people partition and keep track of each rule and its corresponding category. *Knowledge partitioning* – forming different parcels of knowledge that are independent and kept separate from one another – may better allow people to map a given rule to its corresponding category. Once the mapping process has been completed, recognizing that a problem or scenario is a member of a given category can cue people towards applying the category's corresponding rule (Corral, Quilici, & Rutchick, 2013).

Interestingly, one of the primary distinctions between experts and novices is that experts (within their domains of expertise) tend to represent a problem or scenario based on its underlying structure, whereas novices tend to represent such information based on surface features (i.e., information not relevant or diagnostic of a problem or scenario's category, defined by its relational structure; Chi, Feltovich, & Glaser, 1981). As a result, novices may not learn the appropriate categories, making it difficult to partition their knowledge and keep track of a task's different categories and their corresponding rules. The failure to appropriately partition knowledge for a given task may lead novices to incorrectly map the task's categories to the incorrect rule. In contrast, the rich category representations that experts hold (based on a problem or scenario's relational structure) may facilitate the partitioning of knowledge, allowing for a category and its corresponding rule(s) to be more easily mapped.

Although partitioning information for a task into its corresponding categories can provide various learning benefits (Yang & Lewandowsky, 2003, 2004), it often takes people an extensive amount of time to acquire the appropriate category representations (Anderson, 1993; Cooper & Sweller, 1987). A reason for this finding may be that the initial representations that people form are strongly influenced by superfluous information (Lewis & Mayer, 1987). Thus, it may be challenging for people to sift through and filter out surface information, making it difficult to discover the representations that are most important for classifying category members (Sweller & Sweller, 2006).

Findings have also shown that simultaneously learning the categories and rules for a task can place a high strain on working memory, impairing learning, and increasing task difficulty (Owen & Sweller, 1985). One possible explanation for this finding is that without the appropriate category representations, it is difficult to keep track of which rule corresponds to the appropriate category. Consequently, people's ability to learn the scenarios under which it is appropriate to use a specific rule may be impaired. In such instances, people may map a given rule to the incorrect category or may apply one of the rules for a task in an indiscriminate manner (i.e., using the rule for one category to solve problems or scenarios that pertain to different categories). Thus, category formation may be critical, and perhaps necessary for the successful partitioning of knowledge.

During the early stages of learning, people may consider a multitude of incorrect hypotheses, some of which may be strengthened over time and may proactively interfere with subsequent learning. It thus may be difficult to form a coherent, clean mapping (i.e., a mapping that does not contain incorrect or superfluous information) between the rules for solving a problem and its corresponding category. For example, consider the following word problem: Dr. Johnson operated on 10 patients last month and 7 patients this month. By what percentage did the number of patients that Dr. Johnson operated on change this month? A novice may map the correct solution strategy for this word problem to the problem's superfluous information, and thus may attempt to use this word problem's solution strategy in order to solve other word problem's that include similar superfluous information (e.g., doctors or surgeries).

Moreover, upon learning the correct category rule at later stages of learning, people may attempt to integrate their initial incorrect representations (e.g., initial hypothesis of the correct category rule) with the correct category rule, thus making it difficult to form a coherent representation of the task. For example, consider a task with two categories where subjects are presented with stimuli that consist of two adjacent objects that vary on size and brightness, and subjects must determine which category a stimulus is a member of; the left object is bigger than the right for Category A and the right object is bigger than the left for Category B. However, a subject's initial representation of the correct category rules are that the left object is brighter than the right for Category A and the right object is brighter than the left for Category B. After several trials, the subject may begin to partially converge on the correct category rules, but rather than abandon their initial representations of the task's categories, they may integrate the correct category rules with their initial representations (i.e., the left object is brighter and bigger than the right for Category A and the right object is brighter and bigger than the left object for Category B).

Taken together, these findings suggest that prerequisite knowledge (i.e., category formation) may be required before people attempt to discover the rules for solving different problems or scenarios in a rule-contingent task. Acquiring such knowledge may facilitate the process of knowledge partitioning, whereby information that pertains to one category is represented separately from information that pertains to a different category, making the task more manageable (Lewandowsky, Kalish, & Ngang, 2002). Findings also indicate that when people are taught the correct category rule at later stages of learning, they are often resistant to restructuring their representations of the task's categories (Lewandowsky, Kalish, & Griffiths, 2000). Thus, if people do not acquire the appropriate prerequisite concepts at the outset of learning, subsequent learning may be impaired.

Although previous research has established that rule-contingent learning can be improved by learning the task's categories (Mayer, 1982; Sweller, et al., 1983), it is unclear how the stage in learning (i.e., early stages vs. later stages) at which such categories are acquired affects subsequent learning. The central proposal of this paper is that learning a task's categories at the outset of training may lead to less interference from incorrect hypotheses than when those categories are acquired at later stages of learning. Thus, the stage in learning at which people acquire task-relevant categories may be critical to the quality and coherence of the representations for the categories that are subsequently formed. The studies presented here aim to test this hypothesis by manipulating the stage in learning at which subjects learn task-relevant categories (i.e., before vs. after rules for a category are introduced).

CHAPTER II

Experiment 1

The current study used a rule-contingent task to test whether acquiring task-relevant categories at the outset of learning leads to improved performance over acquiring these categories at later stages of learning. A stimulus consisted of a single alien image. Subjects were presented with an alien image and depending on the phase of the experiment, either determined the category membership of the alien or whether the alien was friendly or unfriendly. After entering a response, subjects were provided feedback and informed of the correct answer. The rules for making this distinction differed, depending on the type of alien that was encountered. There were two types of alien species (i.e., Cobsters and Barnets), each composed of six features. One of the features was diagnostic for the alien category and a different feature determined whether the alien was friendly or unfriendly. The feature that determined whether the alien was friendly was different for each alien species. In an attempt to make the manipulation more sensitive, three of the features that were used did not play a role in defining the categories or their corresponding rules. One of these cues correlated with the correct response on 75% of the trials and the other two correlated with the correct response on 50% of the trials. Using these superfluous cues may increase the likelihood that subjects will build up an imperfect or incomplete representation of the task. Furthermore, because one of these features can lead to a high probability of success (i.e., 75% cue), it may be difficult for subjects who start off the experiment using this cue to abandon its usage at later stages.

Half of the subjects learned the alien categories at the outset of learning, followed by the friendly/unfriendly task. The other half of the subjects determined whether the aliens were friendly/unfriendly and then learned the alien categories. In the final task, all subjects were provided with an additional phase of the friendly/unfriendly task. This study invoked an ABB vs. BAB design, where the A task was learning to distinguish between the different alien categories and the B task was determining the aliens that were friendly from those that were unfriendly (see

Figure 1 for summary of design).

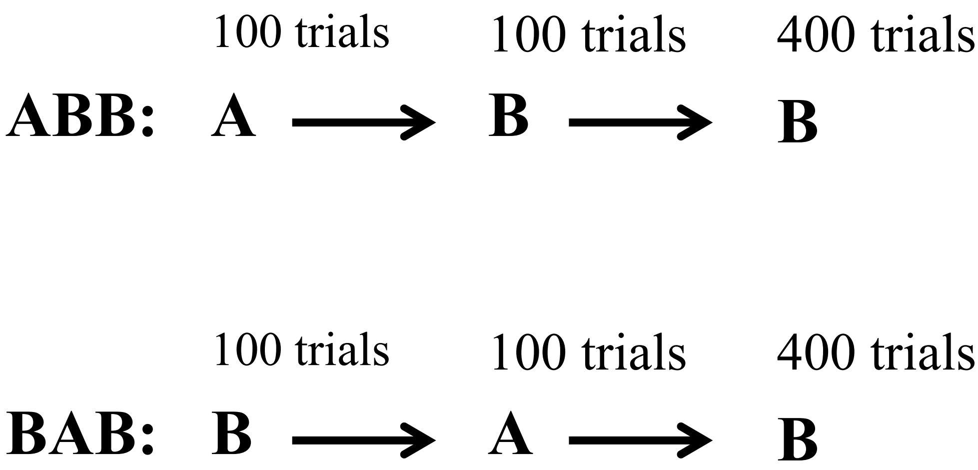

Figure 1. Illustration of experimental design. A = categorization between the two alien species. B = friendly/unfriendly task.

Method

Participants

There were 58 undergraduate students from the University of Colorado Boulder who participated for course credit in an introductory level psychology course. Subjects were randomly assigned to conditions.

Design and Materials

This study used a between-subjects design. The stage in learning at which subjects were provided with categorization training was manipulated (early stages of learning vs. later stages of learning). The dependent variable was performance and was operationally defined as how well subjects distinguished (i.e., percent correct) between friendly and unfriendly aliens.

The experimental stimuli were displayed on a standard LCD monitor. Subjects used a keyboard to type in their answers. One alien image was presented per trial. Images were presented at the center of the screen on a black background. Each image was a composite of 6 features (head, eyes, nose, mouth, hands, and feet) and a torso. Each feature consisted of two levels (i.e., two types of each feature; see Figure 2 for an example of the different aliens and features).

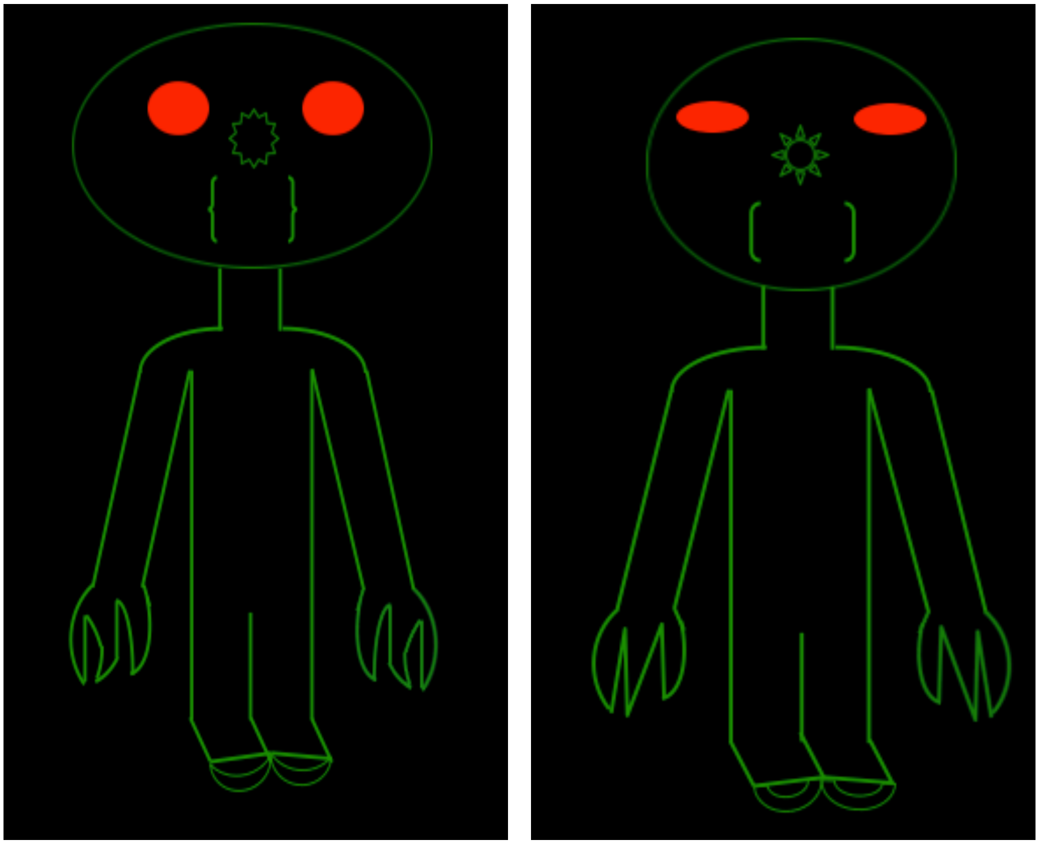

Figure 2. Example of a Cobster on the left and a Barnet on the right, distinguished by their feet. A different level of each feature is displayed on each image.

The aliens could be grouped into two separate categories (Cobsters and Barnets) and were distinguished from one another by their feet. The type of feet (feet type 1 or feet type 2) that corresponded to a specific category (i.e., Cobsters or Barnets) was randomly selected for all subjects. On all trials, the alien species was randomly sampled (i.e., there was a 50% chance of a stimulus being a Cobster or a Barnet).

Two separate features (hands and mouth) were used to distinguish whether the alien was friendly or unfriendly, one for each alien species. One of the features was diagnostic of whether the alien was friendly for one species; the other feature was diagnostic of whether the alien was friendly for the other species. The type of mouth (mouth type 1 or mouth type 2) and hands (hand type 1 or hand type 2) that determined whether an alien was friendly or unfriendly was randomly selected for all subjects. On each trial, the feature cues that were diagnostic of whether the alien was friendly were randomly sampled (i.e., there was a 50% chance that an alien would be friendly). The categories that the friendly cues (i.e., mouth and hands) corresponded to were counterbalanced between conditions.

Of the three remaining features (head, eyes, and nose), one corresponded with the correct response on the B task on 75% of the trials and the other two corresponded with the correct response on 50% of the trials. The role that each of these features played in correlating with the correct response was counterbalanced between conditions. On each trial, the 50% cues were randomly sampled. For the 75% cue, the type of feature (e.g., head type 1 or head type 2) that corresponded with the correct response was randomly selected for all subjects.

Procedure

Subjects were presented with a cover story of being a space explorer who crash-landed on an unknown planet. Subjects were instructed that they must complete a series of tasks before exploring the planet. All subjects engaged in the following tasks: (A) differentiating between Cobsters and Barnets and (B) distinguishing between friendly and unfriendly aliens. The order in which these tasks were presented varied depending on the condition the subject was assigned (i.e., AB vs. BA). The A and B tasks each consisted of 100 trials. On each of these tasks, subjects entered their response using a keyboard.

On each trial of the A task, text was displayed directly above the stimulus asking subjects whether the alien was a Cobster or a Barnet. Subjects were asked to type “c” for Cobsters and "b" for Barnets. On each trial of the B task, text was displayed directly above the stimulus asking subjects whether the alien was friendly or unfriendly. Subjects were asked to type "f" if the alien was friendly and "u" if it was unfriendly. After subjects entered a response, the stimulus was removed and the correct answer was provided for 800 ms directly beneath where the stimulus was previously displayed. Next, the screen was cleared for 300 ms and the image for the following trial was presented.

After completing the A and B tasks, subjects were provided with a cover story that indicated they needed to explore the planet in order to find aid; friendly aliens would provide aid and unfriendly aliens would attack. Subjects were then asked to complete the B task once again. The second B task consisted of 400 trials and was identical to the first, except that on each trial the text displayed above the stimulus asked subjects whether they should approach or avoid the alien; additionally, subjects were asked to hit the "left arrow" to avoid an alien and the "right arrow" to approach the alien. Further, on each trial a cartoon-like astronaut was displayed on the far left side of the screen. After every 100 trials, subjects were provided with a self-paced rest break and were shown their percent correct on those trials.

Results & Discussion

A *t*-test was conducted on the number of correct responses on all trials of the second B task. The analysis revealed no significant differences in performance between the ABB group (M = .61) and the BAB group (M = .61), $t(56) = .03$, $p = .98$. The results also indicate that subjects did not fully learn the actual category distinction between the two alien species in the A task (M = .55). Because learning to distinguish between the two alien species is critical to the manipulation, the results from this experiment do not address the main hypothesis of the paper. Thus, a second study was conducted.

CHAPTER III

Experiment 2

Eighty-six undergraduate students participated in this study. In order to ensure that subjects learned to distinguish between the two alien species, a learning criterion was implemented for the categorization task (i.e., A task). The learning criterion required subjects to answer 20 consecutive trials correctly in order to complete the categorization task. Unlike in Experiment 1, there was no minimum number of trials that subjects had to complete for the A task.

The instructions indicated that the two alien species could be classified by attending to the differences in the alien feet. Additionally, for every seventh error that subjects committed on the categorization task, they were provided with a prompt that reminded them that the two alien species could be distinguished from one another by focusing on the feet. After completing the A task, subjects were instructed that in order to ensure that they had learned how to tell the two alien species apart, they must complete the A task once more. After reading these instructions, subjects completed the A task for a second time. Aside from these changes, the design for this study was identical to Experiment 1.

Results

A *t*-test was conducted on the number of correct responses on all trials of the second B task. The analysis revealed that the ABB group (M = .65, SE = .01) outperformed the BAB group (M = .61, SE = .01), $t(84) = 2.15$, $p = .03$ (see Figure 3 for learning curves). One explanation for this finding is that because the diagnostic feature for a friendly alien depends on the alien's species (i.e., Cobster or Barnet), subjects in the ABB group were better than subjects in the BAB group at mapping the feature cues that were predictive of which aliens were friendly to their corresponding categories.

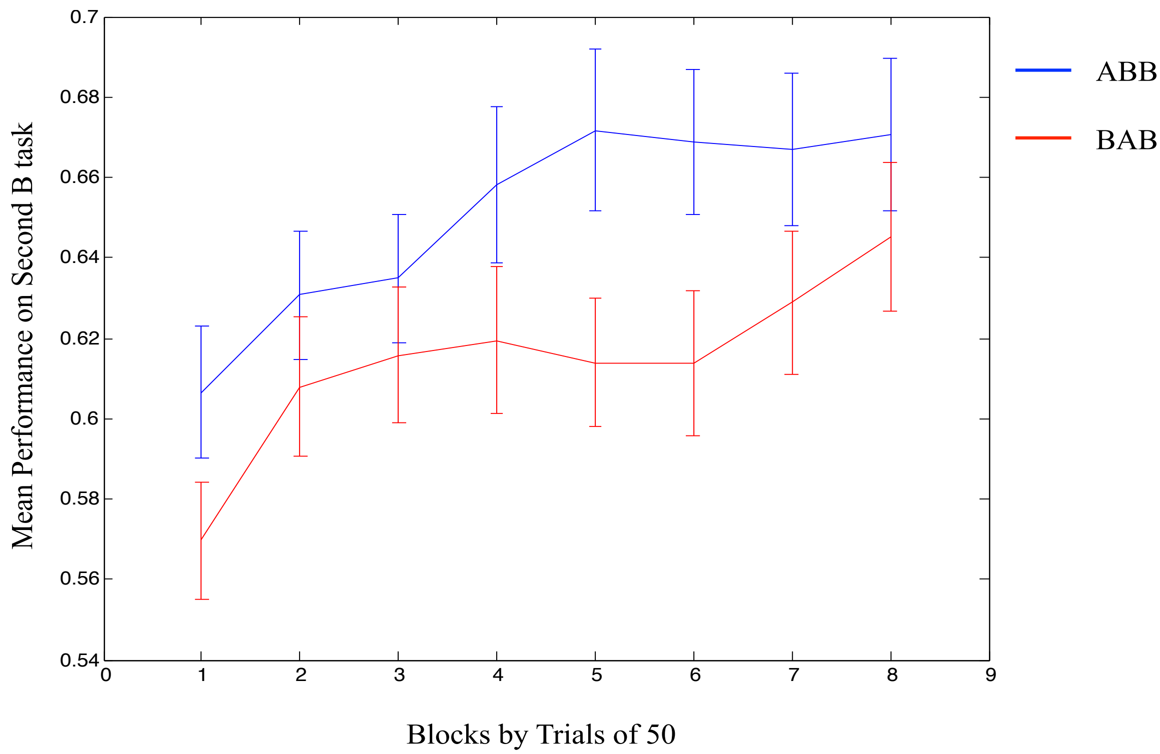

Figure 3. Learning curves for subjects in Experiment 2. Error bars indicate the standard error of the mean.

Importantly, there were three feature cues that could lead to a higher probability of a correct response than the other feature cues: the feature cue that was diagnostic of whether Cobsters are friendly, the feature cue that was diagnostic of whether Barnets are friendly, and the feature cue that correlated with the correct response on 75% of the trials. For brevity, these three feature cues will be referred to as *maximization cues*. One possibility is that the ABB group was more adept at using the maximization cues than the BAB group. This possibility offers an alternative explanation to the central hypothesis of the paper, as it is possible for subjects to learn which cues are more likely to lead to a correct response without ever partitioning their knowledge and mapping the cue that determines whether an alien is friendly to its corresponding category (see discussion section for Experiment 2 for further consideration on this possibility). To address this issue, the feature cues that subjects used during the second B task were examined.

Because the feature cue that was diagnostic of whether an alien was friendly depended on the species of the alien (i.e., Cobsters or Barnets), it was expected that subjects who learned the B task would use the cues that indicated whether an alien was friendly in a discriminative manner, depending on the species (i.e., category) of the alien. Therefore, upon being presented with a Cobster, subjects who learned the B task should use the feature cue that corresponds to whether Cobsters are friendly more than the feature cue that corresponds to whether Barnets are friendly and vice-versa.

Two separate regressions were conducted in order to determine which feature cues were influencing subject responses on the second B task. The two feature cues that indicated whether an alien was friendly were used as predictors in both regressions. One of the regressions predicted subject responses for one of the alien species; the other regression predicted subject responses for the other alien species. In each of the regressions, one of the predictors (i.e., feature cues) corresponds to a specific category (i.e., species) and indicates whether an alien from that category is friendly. These predictors (i.e., feature cues) are referred to as *correct cues*. Likewise, each regression consists of one predictor that does not correspond to the alien category and does not indicate whether aliens from that category are friendly. These predictors are referred to as *incorrect cues*. Accordingly, the correct and incorrect cues were different from one another for each regression (i.e., the feature cue that predicts whether an alien is friendly for the category in one regression is different from the feature cue that predicts whether an alien is friendly in the other category in the second regression).

The regression coefficients of the correct cues for each subject were summed together; the regression coefficients of the incorrect cues for each subject were also summed together. For each subject, the summed regression coefficients of the correct cues were subtracted from the summed regression coefficients of the incorrect cues (see Table 1 for mean regression coefficients for each group's usage of the correct and incorrect cues, and the 75% cue). The difference between the regression coefficients of the correct and the incorrect cues indicates the degree to which subjects used the correct cues in order to differentiate friendly aliens from those that were unfriendly. A *t*-test was conducted on the differences between the regression coefficients of the correct and incorrect cues between subjects in the ABB and BAB groups. The analysis revealed no differences between the ABB (M = -.01) and BAB (M = -.03) groups, $t(84) = .09$, $p = .92$. This finding indicates that neither group used the correct cues in a more discriminative manner than the other in order to determine which aliens were friendly. Importantly, the difference between the regression coefficients for the correct and incorrect cues was approximately zero for both groups, indicating that neither group used the correct cues in a discriminative manner.

Table 1. Regression coefficients for correct and incorrect use of feature cues for each group for Experiments 2-3. CC = Correct friendly cue for determining whether an alien is friendly. IC = Incorrect friendly cue for determining whether an alien is friendly.

	ABB			BAB		
	Friendly Cue #1	Friendly Cue #2	75% Cue	Friendly Cue #1	Friendly Cue #2	75% Cue
Experiment 2						
Species 1	.10 (CC)	.14 (IC)	.28	.05 (CC)	.11 (IC)	.22
Species 2	.09 (IC)	.14 (CC)	.30	.06 (IC)	.12 (CC)	.23
Experiment 3						
Species 1	.30 (CC)	.25 (IC)	n/a	.43 (CC)	.11(IC)	n/a
Species 2	.19 (IC)	.34 (CC)	n/a	.12 (IC)	.35 (CC	n/a

In order to test whether subjects in the ABB group were using the maximization cues more than subjects in the BAB group, a third regression was conducted using the maximization cues as predictors of all subject responses (i.e. collapsing across both alien categories) on the second B task. The regression coefficients of the maximization cues were summed together for each subject. A *t*-test was conducted comparing the summed regression coefficients of the maximization cues between subjects in the ABB and BAB groups. The analysis revealed a main effect for the usage of the maximization cues, $t(84) = 2.12$, $p = .03$, as the ABB group ($M = .53$, $SE = .04$) used the maximization cues more than the BAB group ($M = .40$, $SE = .04$).[1] In both groups, the 75% cue was the strongest predictor of subject responses, with subjects in the ABB

[1] An analysis was conducted using 3 X 2 X 2 mixed model ANOVA. The analysis examined the regression coefficients for subjects' usage of the maximization cues (friendly cue #1 vs. friendly cue #2 vs. 75% cue) by species (species #1 vs. species #2) by condition (ABB vs. BAB). A main effect of condition was found (collapsing across the maximization cues and species), as subjects in the ABB group used the maximization cues more than subjects in the BAB group. This between-subjects effect is identical to the analysis reported above, which examined the difference in each group's usage of the maximization cues. The analysis using the mixed model ANOVA revealed no other statistically reliable differences, and is thus not reported above.

group relying on the cue more heavily than subjects in the BAB group (see Table 1 for each group's regression coefficients on the 75% cue).

Discussion

On the surface, the initial findings from this experiment are in line with the hypothesis, as subjects in the ABB group outperformed subjects in the BAB group on the second B task. However, when the entire results are taken into account, the differences found between the two groups on the second B task were not due to subjects in the ABB group using the correct cues in a more discriminative manner than subjects in the BAB group. Instead, the results showed that subjects in the ABB group figured out which features had a higher probability of leading to a correct response, regardless of species, and developed a preference for selecting such features (i.e., the maximization cues) when making a response. This latter conclusion differs from the central hypothesis of the paper, as subjects seemingly learned the maximization cues without ever mapping the correct cue to its corresponding category. Thus, subjects seem to have used the maximization cues indiscriminately without taking the two alien categories into account.

Because the task in this experiment was likely novel, subjects may have experienced a large degree of uncertainty, leading them to consider many possible hypotheses (e.g., (1) one cue determines whether an alien is friendly for both alien species, (2) the cue that determines whether an alien is friendly depends on the alien's species, (3) the cue that determines whether an alien is friendly changes from trial to trial, etc.). As a result, how the task should be represented and which hypothesis should be tested may have been unclear to subjects, thus the hypothesis space may have been large and unconstrained. When a large number of hypotheses are contained in the hypothesis space, attention may be divided among numerous hypotheses and such hypotheses may concurrently compete for working memory resources. As a result, it may be difficult for subjects to thoroughly attend to and test each hypothesis that is contained in the hypothesis space, and thus hypothesis testing may be impaired. In the current experiment, subjects may have struggled to process and organize task-relevant information in a coherent manner, leading to a vague and unspecified representation of the task.

The categorization task (i.e., A task) may have helped subjects to represent the task in a more concrete manner. One reason that categorization can aid rule-contingent learning (Mayer, 1982; Sweller, et al., 1983; Quilici & Mayer, 2002) is that categories convey information about the objects being categorized (Quillian, 1967; Solomon, Medin, & Lynch, 1999; Yamauchi, & Markman, 2000), allowing for subsequent representations to be conceptualized in a more specific and concrete manner.

The results indicate that the difference that was found between the two groups on the second B task was not due to subjects explicitly applying the knowledge that they acquired during the A task in order to solve the B task. Nonetheless, engaging in the categorization task at the outset of the experiment helped subjects in the ABB group learn the maximization cues better than subjects in the BAB group. Research has shown that people benefit from category learning even when the information that is acquired through the categorization process is not explicitly relevant to the actual task. For example, learning to categorize math problems has been shown to improve learning, even when information about a problem's solution strategy and problem structure are not explicitly conveyed in the categorization task (Mayer, 1982). It has also been shown that even when prior knowledge is not directly related to a given task, it can nonetheless improve subsequent learning and recall (Kole & Healy, 2007; Van Overschelde & Healy, 2001). Furthermore, findings have also shown that nonsense category labels can improve the quality of category representations (Lupyan, Rakison, & McClelland, 2007). Taken together, these findings suggest that people merely require a conceptual base that can be used as a reference point in order to improve the quality of subsequent representations. Hence, forming a category representation for a given task may serve as scaffolding for the subsequent processing of information.

It is possible that a conceptual base allows for the task and its corresponding hypotheses to be represented in a more concrete manner. Indeed, forming a conceptual base may reduce the amount of uncertainty that is associated with the task and may allow for task-relevant information to be processed more coherently, as such information can be organized around the conceptual base. With an improved representation of the task, attention may be better focused towards explicitly testing a smaller number of the task's hypotheses, thus improving hypothesis testing. By considering a smaller number of hypotheses, the hypothesis space is likely to become more constrained, and thereby should place less of a strain on working memory. For example, being able to recognize the alien's species may reduce the amount of uncertainty associated with the task by providing subjects a better sense of the hypotheses that are more likely to be correct, leading subjects to eliminate some of the hypotheses that seem more outlandish or unlikely (e.g., the alien is friendly when feet type #1, head type #2, and hand type #1 are present on every 5th trial).

Although both groups may have formed a conceptual base by engaging in the categorization task, the results from this study suggest that there may be a benefit to forming a conceptual base at the outset of learning rather than at later stages. Constraining the hypothesis space at the outset of a task may allow for information to be processed in a more coherent manner, reducing the number of hypotheses that are contained in the hypothesis space and suppressing their interference on hypothesis testing. However, if a conceptual base is not acquired during the early stages of learning, many of the incorrect hypotheses (e.g., hypotheses that are based on superfluous information contained in the task) that are initially contained in the hypothesis space may persist, making the representation of the task incoherent (i.e., vague and unconstrained). Moreover, when a conceptual base is acquired during the later stages of learning, the representation of the task may become too complex for the conceptual base to aid learning in the same manner as when it is acquired during the early stages of learning.

For example, subjects who complete the A task at the start of the experiment may be more likely to have a better sense of the types of hypothesis that are more likely to be correct (i.e., subjects are less likely to consider overly complex or outlandish hypothesis) and may thus have a greater amount of working memory resources available for learning which cues are more likely to lead to a correct response on the second B task. In contrast, subjects that complete the B task at the start of the experiment may expend a greater amount of working memory resources testing a larger number of hypotheses, many of which may be rather complex. Consequently, these subjects may have fewer working memory resources left over for learning which cues are more likely to lead to a correct response on the B task. Furthermore, because these subjects may be considering a greater number of hypotheses, this may further impair their ability to learn which cues are more likely to lead to a correct response on the B task, as the quality of their hypothesis testing may be impaired and a greater amount of working memory resources may be used.

In Experiment 1, no differences in performance were found on the B task between subjects in the ABB group and subjects in the BAB group. The key difference between the first and second experiments is that subjects did not fully learn to distinguish between the two species in the first experiment, whereas this was not the case in the current experiment. Subjects in

Experiment 2 overlearned the two types of alien categories, whereas in Experiment 1, performance on the A task suggests that subjects were relatively uncertain about the category distinction between the two alien categories. Therefore, these findings seem to suggest that in order for a conceptual base to provide a benefit at the outset of learning, people must thoroughly learn a concept about the task, such that there is little uncertainty about the information that has been acquired. The conceptual base hypothesis is explored further in Experiment 4 reported below.

CHAPTER IV

Experiment 3

A third study was conducted in order to test whether subjects could use the information they learned during the categorization task to meaningfully distinguish which features are diagnostic of friendly aliens (see Table 2 for a summary of how Experiments 1-5 vary). Forty-two undergraduate students participated in this study. In order to increase the chances of finding an effect of knowledge partitioning between the two groups, the task was simplified. Because performance was relatively low in the previous two experiments and the difficulty of the task may inhibit or make it difficult for subjects to use the information they learn during the categorization task, the three extraneous features that correlated with the correct response across 75% and 50% of the trials were held constant for all stimuli. Aliens thus varied along three features (feet, hands, and mouth); each feature consisted of two levels. Besides these changes, the design for this study was similar to Experiment 2.

Table 2. The feature cues that varied (+) and were held constant (–) across Experiments 1-5. C = Category Cue, FC = Friendly Cue. Note: In Experiment 4, the category cue varied between the head and the feet depending on the counterbalancing. The 75% cue correlated with the correct response on 75% of the trials on the B task.

Features	Head	Eyes	Nose	Mouth	Hands	Feet	Learning Criterion
Experiment 1	+	+	+	+ (FC)	+ (FC)	+ (C)	n/a
Experiment 2	+	+	+	+ (FC)	+ (FC)	+ (C)	yes
Experiment 3	-	-	-	+ (FC)	+ (FC)	+ (C)	yes
Experiment 4	+ (C)	-	+ (75%)	+ (FC	+ (FC)	+ (C)	yes
Experiment 5	+ (C)	- (75%)	+ (FC)	+ (FC)	+	-	yes

Results and Discussion

A *t*-test was conducted on all trials of the second B task. The results revealed no differences in performance between the ABB (M = .68, SE = .02) and the BAB (M = .71, SE = .03) group, $t(40) = .94$, $p = .35$. However, because we are interested in how well subjects used the correct feature cues for each species in order to distinguish friendly aliens, examining only the overall performance may not yield the most informative results. As in Experiment 2, two separate regressions (one for each alien category) were conducted on subject responses; the two cues that determined whether an alien was friendly were used as predictors. For each subject, the regression coefficients of the correct cues were summed together; the regression coefficients of the incorrect cues for each subject were also summed together. For each subject, the summed regression coefficients of the correct cues were subtracted from the summed regression coefficients of the incorrect cues. A *t*-test was conducted on the differences between the regression coefficients of the correct and incorrect cues between subjects in the ABB and BAB groups. The analysis indicates that the BAB group ($M = .24$) used the correct cues in order to identify friendly aliens in a more discriminative manner than the ABB group ($M = .08$), $t(40) = 2.18$, $p = .03$ (see Table 1 for mean regression coefficients for each group's usage of the correct and incorrect cues). These results run counter to the prediction that the ABB group would gain a greater benefit from completing the A task at the outset of learning (before learning the category rules) than the BAB group, which completed the A task at later stages of learning (after being introduced to the categories and their corresponding rules simultaneously).

Prior work has shown that when a rule that is applied in the early stages of learning leads to partial success, people are reluctant to abandon its use (Lewandowsky, et al., 2000). However, if this rule does not lead to success, people are more likely to search for alternatives (Kalish, Lewandowsky, & Davies, 2005). It is possible that subjects in the ABB group used their category knowledge to learn the correct feature cue for one of the species, leading to partial success at the outset of the B task. As a result, subjects in the ABB group may have become reluctant to seek out the second feature cue that was predictive of aliens that were friendly for the other species. In contrast, subjects in the BAB group may have struggled during the initial stages of the B task, prompting them to engage in a greater amount of exploratory hypothesis testing. Furthermore, because the stimuli were simplified to only consist of three features, subjects who engaged in a greater amount of hypothesis testing may have been more likely to learn the correct set of rules. Therefore, subjects in the ABB group should perform relatively well at the outset of the B task and improve slowly, whereas subjects in the BAB group should start off poorly and improve rapidly (relative to the ABB group).

In line with this prediction, on the first 50 trials on the first B task, the ABB group ($M = .63$, $SE = .03$) outperformed the BAB group ($M = .54$, $SE = .02$), $t(40) = 2.28$, $p = .02$. Moreover, the ABB group only moderately improved their performance from the first B task (*M* = .63) to the final 100 trials on the second B task (*M* = .70). In contrast, the BAB group showed substantial improvement on the first 50 trials from the first B task (*M* = .54) to the final 100 trials on the second B task (*M* = .75). Additionally, a qualitative analysis of the individual regression coefficients (across all trials) for the use of the correct cues was conducted. Subjects were classified as primarily relying on one feature cue in order to determine whether aliens were friendly if they met both of the following criteria: (1) the regression coefficient for one of the of the friendly cues (mouth or hands) was 10 percent greater than the regression coefficient for the other friendly cue (i.e., the subject was favoring the use of a specific cue) and (2) the regression coefficients (the pattern of cue usage) was similar across both alien categories (i.e., the subject was indiscriminately using a single cue to determine whether an alien was friendly for both alien species). Although these differences were not statistically reliable, the results show that 80% of subjects in the ABB group primarily relied on only one of the two correct feature cues for judging whether an alien was friendly, whereas this was only the case for approximately 64% of subjects in the BAB group.

Thus, the early success on the B task may have led the ABB group to form a rigid representation of the task, making these subjects less likely to engage in additional hypothesis testing. In contrast, due to their initial poor performance, subjects in the BAB group may have been motivated to engage in a greater amount of hypotheses testing (Kalish et al., 2005), increasing their likelihood of acquiring the correct set of rules for the B task. This finding points to scenarios under which it is not more beneficial for people to partition their knowledge at the outset of a task. In certain conditions, such as when the stimulus space is simplified, subjects may gain a greater benefit from attempting to learn a task's categories and their corresponding rules simultaneously, rather than by learning the categories for the task first, and then learning the category's corresponding rules. It is possible that when the stimulus space is simplified, the hypothesis space becomes more manageable, and thus engaging in a greater amount of hypothesis testing increases the likelihood of acquiring the appropriate set of representations for the task.

CHAPTER V

Experiment 4

The findings from Experiment 2 suggest that acquiring a conceptual base at the outset of learning provides a general benefit for processing information, as subjects in the ABB group seemed to outperform (on the second B task) subjects in the BAB group by selecting the features that had a higher probability of leading to a correct response. Furthermore, because the performance differences between the two groups on the second B task was not due to subjects using the information they acquired in the categorization task (i.e., A task) in order to better discriminate between which features were diagnostic of friendly aliens, this suggests that the conceptual base that people acquire at the outset of learning may be beneficial, even when it provides no meaningful information about the task.

The purpose of Experiment 4 is to directly test whether a conceptual base that is acquired at the outset of training can provide learning benefits, even when that conceptual base conveys no meaningful information about the task. This study also examined a third condition that tested whether acquiring a conceptual base at the outset of training that provides meaningful information about the subsequent task (i.e., B task) leads to better learning than when that conceptual base does not provide meaningful information. Thus, an ABB vs. CBB vs. BCB design was employed, where the C task conveys no meaningful information about the B task. This study consisted of 196 subjects.

For clarity, the *alien species* refers to the categorization task that subjects complete during the A and C task, whereas the *category cue* refers to the type of cue that corresponds to the correct friendly cues during the B task. For subjects in the ABB group, the alien species and the category cue were the same. However, the alien species and category cue were not the same for subjects in the CBB and BCB groups.

In the C task, subjects were asked to learn the same distinction between the two alien species as subjects in the A task; however, the friendly cues for the B task were not related to the alien species that subjects learned during the C task. The alien species in both the A and C tasks was determined by either the head or the feet. The role that the head and feet played (i.e., determining the alien species for the A and C tasks) was counterbalanced across subjects. In both the A and C tasks, the instructions indicated which cue (i.e., the head or feet, depending on which cue determined the alien species for the subject) could be used in order to discriminate between the two alien species.

For subjects in the ABB group, the cue that determined the alien species in the A task corresponded to the friendly cues on the B task (as in the previous experiments). However, for subjects in the CBB and BCB groups the cue that determined the alien species on the C task did not correspond to the friendly cues on the B task. Therefore, the cue that determined the alien species on the C task was different from the cue that corresponded to the friendly cues on the B task. For the head and feet cues, the cue that did not determine the alien species during the C task was the cue that corresponded to the friendly cues on the B task. For example, if the feet determined the alien species on the C task, the head would correspond to the friendly cues on the B task. See Table 3 for the relationship between the feature cues across the three conditions.

Aliens varied along 5 feature cues (head, nose, mouth, hands, and feet) and each cue consisted of two levels. As in the previous experiments, one cue determined the alien species, two different cues determined whether the aliens were friendly (one corresponding to each category), one cue correlated with the correct response on 75% of the trials on the B task, and the other cue correlated with the correct response on 50% of the trials on the B task. The remainder of the design and procedure are identical to Experiment 2.

Table 3. Relationship between the feature cues and conditions in Experiment 4. C = Category Cue, CS = Category and Species Cue, S = Species Cue, FC = Friendly Cue, X = feature was held constant and did not vary. Note: The category cue varied depending on the counterbalancing across conditions. The 50% cue correlated with the correct response on 50% of the trials on the B task. The 75% cue correlated with the correct response on 75% of the trials on the B task.

Features	Head	Eyes	Nose	Mouth	Hands	Feet
Category Cue: Head						
ABB	CS	X	75% Cue	FC	FC	50% Cue
CBB	C	X	75% Cue	FC	FC	S (50% Cue)
BCB	C	X	75% Cue	FC	FC	S (50% Cue)
Category Cue: Feet						
ABB	50% Cue	X	75% Cue	FC	FC	CS
CBB	S (50% Cue)	X	75% Cue	FC	FC	C
BCB	S (50% Cue)	X	75% Cue	FC	FC	C

Results and Discussion

An analysis of variance (ANOVA) revealed significant differences among groups in performance on the second B task, $F(2, 193) = 3.75$, $p = .03$. Subjects in the ABB ($M = .68$, $SE = .01$) group outperformed subjects in the CBB ($M = .65$, $SE = .01$) and BCB ($M = .63$, $SE = .01$) groups (see Figure 4 for learning curves). An additional ANOVA was conducted comparing performance on the second B task for subjects in the ABB group to subjects from the other two groups (i.e., ABB vs. CBB and BCB). The results showed a main effect of condition, $F(1, 194) = 6.88$, $p = .01$, as subjects in the ABB group ($M = .68$ $SE = .01$) outperformed subjects in the other two groups ($M = .64$, $SE = .01$).

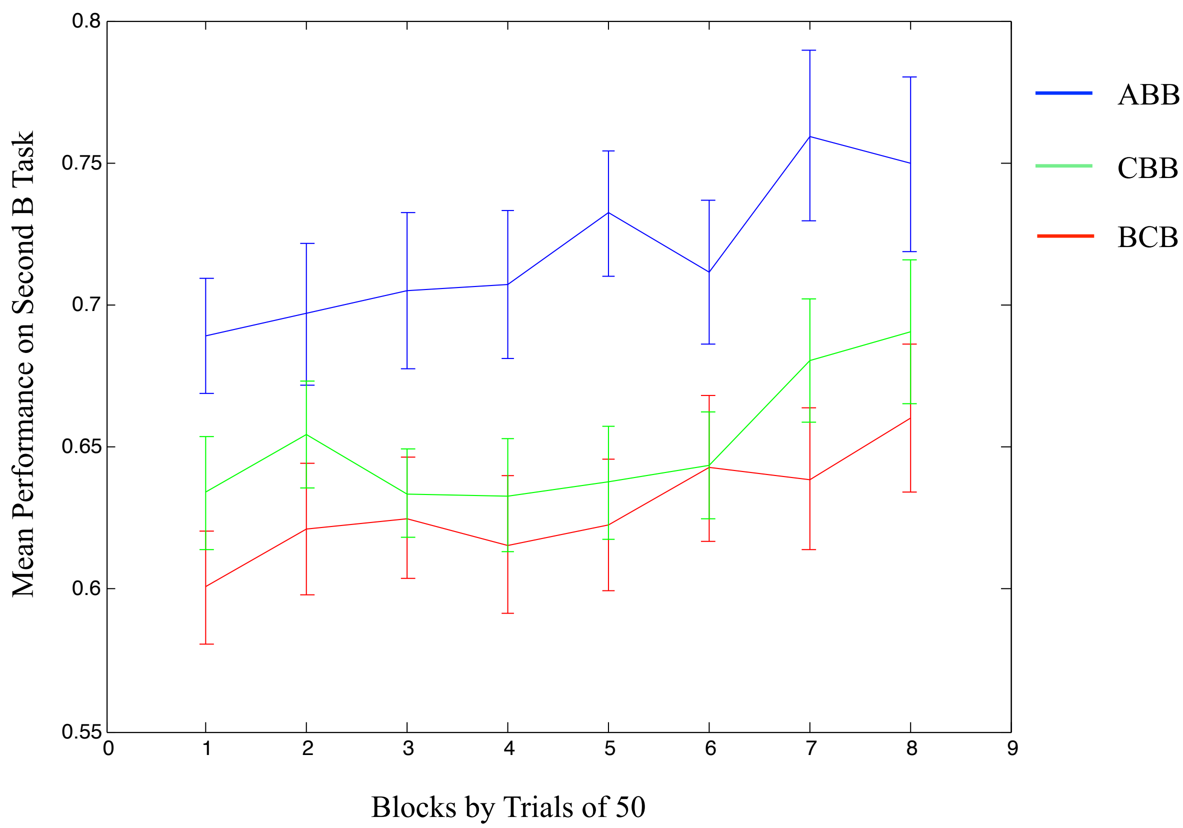

Figure 4. Learning curves for subjects in Experiment 4. Error bars indicate the standard error of the mean.

Two separate ANOVAs were conducted and revealed that the main effect of condition for performance on the second B task was primarily driven by cases in which the head determined category membership, $F(2, 94) = 6.66$, $p = .002$, and not by cases where category membership was determined by the feet, $F(2, 96) < 1$. One possible reason for this finding is that subjects disregarded the alien's feet because they were disconnected from the rest of the features, whereas the head was likely far more noticeable. These findings offer a possible explanation for the reason that a knowledge partitioning effect for the ABB group was not observed in Experiment 2, which used the feet as the cue that determined category membership, as subjects may have disregarded the feet during the B task, and thus the experiment may not have appropriately tested the central hypothesis of the paper.

A *t*-test was also conducted comparing performance on the final 400 trials of the B task between subjects in the ABB and CBB groups for cases where the category was determined by the head. The results show a main effect of condition on performance, $t(63) = 2.70$, $p = .001$, as subjects in the ABB group ($M = .72$, $SE = .02$) outperformed subjects in the CBB group ($M = .65$, $SE = .01$). An analysis (following the same guidelines as described in Experiments 2 and 3) was also conducted in order to examine whether one of the groups was better able to use the correct cues in a more discriminative manner based on the category the alien pertained to. The results showed a main effect of condition, $t(63) = 4.05$, $p < .0001$, as subjects in the ABB group ($M = .41$, $SE = .09$) used the correct cues in a more discriminative manner than subjects in the CBB group ($M = .08$, $SE = .06$; see Table 4 for mean regression coefficients for usage of the correct and incorrect cues, and the 75% cue for subjects in the ABB and CBB group for trials where the category cue is the head). Taken together, these findings show that acquiring a conceptual base that provides meaningful information about the subsequent task at the outset of training allows for better learning than acquiring a conceptual base that does not consist of meaningful information.

Table 4. Mean regression coefficients in Experiment 4 for usage of the correct and incorrect cues, and the 75% cue for subjects in the ABB and CBB group on trials where the category cue is the head. CC = Correct friendly cue for determining whether an alien is friendly. IC = Incorrect friendly cue for determining whether an alien is friendly.

	ABB			CBB		
	Friendly Cue #1	Friendly Cue #2	75% Cue	Friendly Cue #1	Friendly Cue #2	75% Cue
Species 1	.31(CC)	.12 (IC)	.22	.16 (CC)	.22 (IC)	.21
Species 2	.10(IC)	.32(CC)	.22	.11 (IC)	.22 (CC)	.23

A separate analysis used a *t*-test in order to compare the performance of the CBB and BCB groups on all trials of the second B task. The analysis revealed no reliable difference between the two groups, $t(129) = .88$, $p = .38$. Thus, support was not found for the prediction that acquiring a conceptual base that does not consist of meaningful information at the outset of training leads to improved learning over acquiring a conceptual base at later stages of learning. Importantly, the aliens in Experiment 2 varied on 6 features, whereas in the current experiment the aliens varied on 5 features (the eyes were held constant across all trials). Although a one feature difference between the two experiments may seem trivial, having to hold an additional feature in working memory may impair hypothesis testing and strongly affect performance in cases where working memory is already taxed and under high load. Forming a conceptual base at the outset of learning may aid people in representing the task in a more concrete and constrained manner, leading to a conservation of working memory resources, and thus may be most useful in cases where the task is relatively unconstrained and there is a high strain on working memory. Therefore, it is possible that a more difficult task than the B task that was used in Experiment 4 is required to better test the conceptual base hypothesis.

Because the feet were disconnected from the rest of the features and subjects may have ignored them, an additional *t*-test was conducted comparing subject's performance from the CBB and BCB groups on the final 400 trials of the B task for cases where the category was determined by the head (i.e., the alien species was determined by the feet). The results showed no reliable difference in performance between the two groups, $t(64) = .98$, $p = .33$. Importantly, indirect evidence was found for the conceptual base hypothesis in Experiment 2, where the alien was composed of an additional feature cue and thus the B task was more difficult than in the current experiment. It is possible that there was an initial learning advantage for the CBB group during the early stages of the B task, but due to the reduced difficulty of the task in the current experiment, this advantage dissipated as subjects progressed through the task. An exploratory analysis was conducted in order to examine performance on the first 100 trials of the second B task between the CBB and BCB groups for cases when the head determined category membership. The results show a statistical trend, $t(64) = 1.33$, $p = .19$, as subjects in the CBB group ($M = .64$ $SE = .02$) outperformed subjects in the BCB group ($M = .61$ $SE = .02$). When comparing performance for subjects in the CBB and BCB groups for the cases when the alien's head determined category membership, the sample size was decreased to 66 subjects. It is possible that the effect size for the conceptual base hypothesis is relatively small and thus more subjects are required in order to detect this effect.

CHAPTER VI

Experiment 5

The results from Experiment 4 showed a main effect of condition, where subjects in the ABB group outperformed subjects in the CBB and BCB groups on the second B task. However, this main effect of condition was driven by cases where the alien's head determined category membership on the B task and not by cases where category membership was determined by the alien's feet. Because the feet are disconnected from the rest of the feature cues, it is possible that the knowledge partitioning effect for the ABB group was not found in Experiment 2 because subjects disregard the feet on the B task. Thus, Experiment 2 was re-run using the head as the cue that determined category membership.

This study consisted of 68 subjects. A stimulus varied along five feature cues (head, eyes, nose, mouth, and hands); the torso and feet were held constant. In order to increase the likelihood that the most relevant cues did not go unnoticed, both friendly cues, as well as the 75% cue, were located on the head (i.e., eyes, nose, and mouth). The nose and mouth played the roles of the friendly cues and the eyes played the role of the 75% cue. As in the previous experiments, the roles of the friendly cues were counterbalanced across subjects. On the B task, the hands correlated with the correct response on 50% of the trials. The rest of the design and procedure were identical to those of Experiment 2.

Results and Discussion

The results revealed no significant difference in performance on the second B task between the ABB (M = .69, SE = .09) and BAB group (M = .69, SE = .09), t (66) = .04, p = .97. An analysis was also conducted (following the same guidelines as described in Experiments 2 and 3) to examine whether one of the groups used the correct cues in a more discriminative manner; however, no reliable differences were found between the two groups.

Summary: Experiments 1-5

Experiment 1 found no differences on the second B task between the ABB and BAB groups. In Experiment 2, subjects in the ABB group outperformed subjects in the BAB group on the second B task. However, the performance difference between the two groups was not driven by a knowledge partitioning effect. It is possible that the stimuli that were used in Experiments 1-2 made the A and B tasks too difficult, making it challenging for subjects to partition their knowledge for the two alien categories. In Experiment 1, subjects did not fully learn the distinction between the two alien categories during the A task, and although subjects learned to discriminate between the two alien categories in Experiment 2, it was only through explicit instruction that notified subjects of the cue that determined category membership. Thus, the findings from the first two experiments may not directly address the primary hypothesis of the paper.

Experiment 3 simplified the stimuli in an attempt to increase the likelihood of subjects using the correct cues based on the alien category. Contrary to the hypothesis, subjects in the BAB group used the correct cues in a more discriminative manner than subjects in the ABB group. This finding suggests that in scenarios where the stimulus space is simplified, completing the B task (learning the task's categories and their corresponding rules simultaneously) before the A task (learning the task's categories before being introduced to the category's corresponding rules) may lead to better learning than completing the A task before the B task.

In Experiment 4, the A task (for the ABB group) provided information that was relevant to the B task, whereas the C (task for the CBB and BCB groups) did not provide information that was relevant to the B task. As expected, subjects in the ABB group outperformed subjects in the CBB and BCB groups on the second B task. However, the main effect of condition was driven by cases when the alien's head determined the category on the B task and not by cases when the alien's feet determined the category. This finding may account for the reason that a knowledge partitioning effect has not been observed in previous experiments, as it is possible that subjects had a tendency to ignore the alien feet because they were disconnected from the rest of the alien features. In order to address this issue, all of the relevant feature cues for the B task were located on the alien's head in Experiment 5. Nonetheless, no performance differences were observed on the second B task between the ABB and BAB groups.

The experiments described above do not provide evidence in support of the knowledge partitioning hypothesis (although Experiment 4 did not directly test this hypothesis). The findings from Experiments 1 and 2, coupled with subjects low performance on the B task across all five experiments suggest that the stimuli may make the B task too difficult to adequately test the knowledge partitioning hypothesis. The findings from Experiment 4 indicate that the location of the relevant feature cues (i.e., the category and friendly cues) can be critical to how well subjects are able to learn the B task. Moreover, the location of the feature cues can affect whether subjects attend to that feature during the B task. For these reasons, in order to thoroughly test the knowledge partitioning hypothesis with the stimuli used in Experiments 1-5, it may be necessary to examine which location of the feature cues is most likely to be attended to by subjects during the B task. However, addressing this question lies beyond the scope of the current paper. Thus, the alien stimuli used in these experiments may not be appropriate for testing the knowledge partitioning hypothesis.

CHAPTER VII

Experiment 6

Although people are often reluctant to restructure their representations (Lewandowsky et al., 2000), this may not be the case when the representations that must be restructured are relatively simple and the manner in which they must be restructured is straightforward. In the previous five experiments, the stimuli were composed of feature-based properties. In order to distinguish between the two alien categories, subjects merely had to attend to the alien feet (or head in Experiments 4 and 5). Hence, the representations for the alien categories were relatively simple (e.g., one type of feet for Cobsters and a different type for Barnets). Once subjects in the BAB group learned how to discriminate between the two alien categories in the A task, the simplicity of the feature-based cues may have made it easy for subjects to restructure their representation of the categories, making the manipulation less sensitive.

Alternatively, it may be unclear how to restructure more complex representations. For example, in cases where the difference between the categories is subtle, such as when the stimuli are composed of a higher-order or relational structure, people may be required to significantly alter their representation of a task's categories. However, the manner in which such representations should be restructured may not be immediately clear. In such cases, people may struggle to alter their representations once they have been formed and there may be a strong benefit to acquiring the appropriate representations at the outset of learning. Thus, in order to better test the knowledge partitioning hypothesis, it may be necessary to use stimuli that require more complex representations.

The current experiment applies the ABB vs. BAB design used in the previous experiments to a relation-based task. The categorization phase differs from the previous experiments, as subjects must learn a perceptual higher-order structure for three different types of categories. Subjects must subsequently use this knowledge in conjunction with the presence of a particular feature in order to make a binary judgment about the presented stimulus on the B task. There are three total features (one for each category), but only one is presented on a single trial. Accordingly, the feature that corresponds to the correct response depends on the category that a stimulus is a member of.

Method

Participants

This study consisted of 132 undergraduate subjects who participated for course credit in an introductory psychology course. Subjects were randomly assigned to conditions.

Design and Materials

As in the previous experiments described above (e.g., Experiment 1), this was a between subjects study that employed an ABB vs. BAB design. All stimuli were presented on an LCD monitor at the center of the screen on a black background. Subjects entered their responses using a computer keyboard. For the A task, subjects learned to distinguish between three different types of machines (i.e., categories). Because each category can be instantiated in a variety of unique ways, each is considered to consist of a higher-order structure. A stimulus consisted of a machine with three lights (see Figure 5 for an example stimulus from the A task). The lights blinked in a pattern that adhered to a specific higher-order structure. Each machine was characterized by a higher-order structure, defined as the pattern the lights blinked on and off. Each light blinked on for 500 ms and blinked off for 200 ms. Sixteen hundred milliseconds after the blinking pattern was complete, the pattern for the given trial resumed from its starting point.

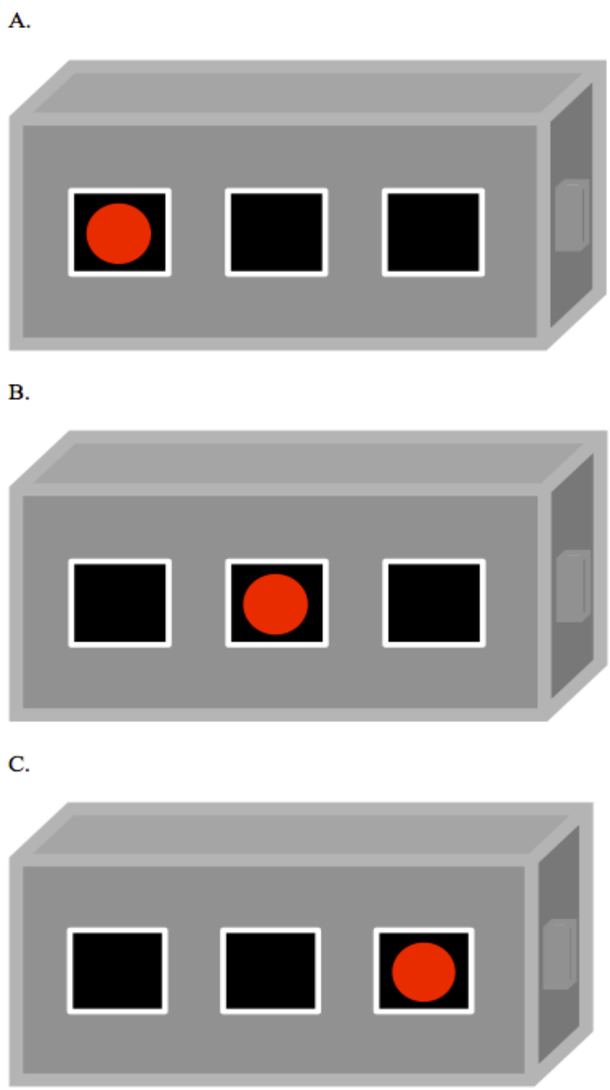

Figure 5. Example of stimulus in Category A from Experiment 6. A: First light blinks in the sequence. B. Second light blinks in the sequence. C. Third light blinks in the sequence. A-C illustrates a temporal progression through the sequence of blinking lights.

Category A was defined as one light blinking, followed by a second unique light blinking, followed by a third unique light blinking. Category B was defined as two lights blinking simultaneously, followed by a unique third light blinking. Category C was defined as one light blinking, followed by a second unique light blinking, followed by the first light blinking again. Categories A and C can be instantiated in 6 unique ways and Category B can be initiated in 3 unique ways. In order to learn the three category-types, subjects must abstract the higher-order structure across each of the category's different instantiations. The categories were named as follows: Category A, Category B, and Category C. For all subjects, the category names were randomly assigned to the category-types. On each trial, the category type was randomly sampled (i.e., there was a 33% chance one of the categories would be selected for any trial).

For the B task, a stimulus consisted of a machine that blinks three lights in a specific higher-order pattern (as in the A task) with a colored gadget attached to its side. There were three colored gadgets (blue, purple, and orange), but only one was attached to a machine per trial (see Figure 6 for an example stimulus from the B task). Each gadget corresponded to a particular category (i.e., type of machine). If the correct gadget was attached to its corresponding machine the machine functioned, otherwise it did not. The gadget that corresponded to a particular category was randomly assigned for all subjects. On each trial of the B task, a gadget was randomly sampled (i.e., there was a 33% chance that a machine functioned).

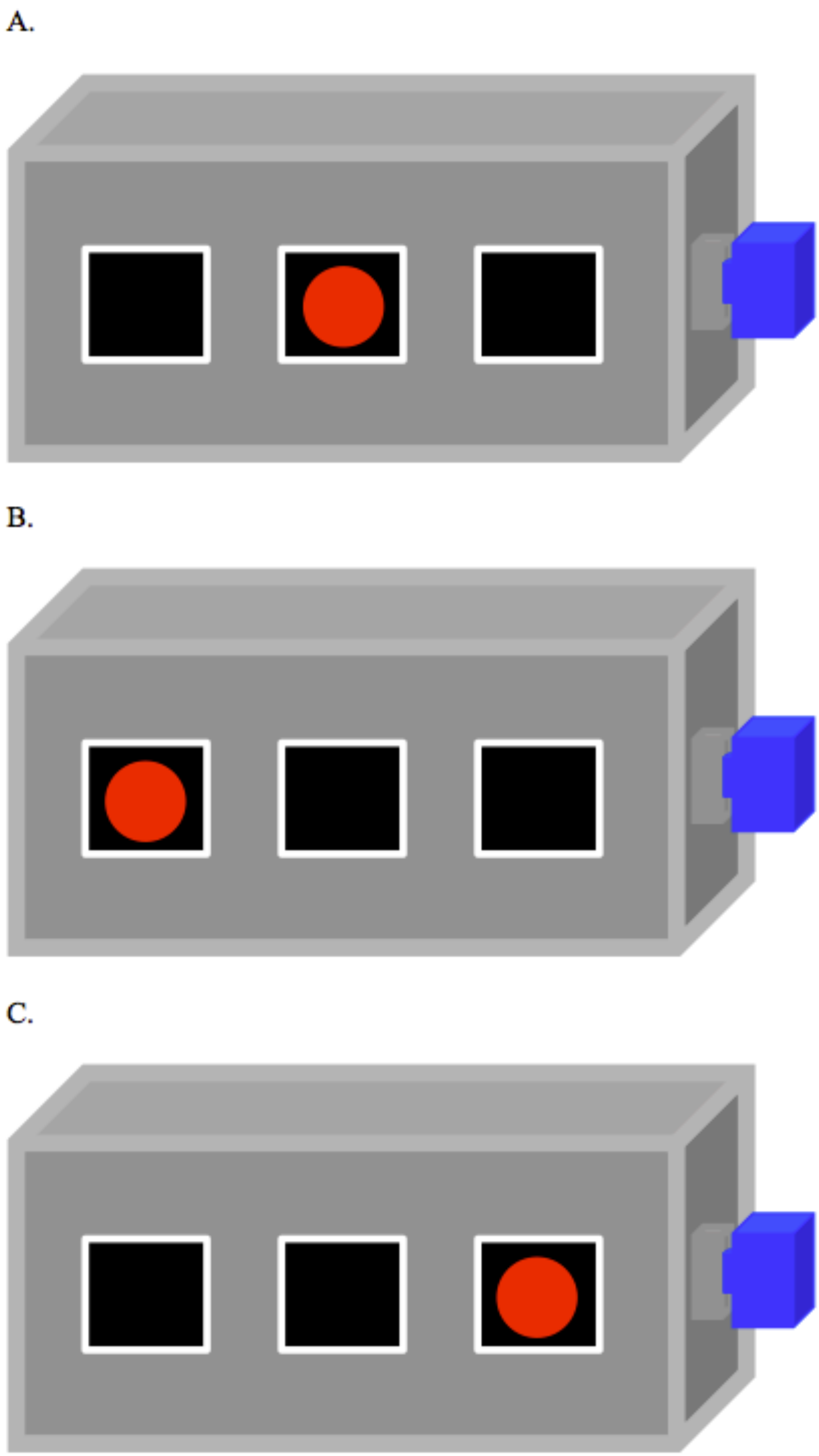

Figure 6. Example stimulus from the B task from Experiment 6. Stimulus is an instantiation of Category A. A-C illustrates a temporal progression through the sequence of blinking lights.

Procedure

Subjects were given a cover story that they were a water filter inspector and their job was to go to a factory and determine which machines would work and which would not. However, subjects were instructed that before they could go to the factory they would need to engage in a series of practice tasks. All subjects carried out the following practice tasks: (A) differentiating between the three different types of machines and (B) determining which machines would work and which would not. As in previous experiments, the order in which these tasks were presented varied depending on the condition the subject was assigned (i.e., AB vs. BA).

On each trial of the A task, text was displayed directly above the stimulus asking subjects whether the machine was Machine Type A, B, or C. Subjects were asked to type “a” for Machine Type A, “b” for Machine Type B, and “c” for Machine Type C. On each trial of the B task, text was displayed directly above the stimulus asking subjects whether the machine would work. Subjects were asked to type “y” for yes and “n” for no. After subjects entered a response and the light pattern was complete, the stimulus was removed and the correct answer was provided for 800 ms directly beneath where the stimulus was previously displayed. Next, the screen was cleared for 300 ms and the image for the following trial was presented.

On the A task, subjects were required to complete a minimum of 100 trials and answer 20 consecutive responses correctly before they could move on to the next task; alternatively, subjects could complete a maximum of 200 trials without answering 20 consecutive responses correctly. On the first B task, subjects completed 100 trials. After completing the A and B tasks, subjects were provided with a cover story that it was time to head to the factory. Subjects were then asked to complete the B task once again. As in the previous experiments, the second B task consisted of 400 trials and was identical to the first B task. After every 100 trials, subjects were provided with a self-paced rest break and were shown their percent correct on those trials.

Results and Discussion

A *t*-test was conducted examining performance on the second B-task between subjects in the ABB and BAB groups. The results revealed a non-significant trend, $t(130) = 1.57$, $p = .11$, with subjects in the ABB group ($M = .94$, $SE = .02$) outperforming subjects in the BAB group ($M = .90$, $SE = .02$). Figure 7 shows learning curves for the first and second B task. Because performance was relatively high, differences between the two groups may be difficult to detect due to a ceiling effect. Thus, the analysis was run on only the first 100 trials on the second B task. The results indicate that there was a significant difference in performance between the two groups in the predicted direction, $t(130) = 2.58$, $p = .01$, as the ABB ($M = .92$, $SE = .02$) group outperformed the BAB ($M = .84$, $SE = .02$) group.

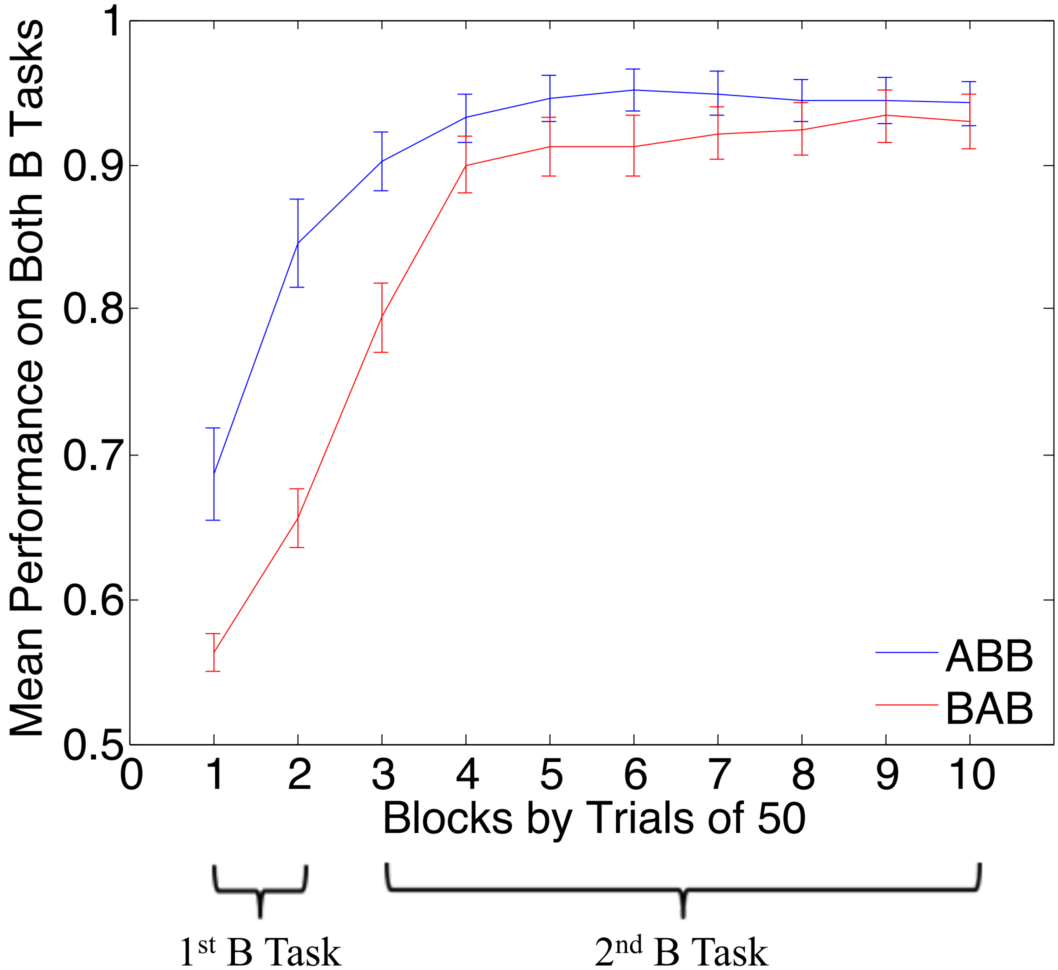

Figure 7. Learning curves for both B tasks of Experiment 6. Blocks 1-2 represent performance on the first B task. Blocks 3-10 represent performance on the second B task. Error bars indicate the standard error of the mean.

These findings provide some support for the hypothesis that learning is improved if subjects learn a task's categories at the outset of learning. More specifically, it is possible that subjects in the ABB group, who learned the different types of categories first, developed a cleaner representation of the task by better mapping the correct rule to its corresponding category, and thus outperformed subjects who did not acquire such representations early in the learning process. However, an alternative explanation is that subjects in the ABB group merely had more practice in applying the knowledge they acquired during the A task than did subjects in the BAB group.

Subjects in the ABB group learned the different types of categories during the A task and then had an opportunity to apply that knowledge during the first B task. Thus, by the time they were tested on the second B task, these subjects had 100 trials of practice in applying their knowledge from the A task to solve the B task. In contrast, subjects in the BAB group did not explicitly know the different categories for the task during the first B task. Hence, the first time subjects in the BAB group had an opportunity to apply their knowledge from the A task to solve the B task is on the second B task.

The ideal comparison to better identify the learning mechanism behind the performance difference between the two groups is to compare performance on the first B task for subject's in the ABB group with performance on the second B task for subject's the BAB group. This comparison reveals that subjects in the BAB group outperform subjects in the ABB group (see Figure 7); however, this comparison stacks the deck against subjects in the ABB group because subjects in the BAB group had an additional 100 trials of practice. Thus, it is not entirely clear how to interpret the current findings. Nonetheless, these findings provide support for the notion that teaching people the relevant categories at the outset of learning leads to faster acquisition than when people acquire those categories at later stages. However, the mechanisms behind this effect remain unclear.

Even though the higher-order pattern of blinking lights was more complex than the alien stimuli used in Experiments 1-5, the representation for the categories may still have been too simple. The simplicity of the task may have contributed to the high performance observed across all subjects. Thus, in order to better test the current hypothesis, it may be necessary for future studies to use stimuli that consist of categories that require subjects to build up more complex representations.

CHAPTER VIII

General Discussion

In many domains that require rule-contingent learning (e.g., mathematics, physics), the rule for solving a problem depends on the category that the problem is a member of. Previous findings have shown that in such domains, learning the task's categories can aid learning (Mayer, 1982; Sweller et al., 1983). However, the stage in learning at which a task's categories are acquired may strongly affect the representations that are subsequently formed. When people encounter a new task, the initial representations that are formed may be durable and resistant to being restructured. Furthermore, the initial representations that people form about a task may consist of superfluous or incorrect information, thus it may be critical that people form the correct set of representations at the outset of learning. The purpose of the current paper was to examine whether the point (early stages vs. later stages) at which people learn a task's categories affects subsequent acquisition on a simple rule-contingent task. The experiments presented here were composed of two parts: (1) subjects engaged in a categorization task (A task or C task for Experiment 4) and (2) subjects carried out a rule- contingent task where the correct rule for a given problem depended on the problem's category (B task). Subjects were either presented with the categorization task first (A or C task), followed by the B task or the B task first followed by the categorization task. All subjects were then presented with a second B task, leading to an ABB vs. BAB design (except for Experiment 4, which used an ABB vs. CBB vs. BCB design).

The results from Experiment 1 show no difference in performance on the second B task between subjects who were presented with a categorization task at the outset of learning and those who were presented with the same task at a later stage (i.e., after the B task). Importantly, subjects in both conditions (ABB and BAB) struggled in learning the categorization task. Because learning the task's categories was critical to the manipulation, it is difficult to draw a conclusion from these findings.

Experiment 2 employed a learning criterion on the categorization task to ensure that subjects fully learned the necessary categories. As expected, the ABB group outperformed the BAB group on the second B task. However, the performance difference between the two groups was not due to subjects in the ABB group using the correct cues in a more discriminative manner than subjects in the BAB group. Instead, the performance difference between the two groups was due to subjects in the ABB group making greater use of the maximization cues than subjects in the BAB group. Because subjects were not explicitly using the knowledge they acquired in the categorization task to solve the B task, it is possible that engaging in a categorization task aids rule- contingent learning, even when the categorization task conveys no meaningful information about the rule-contingent task (i.e., B task). One possible explanation for this finding is that the categorization task aids people in forming a conceptual base, allowing for a more concrete representation of the task. Forming a conceptual base at the outset of the task may allow for the task to be represented in a more concrete manner, allowing for improved hypothesis testing. Moreover, when Experiments 1 and 2 are taken together, they suggest that in order to form a conceptual base or for a conceptual base to aid learning, subjects must fully learn the category distinctions during the categorization task.

Experiment 3 simplified the stimulus space by reducing the number of features on which that the stimulus varied from six (Experiments 1-2) to three. The results showed that subjects in the BAB group used the correct cues in a more discriminative manner on the second B task than subjects in the ABB group. One explanation for this finding is that in cases where the stimulus space is relatively simple, it is easy for people to restructure their representations of the task's categories, and therefore there is a greater benefit to in attempting to learn a task's categories and their corresponding rules simultaneously (i.e., B task) than learning the task's categories (i.e., A task) before being presented the category's corresponding rules.

Experiment 4 revisited the conceptual base hypothesis, testing it in a more direct manner than Experiment 2 by using a categorization task that conveyed no meaningful information about the B task. This manipulation led to an ABB vs. CBB vs. BCB design. It was expected that acquiring useful information about a task at the outset of learning would be more beneficial than merely forming a conceptual base that conveys no meaningful information about the B task. Thus, it was predicted that the ABB group would do best on the second B task and the CBB group would outperform the BCB group. However, although the performance differences were in the predicted direction for all conditions, no reliable differences were found between the CBB and BCB groups. Hence, this study failed to provide support for the conceptual base hypothesis.

Importantly, subjects may have disregarded or ignored the category cues in cases where they were located on the feet. An analysis examined performance on the second B task between subjects in CBB and BCB groups for cases in which the head was the category cue. Although the performance difference was in the predicted direction, no differences were found between the two groups. This analysis reduced sample size to 66 subjects. It is possible that the effect size for the conceptual base hypothesis is relatively small and in order to be detected requires a larger sample size than what was used in the current study.

It is also plausible that a conceptual base is most effective in tasks where the hypothesis space is largely unconstrained (i.e., tasks of high difficulty). This explanation may account for the reason that support (albeit indirect) was found for the conceptual base hypothesis in Experiment 2, but not in Experiment 4, as fewer feature cues were used in Experiment 4 and thus the B task's hypothesis space was likely smaller than in Experiment 2. Although it may seem that a difference of one feature cue between the stimuli in the two experiments is not sufficient to significantly alter the difficulty level of the B task, adding an additional feature cue to the stimuli leads to an additional four possible hypotheses for subjects to consider. This increase in the hypothesis space can be critical in cases where working memory is already under high load. Future studies should seek to test the conceptual base hypothesis by using tasks that are of greater difficulty than those employed in Experiment 4.

Importantly, Experiments 1-5 failed to provide support for the hypothesis that learning a task's categories at the outset of training may aid people in partitioning the different rules for a task into their corresponding categories, improving subsequent learning. It is possible that the feature-based stimuli used in the first five experiments allowed for representations that were too simplistic in nature and were thus not sufficiently sensitive to test the aforementioned hypothesis. In order to address this issue, Experiment 6 used relational stimuli consisting of a higher-order structure.

In Experiment 6, subjects in the ABB group outperformed subjects in the BAB group on the first 100 trials of the second B task. However, it is unclear how to interpret these findings. One possibility is in line with the original hypothesis: learning a task's categories at the outset of training allows for the rules of the task to be more readily mapped onto their corresponding categories, leading to cleaner representations and improved learning. An alternative account is that the ABB group had a greater opportunity to apply their knowledge from the A task during the B task. More specifically, during the A task subjects in the ABB group learned the categories contained in the B task. These subjects then completed 100 trials on the first B task. This form of training allowed subjects in the ABB group 100 trials of practice, whereby they could apply their knowledge from the A task in order to solve and learn the B task. Thus, it is possible that the effect found in Experiment 6 is simply due to a practice effect that favored the ABB group.

Analysis that equated both groups on the amount of practice they had on the B task once they learned the A task (e.g., second B task: ABB (trials 1-100) vs. BAB (trials 101-200)) found no reliable differences between the two groups. One possibility is that these results were due to a ceiling effect, as both groups learned the B task exceptionally well. In order to address the ceiling effect and carry out the aforementioned analysis, future studies should seek to use a B task that is of greater difficulty than the one employed in Experiment 6.

Many rule-contingent tasks (e.g., mathematics, programing, physics) often require the concurrent learning of a task's categories and its corresponding rules, placing a large load on working memory and increasing task difficulty (Ward & Sweller, 1990). Although it is difficult to draw a clear theoretical conclusion from the findings in Experiment 6, it seems that learning on these types of tasks may be improved if the task's categories are learned separately from its rules. The ABB group displayed a faster learning rate on the B task than the BAB group. This finding may suggest that in order to improve learning rates, it is important to first teach people the appropriate prerequisite concepts. This finding may provide insight into the fields of category and concept acquisition, as well as the development of expertise. Importantly, it remains unclear whether this effect is due to subjects learning the categories for the B task before the rules, allowing for a cleaner and more coherent representation of the B task or whether the effect is purely driven by the fact that the learning of the categories and rules was teased apart, decreasing subject's working memory load and thereby making the B task more manageable. Future studies should seek to test this issue more directly. Nonetheless, these results seem to have direct applicability for various educational domains, such as the teaching of mathematics, physics, and computer science.

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