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Category Learning with a Goal: How Goals Constrain Conceptual Acquisition

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Abstract

The current study uses a novel task to examine the roles that goals play in concept acquisition. In Experiment 1, we varied the type of interaction, and thus the task goal, of participants working in a novel domain. Following those interactions, participant responses showed that they had organized their knowledge of items from the domain in terms of the goal-relevant features. Using a variation of the same methodology, Experiment 2 provided evidence that the goal relevance also played a role in how the participants structured their knowledge of the items, specifically what information about the items was associated with differentiating the categories encountered. The results suggest that the goals not only highlighted particular features, they determined the centrality of those features in the conceptual knowledge. We discuss the results in terms of the *goal-framework hypothesis;* the idea that goals structure information in a way that provides coherence to the concepts that are acquired. The data are discussed in terms of how this approach informs category learning research.

Keywords: category learning, conceptual knowledge, goals, similarity.

Our ability to organize our knowledge in terms of the classes of items and events that we recognize in the world has a meaningful impact on a multitude of cognitive processes. When we reason, infer, communicate, and problem solve, we draw on conceptual knowledge to connect the specific item or event we currently face with our knowledge of the general class to which it belongs. Thus, a critical question is how that conceptual knowledge is structured – how do we organize what we know about categories and the items that belong to them? The premise of the current study is that we learn about items, and the categories they belong to, through goal-directed interactions.

Jee and Wiley (2007) provided evidence that having a particular goal when interacting within a domain results in the goal relevant information being highlighted within the associated category knowledge. The current study extends this finding, focusing on the role goals play in concept acquisition within a novel domain. The basic thesis of the paper is that goals provide a framework that structures interactions with the environment and thus meaningfully constrain both what is learned from the encounters and how acquired knowledge is organized.

Goals Provide Structure for Interactions

The notion that human behavior is goal-directed has a long and rich history in psychology (for one overview see Austin & Vancouver, 1996). A primary function of a goal construct has been to account for complex behaviors (e.g. Tolman, 1949) and to provide structure to those behaviors (e.g. Aarts & Dijksterhuis, 2000; Miller, 1960). For the purposes of this project, we will focus on the concept of a *task goal*, which we define as a currently unrealized, yet desired, future state within a particular situation (Ram & Leake, 1995). A task goal could be something as simple as "put sugar into my coffee" or as complex as "replace the kitchen sink". Importantly, the goal provides a framework that constrains the conceptualization of on-going behaviors and the information in the environment.

Within this framework any action taken or information available can be considered to be goal-relevant if it has the potential to change the individual's position relative to the goal-state (either closer to or further from the goal) or goal-irrelevant if it does not. For the purpose of this study, we do not make any specific assumptions about the structure of the goal framework (e.g. if it is a hierarchy or sequence of subgoals or whether that structure is variable across situations) at the outset. However, we do propose that the goal framework develops as the individual seeks to attain the goal state. Initially, the individual is able to recognize the goal, and possibly some of the intermediate states that precede that goal, but the goal structure emerges during the interactions associated with that goal. As the individual engages in goal-directed behaviors, the immediate context constrains movement relative to that goal so that at any point some goal-directed behaviors are possible, and some are not. Some behaviors move the person closer to the goal, and some either have no effect or possibly move the person away from the goal state. These attempted and fully realized actions by the individual and the feedback that they receive from the environment are remembered in terms of the goal framework (Barsalou, 1995). In this way, the structure of the goal-framework emerges from on-going interactions with the environment.

As goals structure interactions with the world, it stands to reason that goals should also play an important role in how people organize their knowledge of the world (Barsalou, 1995; Schank, Collins, & Hunter, 1986). Although there has been some recent acknowledgement of this relationship (Jee & Wiley, 2007; Love, 2005), most work in category learning has not meaningfully engaged with this issue.

Goals and Category Learning

Category learning research addresses the fundamental question of how we learn to recognize coherent categories of items in the world. The current study is designed to explore the roles that goals play in establishing that coherence. There are two primary points that we emphasize: Goals guide the processing that occurs during interactions and naturally constrain similarity among items in a meaningful way that underlies the category coherence. We explore both of those ideas in the following sections.

Goals Constrain Similarity. Theories of categorization need to address what ties together items within a category and subsequently structures the conceptual organization that reflects those categories. Most category learning theories rely on a notion of similarity to ground that cohesion (Hahn & Ramscar, 2001), so the question shifts to how similarity is determined. There have been two basic approaches to addressing the source of similarity (Malt, 1995). The first assumes that the environment constrains the similarity – items in the world occur in reliable clusters and the conceptual system learns to recognize that structure (e.g. Anderson, 1991; Rosch et al., 1976). That view can be contrasted with one that places much of the emphasis on pragmatic factors to constrain the similarity (e.g.

Murphy & Medin, 1985). Although most researchers interested in concepts and categories stake out some middle ground in this debate, much of the experimental work in human category learning reflects the assumption that the environment provides the necessary structure to constrain similarity (Markman, 2005). Experimental studies of category learning have almost exclusively used stimuli comprised of easily separable features and category structures with only one "correct" organization for the items. This creates a situation where the structure, both in terms of the feature information and the categorical structure, is explicitly "out there" and participant is tasked with learning how to correctly respond in terms of that structure. Within these experimental contexts, we learn about the participant's ability to discover a particular category structure – a focus that assumes that category learning primarily involves learning to recognize the structure of the world. However, if category learning is also guided by pragmatic factors, and below we discuss ample evidence that this is the case, then the typical experimental approach provides an incomplete, and possibly misleading, picture of how category coherence develops.

We begin this research with the assumption that the environment does provide structure, but the immediate situation of the individual – their knowledge, experiences, goals, etc. – interacts with that structure, shaping how it is interpreted and incorporated into the conceptual knowledge (Goldstone & Barsalou, 1998). The interaction between these pragmatic factors and the environment occurs at multiple levels, including both the interpretation of relevant feature information (Landy & Goldstone, 2005; Schyns, Goldstone, & Thibault, 1998; Wisnewski & Medin, 1994) and the conceptual organization of the domain (Jee & Wiley, 2007; Love, 2005). Medin, Lynch, Coley, and Atran (1997) provide an illustration of these influences in a naturalistic domain. When various tree experts were asked to organize trees into coherent groupings, tree experts concerned with research and teaching tended to create groups that were highly correlated with the biological taxonomy, but landscapers tended to create groups that reflect the way the trees would be incorporated into landscaping decisions, e.g. a shade tree versus a weed tree. These organizations are divergent, yet both coherent, and they rely on different feature sets to constrain the similarity that coheres the categories. This naturalistic study provides an illustration how goals can help to determine what is a relevant feature, whether leaf shape or amount of shade provided, and how that information can then be used to create useful and coherent categories. Acknowledging the complexity of real world categories does not mean that we take the position that conceptual structure is entirely up for grabs, but it does mean that the complexity has to be addressed. If we accept that people learn about categories in the course of working towards goals, the complexity and coherence we see in real world categories becomes tractable without relying on the assumption that the structure is invariant and predetermined.

The Function of Goals in Category Learning. The process of feature selection has been central to theories of classification learning (e.g. Kruschke, 2003; Nosofsky, 1984; Rehder & Hoffman, 2005). Research extending the scope of category learning beyond the classification paradigm has also found that feature selection plays a role (Ross, 1997, 1999, 2000), and that this process depends on the goal of the learner. For instance, when participants used particular features to make predictions about items after having classified them, those features were used in later classification decisions even though they were initially non-diagnostic of the categories (Ross, 1997). More directly related to the current studies, Jee and Wiley (2007) showed that manipulating the goal of participants as they interacted with a set of items, whether they sought to learn about predation or food sources within categories of novel creatures, resulted in a shift in the feature selection and subsequently how they structured those categories. Across a variety of situations, feature selection has been identified as a critical process associated with category learning, and there is clear evidence that the learner is oriented towards features that are goal relevant. Thus, there is strong evidence that goals guide attention to goal-relevant features and thus help to select out those features for incorporation in the resulting conceptual organization. We will call this the *goal-orientation hypothesis*.

However, the goal-orientation hypothesis rests on two assumptions that we find to be problematic. First, the feature information must be available at the onset of the learning. Second, this approach posits that simply attending to particular information, or features, is sufficient to embed that information into the categorical knowledge. In order to address these issues, we propose a *goal-framework hypothesis* as an alternative way of conceptualizing the role of goals in category learning. As has been noted above, the goal acts as an organizational structure that guides the recognition of what is relevant and how various pieces of information fit together. This approach subsumes the notion of feature selection, because the goal continues to play the critical role of identifying relevant information during the interaction. However, it also provides a way to account for the development of feature language and to distinguish between simply attending to a piece of information and incorporating it into a coherent conceptual framework.

The first issue involves how information about features develops during the category learning process. If the information underlying the categories is ambiguous, then feature selection by itself is not able to capture the totality of the processing involved in category learning. Just as the environment does not provide clearly demarcated categories of items, the environment does not provide clearly defined features, and the feature language for a particular situation has to be learned (Landy & Goldstone, 2005; Schyns, Goldstone, & Thibault, 1998; Wisnewski & Medin, 1994). In order to accommodate the development of a feature language and the subsequent feature selection, a more comprehensive processing framework is necessary. A goal framework provides just such a structure, one that can accommodate the emergence of the feature language during the interactions within a domain. A clear example of this occurring can be found in Schyns and Rodet (1997). When the participants were given the goal of categorizing a set of "martian cells", they came to recognize a set of features in the items that reflected the classifications they had made to that point. Altering that classification experience altered what features the participants recognized in the stimuli. Schyns (1998) proposed that the features arise from an interaction between the information available from the environment and the demands of the task being completed. The focus of Schyns and Rodet (1997) was on a classification task, but we propose that any task requiring the differentiation of components of the items would entail the development of a feature language that reflects the particular demands of that task. The goal construct provides a structure that would constrain that process.

The second issue relates to the notion of category coherence addressed above. Oftentimes, the coherence is affected by the presence of prior knowledge related to the particular goal of the individual. For instance, Pazzani (1991) showed that participants pictures of individuals interacting with balloons and asked the participants to either classify the picture according to an arbitrary label, "alpha/not alpha", or whether the pictures showed a situation when the balloon would be inflated. In the arbitrary label condition, participants more quickly discovered a conjunctive rule, the balloon involved was small and yellow, than a disjunctive rule, the person was an adult or the balloon was being stretched. Those results fit nicely with earlier research showing that conjunctive rules are easier to learn than disjunctive ones (e.g. Bruner, Goodnow, & Austin, 1956). However, when the goal was to classify the picture in terms of whether the balloon would be successfully inflated, the participants were faster to learn the disjunctive rule than the conjunctive one because prior knowledge suggests that the age of the person inflating the balloon and how it is handled impact whether the balloon will inflate. Simply attending to particular information, as occurs during feature selection, does not address what connects the various facets of the category knowledge. Just as prior knowledge provides a way to bind category knowledge (Murphy & Medin, 1985), we argue that a goal framework provides a meaningful way to organize and cohere the information acquired about a category.

As the individual engages in a goal-directed task, the goal framework develops through those interactions. In the case that the individual encounters the same type of item repeatedly, she would learn about that type of item, including what would be considered goal-relevant features based on her interactions. Importantly, if the individual's interactions bring her into contact with items that differ in terms of how she would interact with them in order to reach her goal, then the structure would develop in a way that reflects those variations among the items. This is a dynamic process that Love (2005) describes as a "flexible search for structure", and it accounts for the development of the inter-category structure, the differentiation of the categories, that most category learning studies have focused on.

The goal-framework hypothesis extends previous study of category learning in two ways. First, it provides a way to understand what guides the selection of information that underlies the development of a useful feature language, one that will support goal-directed interactions. Second, it accounts more fully for structure of conceptual knowledge. Specifically, it provides a means to organize the information both in terms of the internal structure, how the features of the items cohere, and the categorical structure, what differentiates different types of items that might be encountered.

The Current Study

Having a goal orients an individual to the world in a particular way, and this occurs at a very basic level of our experience (Dijksterhuis & Aarts, 2010; Vogt, Houwer, Moors, Van Damme, & Crombez, 2010). The orientation supports the development of a suitable feature language (Landy & Goldstone, 2005) that allows the individual works towards her goal. Throughout, the goal framework provides a structure to these processes, from picking out and interpreting features to providing structure for the conceptual knowledge. This process occurs as a result of the goal-directed interactions – even in a situation when the person has no intention for "category learning" and it is not provided with any information about the presence of distinct categories or even what constitutes a feature within the domain.

In the experiments reported below, we examined category learning that occurs as the result of goal-directed interactions in order to test the goal-framework hypothesis. The items the participants interacted with were from a novel domain – "Flux Capacitor Boards," physical boards with various electrical components (non-functioning) affixed to them. Participants were given tasks to complete with the boards; the tasks primarily involved placing connectors onto the boards, although a classification condition was included in Experiment 1 in order to allow us to examine that learning task within this experimental paradigm. As is described in the Methods section, we created the boards so that there were two types of boards that the participant would encounter during her initial task, and in the non-classification conditions the placement of the connectors reflected the different types of boards. It is critical to note that the participants in the non-classification conditions were not informed that these categories existed; they were simply asked to complete their assigned task with the boards. The only feedback the participants in those conditions received was inherent in the task they completed; successful placement of the connectors onto a board constituted positive feedback, and an inability to place the connectors onto the board constituted negative feedback. For each of the non-classification conditions, particular features of the boards were relevant to the placement of the connectors, and the focus of the study was on how these *goal-relevant features* of the boards were incorporated into the knowledge acquired by completing the task.

The primary hypothesis for both experiments was that the goal-directed interactions would guide the development of useful and coherent conceptual knowledge within a novel domain. In Experiment 1, we considered two secondary hypotheses. First, we predicted that the goal-directed learning would allow participants to capture information about both concrete and relational features in their conceptual knowledge. Second, we predicted that classification learning would result in the participants developing some knowledge of the boards, but it would be variable across the participants because the domain did not have a single, specific structure guiding the classification feedback. In Experiment 2, we focused on differentiating the goal-orientation and the goal-framework hypotheses. We predicted that simply having to attend to an aspect of the boards would not be sufficient for it to be fully integrated into the conceptual knowledge. Instead, the feature would need to fit within the goal framework in order for it to become a meaningful component of the conceptual knowledge.

Experiment 1

The first experiment was designed to test the first set of hypotheses outlined in the Introduction. Participants interacted with the same set of items, but were given different tasks so that goal-frameworks differed across the conditions. The transfer tasks were designed to assess how the participants organized their knowledge of the items.

Methods

Participants and Design. Fifty-seven participants were randomly assigned to three experimental conditions: 18 participants were assigned to the *flexible condition*, 19 to the *solid condition*, and 20 to the *classification condition*. Two participants in the classification condition failed to show evidence of learning during the initial task, so their data were removed from all analyses. All participants interacted with the same set of "Flux Capacitor Boards" during the initial task and completed the same transfer tasks. The presentation order of items during the initial and transfer tasks was randomized for each participant.

Materials and Procedure. The primary materials for the study consisted of "Flux Capacitor boards" and the connectors used to complete the boards. Each board had a series of nine terminal posts and various electrical components affixed to the board. Figure 1 provides simplified schematics of the boards. The posts on each board were organized into three sets: One set in the upper, left-hand region of the board, one in the middle region, and one in the lower, right-hand region. The other components were placed around these posts according to the parameters described below. The boards were designed so that there were

Figure 1: Schematic of Problem Boards from Experiment 1

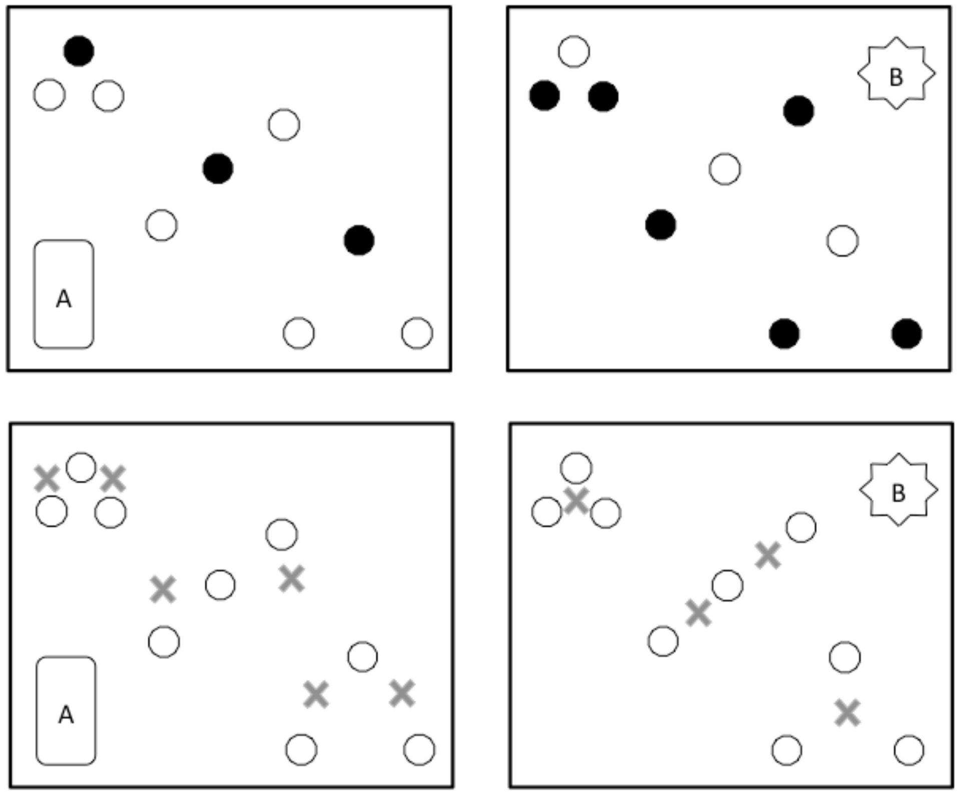

Figure Note: The boards on the left represent Type A boards, and the boards on the right represent Type B boards. The top boards show the distribution of the capped and drilled (filled circles) and open (unfilled circles) terminal posts that were goal-relevant in the flexible condition. The bottom boards show the possible placement of the blocking components (each represented by an "x") that were goal-relevant in the solid condition. On the Type A boards, the rectangle in the lower, left-hand corner represents the correlated component. On the Type B boards, the star in the upper, right-hand corner represents the correlated component.

two types of boards that the participants encountered during the initial task, described below as Type A and Type B boards, and variations of these two types of boards were created for the transfer tasks. During the initial task, participants in the flexible and solid conditions were given connectors that they placed onto the terminal posts to complete each board. The participants in the classification condition did not use connectors during their initial task.

Figure 2 provides examples of the actual boards used in the study. As in Figure 1, the Type A boards are on the left, and the Type B boards are on the right. In the top set of boards, there are no connectors present and configuration of the posts and components can be seen for each type of board.

Figure 2: Example Problem Boards from Experiment 1

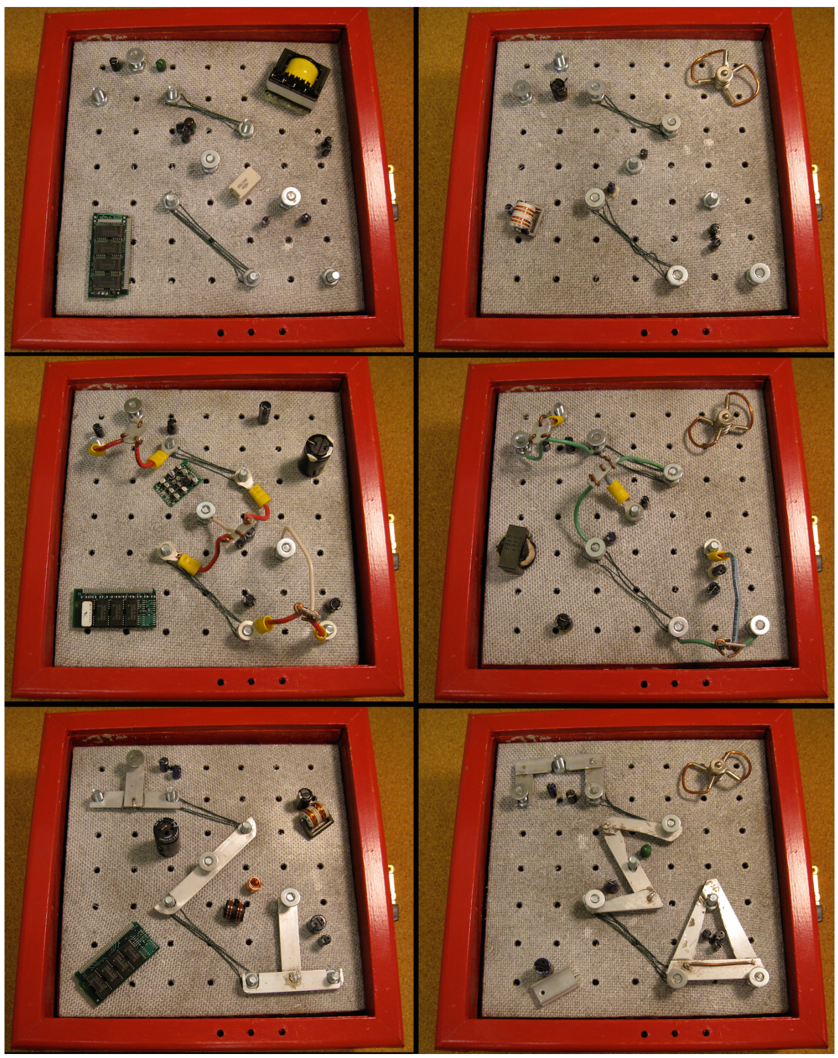

Figure Note: The boards on the left are Type A boards, and the boards on the right are Type B boards. The top images show boards with no operators present. The center images show boards completed with the flexible connectors. The bottom images show boards completed with the solid connectors.

In the middle set of boards, the flexible connectors are in place. These connectors were made of wire and varied in terms of how they fit onto the terminal posts: The connector either fit over an open post or was inserted into a hole drilled into a "capped and drilled" post. Each set of terminal posts in the Type A boards featured one post that has been capped and drilled and two posts that were open. In contrast, the Type B boards featured sets consisting of two capped and drilled posts and one open post. The configuration of the posts is considered to be the goal-relevant feature for the flexible condition because they constrain how the flexible connectors can be placed onto the board. The relationship of the components around the posts did not affect the placement of the flexible connectors.

In the bottom set of boards, the solid connectors are in place. In the solid condition, the connectors were made of inflexible aluminum pieces, and the placement of these connectors was constrained by the presence of components situated near the terminal posts. For the Type A boards, the connectors had to go between components in order to fit onto the posts. For the Type B boards, the connectors had to go around the components. Thus, the relationship of the components to the posts is considered the goal-relevant feature for the solid condition because it constrained how the solid connectors could be placed onto the board. The configuration of posts, whether they were open or capped and drilled, did not affect the placement of the solid connectors.

The electrical components placed around the posts were unique to each board. However, each of the boards featured a perceptually salient *correlated component*. The correlated component for the Type A boards was a two-inch section of a computer memory module placed in the near left corner, and the correlated component for the Type B boards was a stack of silver clips with copper wire loops placed in the far right corner. These components were not implicated in how the connectors in either condition could be placed onto the board but they were perceptually salient and perfectly diagnostic of the two board types.

There were eight boards used in the initial task phase, half were Type A and half were Type B, and each board was encountered twice during this task. Participants in the classification condition were told that the boards needed to be identified as "positive flux" or "negative flux" boards. At the start of each trial, a board was placed into a holder set in front of the participant, and after the participant responded with either "positive flux" (correct for the Type A boards) or "negative flux" (correct for the Type B boards) the experimenter provided feedback about the classification and allowed the participant to study the board. Participants in the solid and flexible conditions were asked to complete the boards by placing three of the six connectors onto the terminal posts. The set of connectors they had to work with depended on their condition. The experimenter placed a board into the holder, and the participant attempted to place connectors onto the board. Participants were told a variant of "good job" once the three connectors had been placed onto the board. After each trial, the board was removed from sight and a new board was placed into the holder.

After the initial task, all participants completed the same transfer tasks. The materials for the transfer tasks consisted of photographs of flux capacitor boards the participants had not encountered during the initial task. The boards in the images varied in terms of how they related to the Type A/Type B board distinction that had been present during the initial task. No feedback was given to participants as they completed the transfer tasks.

First, the participants completed the *same-different task*. During each trial, the participant was presented with images of two boards affixed to a single piece of paper. She was asked to indicate whether she would consider the two boards pictured to be the same type of board or different types of boards. No specification was provided as to what was meant by "type", and the participant was instructed to use her best judgment. Across the sixteen items in the same-different task, we balanced whether the boards matched or mismatched in terms of the goal-relevant features for each condition. Eight of the pairs of boards maintained the same structure as the initial tasks boards; four of those pairs matched in terms of the goal-relevant features for both the flexible and solid conditions and four mismatched with regard to both types of goal-relevant features. All participants regardless of condition should identify the subset of matched boards as the same and the mismatched boards as different if they picked up on any of the sources of information that differentiated the Type A and Type B boards during the initial task. The other eight boards were designed so that the goal-relevant features for the solid and flexible conditions were placed into opposition. Four of these board pairs were designed so that flexible condition goal-relevant features matched while the solid condition goal-relevant features mismatched. The other four board pairs were designed so the flexible condition goal-relevant features mismatched while the solid condition goal-relevant features matched. The correlated components were replaced by perceptually dissimilar components on these boards so that those features would not affect the same-different judgments.

In the *sorting task*, participants were given pictures of eight novel boards that were structured like those encountered during the same-different task. The boards were balanced as to whether the goal-relevant features for the solid or flexible condition matched the Type A boards or the Type B boards encountered during the initial task. At the start of the sorting task, the stimuli were spread out randomly on the desk in front of the participant, and she was asked to sort the boards into groups that reflected which boards she thought belonged together. Once the participant indicated the grouping was complete, the experimenter recorded which boards had been placed together. Inadvertently, the participants in the flexible and solid conditions were explicitly told to create two groups of boards while the participants in the classification condition were not given that specific instruction.

The *category goodness-rating task* was the final task. The participant was first shown a target board, one of the boards solved during the initial task phase, and was told that the board was either an “X-12” (Type A) or “G-59” (Type B) board. She was asked to rate each subsequent board in that block of items in terms of the category represented by the target board on a scale from one (“not this board type ”) to nine (“excellent example of this board type”)[1]; also anchored at three (“poor example of this board type”), five (“ok example of this board type”), and seven (“good example of this board type”). After the participant studied the target board for a minute, it was removed, and the items for the goodness-rating task were shown to the participant one at a time. There were five types of boards pictured in the stimuli for this task, and the participant rated two of each type for each of the categories. The *category consistent* boards were structurally identical to the

[1] The category goodness scale was reverse scored for this experiment. In the study, the participants responded to a scale where lower values indicated a better member of the category. The scaling presented here was used in Experiment 2 and reviewers thought it provided a more intuitive measure of category goodness, so we report the reverse scored results for this experiment.

target board. The *category inconsistent* boards were structured like the other type of board; so if the target board was a Type A board, the category inconsistent board was a Type B board. The *correlation violation* boards were the same type of board as the target board, but the correlated feature was replaced by a small, perceptually dissimilar component. The *flexible violation* boards were of the same type as the target board, but were altered so the flexible connectors would not fit onto the posts. The *solid violation* boards were also of the same type as the target board, but they were altered so the solid connectors would not fit. Once the participant completed rating the ten boards for the first type, the target board for the second type was shown to the participant, and the task repeated for the second type of board. The order of the category blocks was balanced across the participants.

Results and Discussion

Same-Different Task. The proportion of each type of item identified as "the same" by each of the conditions is reported in Table 1. The responses of the flexible and solid conditions clearly track whether the boards matched in terms of the goal-relevant features of each condition. For instance, when a set of boards matched in terms of the flexible-relevant features (flexible +), the participants in the flexible condition judged the boards to be "the same", and when they mismatched (flexible -), they did not consider them to be "the same". Across all items in the task, both the flexible condition, $M = 0.95$, $SD = 0.13$, $t(17) = 14.72$, $p < 0.001$, and the solid condition, $M = 0.87$, $SD = 0.18$, $t(18) = 8.64$, $p < 0.001$, were above chance performance in terms of assigning the pairs as the same or different in terms of the goal-relevant features for their conditions. The difference between the flexible and solid conditions was not significant, $t(35) = 1.57$, $p = 0.12$.

A similar summarization of the results for the classification condition is not possible because there was no a priori prediction of how the classification participants would judge the items when the features relevant for the solid and flexible conditions were placed in opposition. However, as can be seen in Table 1, when both of the goal-relevant features matched, the participants in the classification condition tended to consider the boards as the same, and when both did not match, they tended to consider the boards as different. When the goal-relevant features for the flexible and solid conditions were put into opposition (as in the "Flex + / Solid -" and "Flex - / Solid +" items), the participants in the classification condition did not show a strong preference for one source of information over the other as a group. Within the classification condition, five participants had a pattern of response that indicated that they were using information about the goal-relevant features for the flexible condition, four participants appeared to be using information about the goal-relevant features for the solid condition, and nine participants had a pattern of responding that did not clearly indicate a preference for either source of information.

Table 1: Proportion of Items (standard deviation) Identified as "the same" in the Same-Different Task from Experiment 1

	Relationship of Boards in the Pair Evaluated			
	Flex +	Flex -	Flex +	Flex -
Condition	Solid +	Solid -	Solid -	Solid +
Flexible	0.94	0.01	0.90	0.04
	(*0.24*)	(*0.06*)	(*0.26*)	(*0.18*)
Solid	0.86	0.11	0.15	0.86
	(*0.21*)	(*0.23*)	(*0.29*)	(*0.21*)
Classification	0.83	0.19	0.46	0.36
	(*0.33*)	(*0.24*)	(*0.39*)	(*0.36*)

Table Notes: For each item, the boards pictured either matched in terms of the goal-relevant features for the flexible (Flex +) or solid (Solid +) conditions or mismatched in terms of those features for the flexible (Flex -) or solid (Solid -) conditions.

Sorting Task. Due to the nonequivalent task instructions given to the classification and other conditions noted in the Methods section, the results from the sorting task cannot be compared across all three conditions. However, descriptive results from the task are useful to consider. In the flexible and solid conditions, nearly all participants sorted the boards into piles that reflected the goal-relevant features. In the solid condition, 18 out of 19 participants put the boards into groupings that reflected the organization of the components around the posts. In the flexible condition, 17 out of 18 participants put the boards into groupings that matched the configuration of the posts. In the classification condition, 5 participants grouped the boards like the solid condition, 4 grouped them like the flexible condition, and 9 participants provided some other sort for the boards in the task.

Category-Goodness Rating Task. The data from the category-goodness rating task (see Figure 3) were analyzed using a series of mixed ANOVAs. Across these tests, the ratings for the consistent boards were compared to the ratings given to each of the other types of boards in order to determine what aspects of the boards affected the goodness ratings of each condition. In these analyses, the consistent boards provide a baseline for the ratings of boards considered to be "good members" of the target category and the other types of boards represent different ways that the boards can differ from those items. Each of the omnibus tests was followed up with a series of paired sample *t*-tests that compared the ratings of the two types of boards involved in the analyses within each condition.

Figure 3: Mean Category-Goodness Ratings by Condition and Item Type from Experiment 1

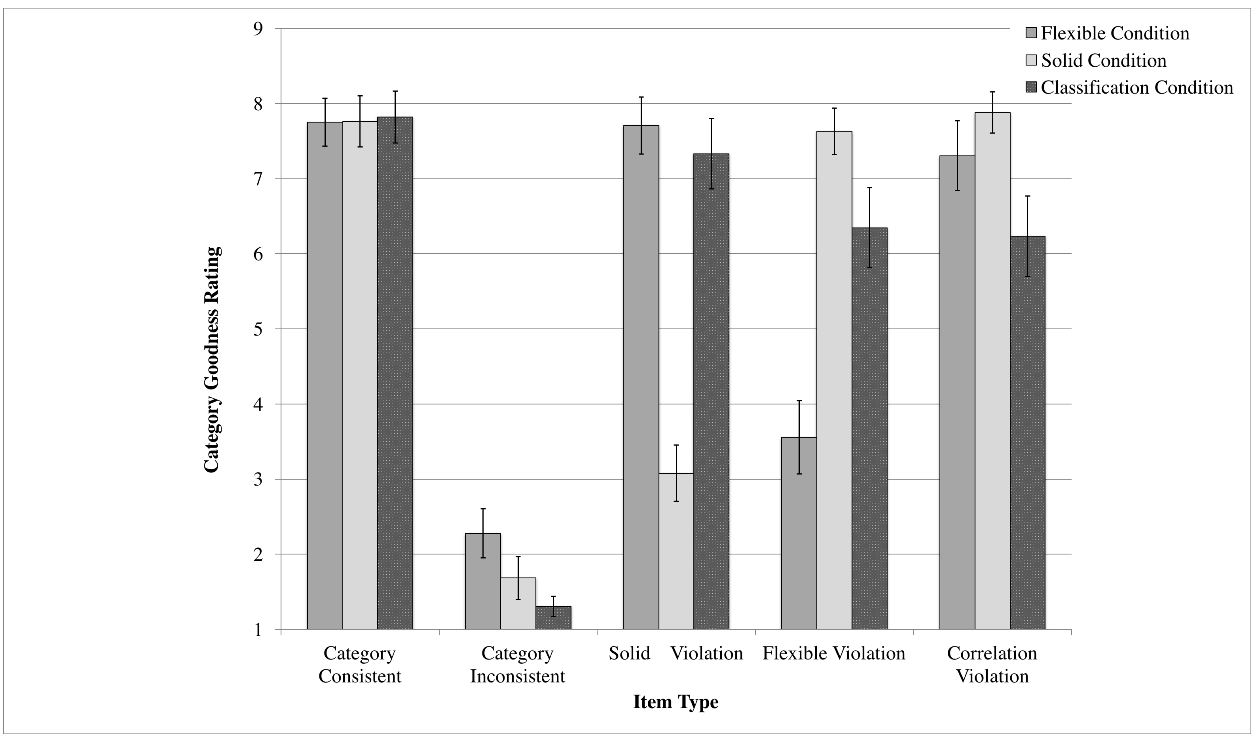

Figure Note: The category-goodness rating scale ranged from one ("not this board type") to nine ("excellent example of this board type"). Error bars represent +/- one standard error of the mean.

The first comparison is between the ratings for the consistent and inconsistent boards. A 2 (type of board: consistent, inconsistent) X 3 (condition: classification, solid, flexible) mixed ANOVA revealed a main effect of the type of board, $F(1, 52) = 522.63$, $p < .001$, $\eta_p^2 = .91$, but no effect of condition, $F(2, 52) = 1.31$, $p < .27$, $\eta_p^2 = .05$, and no interaction, $F(2, 52) = 1.29$, $p = .28$, $\eta_p^2 = .05$. All three conditions showed a similarly large difference between the ratings for the board types, all ts > 10.00.

The second comparison examines the ratings for the consistent and correlation violation boards. A 2 (type of board: consistent, correlation violation) X 3 (condition) mixed ANOVA revealed a main effect of the type of board, $F(1, 52) = 13.33$, $p = .001$, $\eta_p^2 = .20$, no effect of condition, $F(2, 52) = 1.27$, $p < .29$, $\eta_p^2 = .05$, but a significant interaction, $F(2, 52) = 8.27$, $p = .001$, $\eta_p^2 = .24$. The interaction is present because the classification condition showed a difference in their ratings of the consistent and correlation violation boards, $t(17) = 3.56$, $p = .002$, the flexible conditions showed a marginal difference, $t(18) = 1.82$, $p = .09$, and the solid condition showed no meaningful difference, $t(18) < 1.00$.

The third comparison examines the ratings for the consistent and solid violation boards. A 2 (type of board: consistent, solid violation) X 3 (condition) mixed ANOVA showed a main effect of the type of board, $F(1, 52) = 50.73$, $p < .001$, $\eta_p^2 = .49$, a main effect of condition, $F(2, 52) = 17.85$, $p < .001$, $\eta_p^2 = .41$, and a significant interaction, $F(2, 52) = 37.42$, $p < .001$, $\eta_p^2 = .59$. The interaction in this analysis occurs because the ratings of the boards differed in the solid condition, $t(18) = 7.59$, $p < .001$, but not in the other two conditions, both ts < 1.60.

The final analysis in this series compares the ratings of the consistent and flexible violation boards. A 2 (type of board: consistent, flexible violation) X 3 (condition) mixed ANOVA revealed a main effect of the type of board, $F(1, 52) = 49.09$, $p < .001$, $\eta_p^2 = .49$, a main effect of condition, $F(2, 52) = 11.00$, $p < .001$, $\eta_p^2 = .30$, and a significant interaction, $F(2, 52) = 18.83$, $p < .001$, $\eta_p^2 = .42$. When rating these types of boards, both the classification condition, $t(17) = 2.68$, $p = .02$, and the flexible condition, $t(17) = 6.98$, $p < .001$, rated the two types of boards differently, but the solid condition rated them similarly, $t(18) < 1.00$.

Discussion. Across the three dependent measures, there is strong support for our initial hypotheses. The results show that the participants in the flexible and solid conditions consistently made judgments about novel boards that corresponded to the goal-relevant information. The participants in the flexible condition were sensitive to the configuration of the posts, and those in the solid condition were sensitive to the relationships between the posts and the other components on the board. In this experiment, participants were able to learn about both concrete and relational features. In each case, they developed a feature language that reflected the goal-relevant aspects of the boards. The process also made the participants less likely to pick up on changes to the non-relevant aspects of the boards. This can be most clearly seen in the category-goodness rating task where the participants in the solid conditions did not respond to changes in the terminal posts and participants in the flexible condition did not respond to changes in how the components sat in relation to the posts. Neither of these conditions responded to changes in the correlated component despite its relative salience and invariance across the boards of each type. Importantly, this category learning occurred naturally as the participants were focused on completing their task, not on specifically learning about the categories.

The classification condition was included as a point of comparison and to illustrate how that learning paradigm extends into a situation using a more complex category structure. The majority of the participants in the classification condition were able to accurately classify the boards during their initial task, but the presence of redundant diagnostic cues meant that across the condition they varied as to what features they used to organize their knowledge of the categories. As a group, they showed that they used information about the correlated components and the terminal posts to some degree during the transfer tasks. However, it is less clear whether they picked up on the relations between the terminal posts and the other components in the way that participants in the solid condition did as their performance on the most sensitive test of that information, the category-goodness rating, did not show that they were sensitive to that information.

Experiment 2

The initial experiment provided clear evidence that goal-directed interactions within a domain result in the acquisition of conceptual knowledge that reflects the goal.

However, in the previous experiment it is difficult to untangle what role the goal played and what role the interaction had. For instance, the participants in the flexible condition always interacted directly with the terminal posts as they placed the connectors onto them, and the configuration of the posts captured the goal-relevant information. Thus, one way to interpret the findings of the previous experiment is that the assigned task guides attention that then constrains what subset of the information is captured in the category knowledge. This notion is line with the goal-orientation hypothesis. We have proposed a more integral role for the goal framework. Instead of simply directing attention, the goal provides a means to organize the knowledge, and the goal-relevance of the information acquired during the interactions has a foundational role in that organization. Jee and Wiley (2007, Exp. 3) began to explore a similar idea by having participants interact with the stimuli without a clear goal in mind, what they termed a "mere use" condition. They found that this experience did not result in the same kind of shift in the organization of the knowledge that had occurred in their goal-directed conditions. They suggested that this occurred because the participants did not have a clear goal to cohere the information. We extend the exploration of that idea in this experiment.

In order to differentiate between the goal-orientation and goal-framework hypotheses, we revised the initial task associated with the flexible condition from the previous experiment. All participants in Experiment 2 had to place flexible connectors onto the terminal posts during the initial task, so the interactions of all participants oriented them to the terminal posts. In the *middle-relevant condition*, the participants completed the boards using the flexible connectors used in Experiment 1, replicating the flexible condition from that experiment. In the *middle-irrelevant condition*, the participants were given a new set of flexible connectors. The connectors that fit onto two sets of the terminal posts were identical to those used in the other condition, but only one connector was provided for the center set of terminal posts – regardless of the board type encountered, the participants in the middle-irrelevant condition would place the same connector onto the center set of terminal posts. Even though the configuration of the center set of terminal posts distinguished the two types of boards and the participants were oriented to those terminal posts as they placed the connector onto them, we predicted that the participants in the middle-irrelevant condition would not be as sensitive to the configuration of the center set of terminal posts as the other post sets. This would occur because the configuration of the middle set of posts did not distinguish the placement of a connector in the way that they did in the middle-relevant condition. In other words, the specific configuration of the middle set of terminal posts would not be goal-relevant (it would not affect how the connectors were placed) and so it would not be fully integrated into the knowledge of the different types of boards.

Methods

Participants and Design. Thirty participants were randomly assigned to either the middle-relevant condition or the middle-irrelevant condition. All participants interacted with the same set of “flux capacitor boards” during the initial task and completed the same category-goodness rating task during transfer. The presentation order of items during the initial and transfer task was randomized for each participant. The order of the category-goodness rating blocks was balanced across participants.

*Materials and Procedure***.** The experiment used procedures and materials that were much like those used in the flexible condition in Experiment 1. The initial instructions and basic procedure for the experiment was unchanged. Participants were provided with a set of connectors and were asked to complete each of the boards they were given with a subset of the connectors. Once the connectors were correctly placed onto a board, the trial ended and the participant was given the next board to complete. As prior, the participants interacted with eight boards during the initial task, completing each board twice. No mention was made about types or categories of boards during the initial task, and the only feedback provided was in terms of whether the connectors had been properly placed onto the boards.

The participants in the middle-relevant condition were given the same six flexible connectors that had been used in Experiment 1. The participants in the middle-irrelevant condition were given five flexible connectors. The four connectors that fit onto the two outer sets of posts were identical to those used in the middle-relevant condition, and the placement of those connectors depended on the configuration of the posts. However, the two connectors used on the middle set of posts were replaced with a single connector that could be used on the middle set of connection posts of all of the boards encountered during the initial task. This meant that the participants in the middle-irrelevant condition had to specifically attend to the middle posts during the task so that they could place the connector, but the characteristics of those posts were not relevant to the placement of the connector.

In Experiment 2, the participants only completed the category-goodness rating task during transfer. After being introduced to the task, the participants saw a target board, which was one of the boards completed during the initial task, and then were asked to rate a series of boards that differed in their relationship to that target board. The participants were provided with a scale ranging from one ("not this type of board") to nine ("excellent example of this board type") with the same intermediate anchors described previously. As before, the target board was removed from sight before the ratings were made, and participants rated *consistent*, *inconsistent*, *flexible violation*, and *solid violation* boards. Participants were not asked to rate correlation violation boards in Experiment 2. In order to assess differences in sensitivity to the three sets of posts on the boards, new transfer boards were created for the task. In addition to the flexible violation boards, that featured violations to all three sets of posts, the new types of boards varied in terms of whether the violation occurred to the center set of posts or one of the two outer sets of posts. Violations were made independently to the top-left or bottom-right sets of posts, referred to as *outer-violations*, or the middle set of posts, referred to as a *mid-violation*. Participants rated three of each kind of board during the task resulting in 18 Type A and 18 Type B boards being rated. After participants completed the rating for one of the board types, they were asked to complete the ratings for the other board type.

Results and Discussion

Category-Goodness Rating Task. The ratings for each of the types of boards are reported in Figure 4. After the data were collected, it was discovered that the Type A solid violation boards used in the experiment had a violation to the top-left set of posts, so only the results of the solid-violation boards for the Type B boards are considered in the Results section. This issue does not impact the results critical to the primary hypotheses of the experiment as the participants' ratings for boards that had violations to the outer sets of the posts were collapsed together into one term. A preliminary analysis showed no difference in the participants' ratings for the top-left and bottom-right violations regardless of the condition, so this summarization of data appears appropriate and facilitates our comparison of the effect of a violation to the middle set of posts to the effect of a violation of those outer sets of posts.

Figure 4: Mean Category-Goodness Ratings by Condition and Item Type from Experiment 2

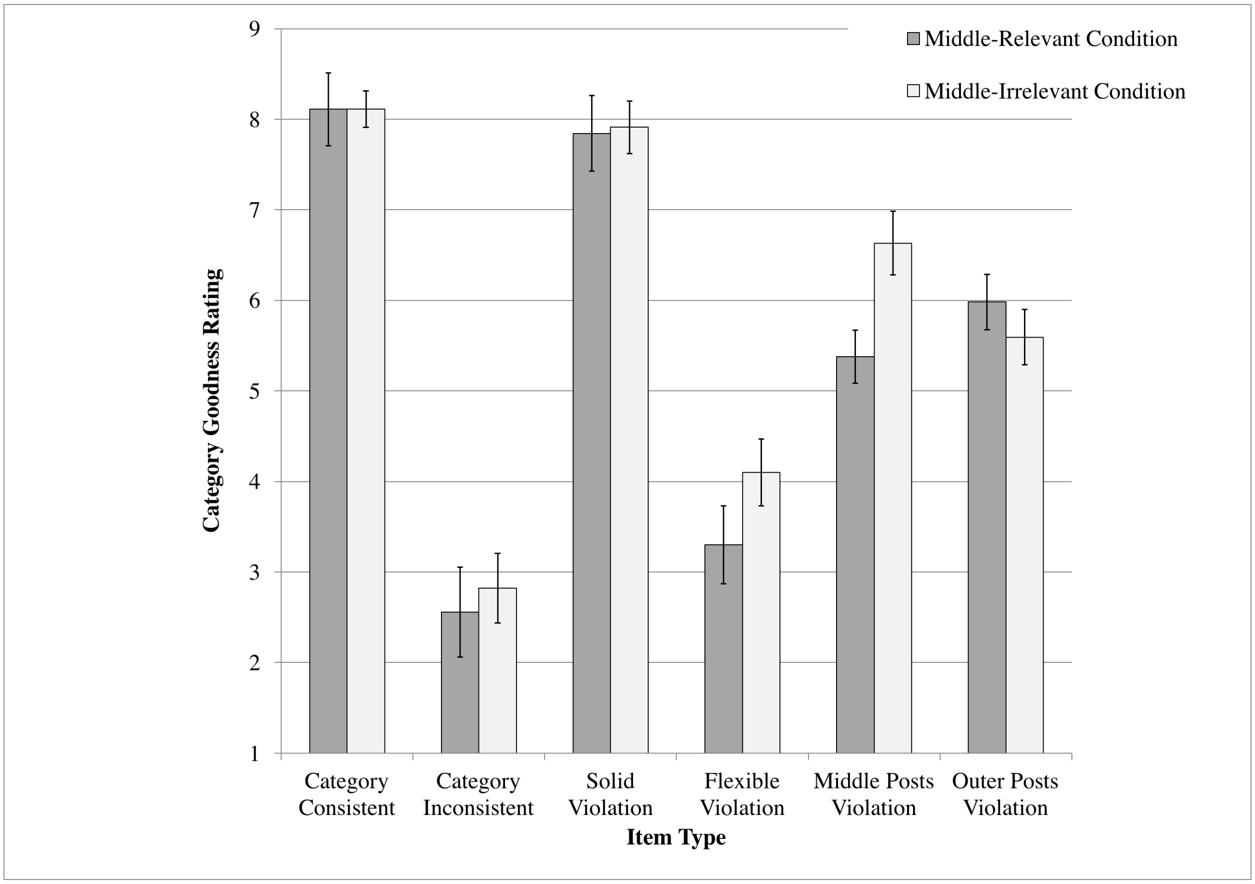

Figure Note: The category-goodness rating scale ranged from one ("not this board type") to nine ("excellent example of this type of board"). Error bars represent +/- one standard error of the mean.

Initially, we examined the participant ratings of the consistent, inconsistent, flexible violation, and solid violation boards. We assumed the two conditions would not differ in how they rated these boards – the consistent and solid violation boards would be rated as good matches of the target category while the inconsistent and flexible violation boards would be rated as poor members of the category. A 2 (condition: middle-relevant, middle-irrelevant) X 4 (board type: consistent, inconsistent, flexible violation, solid violation) mixed ANOVA was used to analyze the ratings for these types of boards. There was a main effect of board type, $F(3, 84) = 103.72$, $p < .001$, $\eta_p^2 = 0.79$, no main effect of the condition, $F(1, 28) = 1.19$, $p = .29$, $\eta_p^2 = 0.04$, and no interaction between the factors, $F(3, 84) = 0.43$, $p = .73$, $\eta_p^2 = 0.02$. The consistent boards were rated as significantly better members of the category than the inconsistent boards and the flexible violation boards, both $t(29)$s > 10.00. There was no difference in the ratings for the consistent and the solid violation boards, $t(29) = 1.49$, $p = .15$. With regard to their ratings of this subset of the boards, the two conditions performed equivalently.

The primary hypothesis focuses on the ratings for the mid-violation and outer-violation boards. A 2 (condition: middle-relevant, middle-irrelevant) X 2 (board type: outer-violation, mid-violation) mixed ANOVA shows that there was no main effect of condition, $F(1, 28) = 1.12$, $p = .30$, $\eta_p^2 = 0.04$, no main effect of the type of board being rated, $F(1, 28) = 1.20$, $p = .28$, $\eta_p^2 = 0.04$, but there was a significant interaction between the factors, $F(1, 28) = 16.19$, $p < .001$, $\eta_p^2 = 0.37$. The interaction occurred because the middle-relevant condition rated the mid-violation boards as marginally worse category members than the outer-violation boards, $t(14) = -1.98$, $p = .07$, while the middle-irrelevant condition rated the mid-violation boards as significantly better category members than the outer-violation boards, $t(14) = 3.85$, $p = .002$.

Discussion. In order to test whether the goal does more than simply orient attention, we manipulated the participants' interactions with a subset of terminal posts on the boards. In both conditions, a flexible operator had to be placed onto the critical set of posts, so the participant had to attend to the posts in order to correctly place the operator. The difference between the conditions was whether the features of the posts, whether they were capped and drilled or not, were relevant to placing the operator. So, all participants were oriented to the center posts while completing the task, but only the middle-relevant condition used those posts help to determine what connector should be used. As predicted, the participants in the middle-relevant condition were more sensitive than the participants in the middle-irrelevant condition to changes to the middle set of posts during the transfer task. Interestingly, the middle-relevant condition, where all three sets of posts were goal-relevant, appeared to put somewhat greater emphasis on the center set of posts compared to the outer sets, indicating that a violation to the center posts was considered more detrimental to the category membership than a comparable violation to one of the sets of outer posts. Regardless, we still found that participants in the middle-irrelevant condition were less sensitive to violations to the center posts compared to violations to the outer sets. The results of this experiment provide evidence that the goal frameworks are implicated in the processing that extends beyond directing attention to particular regions of the boards during the interactions. The goals provide a way to meaningfully organize the information acquired as a result of the interactions.

General Discussion

This study was designed to explore factors that play a role in the content and structure of conceptual knowledge. In Experiment 1, the participants in both the solid and flexible conditions showed a pattern of responding that indicated that they had organized their knowledge of the boards in terms of their respective task goals. It is important to note that participants were able to pick up on both concrete features, e.g. the type of terminal posts present, and relational features, e.g. the spatial relationship between terminal posts and other components on the board, through their interactions with the boards. Because the participants began their interactions without knowledge of what constituted a feature of the boards, this reflects the development of a suitable feature language to differentiate the types of boards that they encountered. In Experiment 2, participants in both conditions had the same task goal, the placement of flexible connectors, so they were all oriented to the terminal posts as they completed their tasks. However, for the middle-irrelevant condition, the configuration of the posts was not informative in terms of the task because the middle connector could be placed regardless. In the category-goodness rating task, we saw less emphasis put on violations to the configuration of those posts in that condition. The results of the current study provide support for the goal-framework hypothesis; the task goal both orients the person to a subset of information available about the boards, the goal-relevant features, and provides structure for organizing that information based on how it relates to the goal.

In summary, the results of both experiments reported here clearly illustrate how having a particular goal shapes what information is selected and incorporated into the category knowledge. The results of the second experiment also provide evidence that the information acquired is organized in terms of those goals, suggesting that the goal construct is playing a role in structuring the conceptual knowledge. However, we also recognize that there is considerable work to be done in order to fully develop this notion. In our account, the results are explained by the goal affecting how the acquired knowledge is organized. However, there are possibly other ways to account for the difference we found without the goal fulfilling that role. There is the possibility that the placement of the connectors in the middle-relevant condition of Exp. 2 required more effort which could explain why the configuration of those posts was more important in their category ratings. There is also a possibility that the difference between the conditions could be explained by a difference in how the center posts were encoded into the category knowledge. If the feature information did not reflect the types of posts in the middle set, changes to the configuration would not have an effect on the category-goodness ratings. With further study, we plan to address both of these concerns. We are also exploring other ways to assess to what extant the goal is helping to organize the category knowledge by assessing the organization of the acquired knowledge more directly. The results reported in this study provide a useful foundation for this continued line of inquiry.

The Goal-Framework

We propose that goal-frameworks play a role in how conceptual knowledge is organized, both in terms of the internal structure of a particular category and how the knowledge reflects different categories of items. Initially, we focused on the possibility that the structure might function like schemata (e.g. Rumelhart, 1980). In this case, the goal-framework would provide potential slots, and relations between those slots, that could then be filled by the information acquired during the goal-directed interactions. Although this provides a way for the goal-framework to structure conceptual knowledge, it also creates a disconnect between the goal-framework and conceptual knowledge – in a schema, the concepts that instantiate the slots are more basic and can be considered as primitive building blocks while the schema is the organizational structure. This does not accurately reflect our views of how the goal-framework operates during concept acquisition.

One issue that a goal schemata approach fails to address is how the participants developed a functional "feature language" (Landy & Goldstone, 2005) during the course of the task they completed. Our findings suggest that there was some low-level perceptual learning that occurred as the participants adopted very different feature knowledge depending on their interactions with the boards. In the flexible connector conditions, participants organized their knowledge around the particular terminal posts that appeared on the boards. In the solid connector conditions, they used information about the spatial relations between various components on the boards and the terminal posts. The fact that participants could use both information about concrete features and spatial relations suggests that the development of the feature language was operating at a basic level. This paradigm provides a unique way to approach these types of questions and to situate the study of them within a larger framework intended to guide our understanding of the acquisition of conceptual knowledge and how it relates to our perceptual experiences (Goldstone & Barsalou, 1998). However, the results from the current study are not sufficient to determine whether the participants came to adopt different representations of the features of the boards (e.g. Schyns, Goldstone, & Thibault, 1998) or whether they learned to ignore certain information (e.g. Denton & Kruschke, 2006; Dreisbach & Haider, 2009) as they better discriminated the features during the learning.

Barsalou's perceptual symbol system (1999, 2009) provides an approach that is able to address the prior issue and is better aligned overall with our perspective. In this account, records of processing episodes are captured and then used as the basis of later simulations. Importantly, when there are repeated encounters with items that have correlated sets of features, as one would find among the items of a particular category, the overlap among the processing episodes allows the development of a simulator that captures the shared system of features. The simulator associated with a particular concept, e.g. "bicycle" or "x type of Flux Board", provides the structure necessary to organize and integrate perceptual symbols that arise from interactions with items of that type. In the case of our tasks, the placement of connectors onto the Type A board required a different set of information and actions than the placement of connectors onto the Type B board, and so the repeated trials of each type led to the development of differentiated simulators. In this manner, the within-category structure, what interactions occur with a particular type of board, and the between-category structure, how the types of boards are differentiated by the interactions they entail, are both reflected in the simulators. Because the simulators develop dynamically in response to the interactions, they reflect the structure inherent in those interactions (Barsalou, 2003), and so the goal framework is an essential element of the conceptual knowledge instead of being an external assembly.

Emergent Structure. An important aspect of the goal-framework approach is that the goal framework is constrained both by the goal of the individual and the environment, and as such it is not specified a priori. We do not propose that a participant in the current study begins as a blank slate; in fact she brings a rich and useful body of knowledge to the experiment. However, her eventual conceptualization of the flux capacitor boards emerges through her interactions. Initially, she might have a rough idea that the boards are silver colored and have some electronic components on them, but that conceptualization is subsequently tuned by her experiences with the boards. Each time she attempts to place a particular connector onto the board, she receives either positive feedback (when the connector fits as anticipated) or negative feedback (when the connector does not fit) that is specifically tied to her goal-directed behaviors. Coming to recognize that the spatial relationships among the components on the board and the posts is critical when the goal involves placing the solid connectors is not a process of simply “attending to” that aspect of the boards. The participant makes attempts to place the connectors that in turn allow her to develop those relations into a goal-relevant feature of the boards. By the time that the participant reaches the second part of the experiment, she has a way to understand the boards more fully – she has developed a sense of what constitutes a useful feature of the boards, and although the boards are each unique, there are ways that some boards are similar to one another that is not true for other boards. At that point, the participant does not have a label for these different types of boards she is encountering, and anecdotal evidence suggests that often the participants did not even explicitly recognize that there were two types of boards until the experimenter mentioned it before the category-goodness rating task. Even though the participants may not have been explicitly aware of the presence of categories, the pattern of responses across the similarity judgment and sorting measures clearly shows that they organized their knowledge of the domain in a meaningful way that reflected the goal-framework. The intention to learn, or even awareness of learning, is not required for the development of categorical knowledge (Barsalou, 1995, 2009). This result has also been observed in research examining unsupervised category learning (e.g. Clapper & Bower, 1994, 2002). Clapper and Bower

(2002, p. 921) state, “What does this research imply about people’s learning in the everyday world? As in our experiments, people often seem fully engaged with whatever goal they are pursuing at the moment and appear to have no explicit goal of inventing categories and computing generalizations.” Even though the intent to learn about categories is not present, the structure emerges naturally as a by-product of the goal-directed interactions.

If goals are critical in establishing conceptual knowledge, what happens when the goals directing our interactions within a particular domain shift? Although our study was not designed to address this issue, we would predict that continued interactions with the boards, especially ones that involved new goals, would result in modifications to this conceptual knowledge which would then impact the responses that tapped into this knowledge of categories. This is the arguably the pattern shown in Ross (1997, 1999). As most theories of conceptual acquisition are not able to accommodate this kind of flexibility (see Love, 2005, for a discussion on this point), it is important that we develop formalizations that are able to accommodate the richness and complexity of these goal-directed experiences.

Implications for Category Learning

Category learning research has tended to focus on a single category learning paradigm, classification learning. In classification learning, participants learn about novel categories by predicting the category membership of items and receiving feedback on those classifications. It appears that classification learning results in a category representation with limited applicability to other category-based tasks (Hoffman & Rehder, 2010) and may not reflect how people learn about categories more generally (Brooks, Squire-Graydon, & Wood, 2007; Markman & Ross, 2003; Ross, Chin-Parker, & Diaz, 2005). Granted, the use of the classification learning paradigm has led to some informative and influential formal models of category learning (e.g. Kruschke, 1992; Medin & Schaffer, 1978), but category learning occurs through a variety of means including feature prediction (Yamuachi & Markman, 1998), referential communication (Markman & Makin, 1998), and problem solving (Bernardo, 1994; Ross, 1996). To best understand category learning, we require a framework theory and accompanying formalizations that are able to accommodate various forms of category learning as opposed to being tied to a single learning paradigm.

The goal-framework approach is such a framework theory in that it is able to accommodate multiple perspectives on category learning. For instance, we consider classification learning to be a special case of category learning. When an individual engages in classification learning, she has the goal of explicitly learning the class membership of the items in the prescribed categories, and the information that is pertinent to that goal is used to organize the category knowledge. Several studies have shown that classification learning indeed focuses the individual on the classification relevant information at the expense of other information about the categories and items that comprise them (Chin-Parker & Ross, 2004; Hoffman & Rehder, 2010). Another individual might encounter the same items but have the goal of being able to predict missing feature information. Several lines of research have shown that this new goal leads to learning that is not equivalent to the classification learning (e.g. Anderson, Ross, & Chin-Parker, 2002; Yamauchi & Markman, 1998), and that inference learners acquire knowledge of the categories that support their goal of feature prediction (Chin-Parker & Ross, 2004). As seen in the current study, the goal-framework approach also is able to account for category learning that takes place when the participant is indirectly interacting with the categories, i.e. the participants received no explicit category-based feedback during the learning (also see Brooks, Squire-Graydon, & Wood, 2007; Minda & Ross, 2004). Although there is much work to be done to specify how different tasks goals would affect the conceptual acquisition, the goal-framework approach provides a workable framework theory for conducting that research.

It is a critical problem that most category learning research has tended to isolate categorization from other activities (Markman & Ross, 2003). If we accept that goal-directed behaviors provide structure to concept acquisition, then category learning becomes a part of the on-going and varied activities of the person. For instance, in Markman and Makin (1998) participants communicated about toy construction pieces as they worked together to build various objects. The participants' communications were focused on how they could jointly achieve that goal, and these interactions led to an alignment of their conceptualization of the pieces. In this case, the goal to communicate was seamlessly tied to the conceptual organization the participants acquired. The goal-framework approach also is intended to allow for the integration of various sources of information available during interactions with the items in a category. For instance, when a goal requires identifying the properties of an object as well as some motor movements, these pieces of information are jointly incorporated into the individual's knowledge of the object category (Ross, Wang, Kramer, Simons, & Crowell, 2007). The perceptual symbols system approach considered above explicitly engages with how "embodied" information is an important part of what we learn from our interactions (Barsalou, 2010). Although this study was not designed to specifically test whether embodied information was incorporated into the conceptual knowledge in, we do think that the paradigm used in this study lends itself to future study of that issue. We are interested in exploring how category learning relates to other activities, both cognitive and grounded, so we think that the goal-framework perspective is useful because it allows for consideration of an embodied approach.

Finally, the goal-directed approach addresses aspects of the disconnect that exists between laboratory and naturalistic studies of category learning, a concern that has shadowed experimental category learning research (Murphy, 2005). Most studies of category learning begin by stating that the concepts are ubiquitous in our daily mental life, but then the studies focus on how people learn about binary categories of colored shapes of varying size or crudely drawn bugs (a reference to the first author's own stimuli) that capture some prescribed categorical structure. The naturalistic studies tend to involve the comparison of the use of categorical knowledge by different expert populations, such as landscapers and taxonomists (Proffitt, Coley, & Medin, 2000), or individuals from different cultures (e.g. Shafto & Coley, 2003), and it is difficult to reconcile those findings with what is occurring on a trial-by-trial basis during an experimental learning task. There are important issues that lie outside of the scope of the current study, e.g. how goals related to artifact and natural kind categories might be differently conceptualized (Keil, 1989), and further research is necessary to more fully explore those topics. However, we propose that adopting the goal-framework approach to category learning allows us to maintain the control and ask questions that are at a suitable scale of theorizing while also capturing some of the richness and complexity that are the hallmark of our day-to-day experiences. Importantly, conducting this type of study allows us to explore the interaction between the individual and the environment that helps to shape the acquisition of conceptual knowledge.

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