University of Alberta

Consumer Prior Expectations and Analytic Categorization

by

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ABSTRACT

Considerable previous research has shown that cognitive constraints impair the performance on a variety of cognitive tasks (Drolet and Luce 2004; Hutchison and Alba 1991; Nowlis and Shiv 2005; Pontari and Schlenker 2000; Yzerbytm, Coull, and Rocher 1999). However, this study provides evidence that cognitive constraints can facilitate analytic categorization when the category rule is consistent with prior expectations. Evidence further shows that constraints facilitate learning by reducing the influence of irrelevant information rather than by heuristic application of prior expectations. But cognitive constraints enhance learning only when the rule flawlessly matches prior expectations, more specifically, when the rule is based on the single attribute that is expected to be the most likely discriminating attribute. When the rule departs from prior expectations, constraints inhibit category learning. Two situations are investigated where the rule departs from prior expectations: a pseudorule based on the attribute that is expected to be most important or a conjunctive rule based on two attributes that are expected to be most important. The findings suggest that individuals tend to look for a simple rule to categorize items and when constrained, individuals primarily devote their processing resources to the attribute that is expected to be the most important.

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INTRODUCTION

Imagine that you try a new fruit while you are on vacation in a foreign country and it tastes like a slice of heaven. You eagerly buy another and it is extremely disappointing. You later find out that there are two varieties of this fruit and one of the varieties is consistently excellent, but the other is usually bad. How might you learn to consistently find the good variety?

People regularly face categorization decisions like this. Categorization helps us to understand and organize the world. Categorization also identifies new products and gives meaning to them by identifying the extent to which a new product is differentiated from existing products (Cohen and Basu 1987; Moreau, Markman, and Lehmann 2001).

The two common strategies for learning categories can be characterized as analytic categorization and holistic categorization. Analytic categorization refers to rule-based categorization, where people learn to identify the key attributes that distinguish between categories and rely solely on rules based on these discriminating attributes. In holistic categorization, people rely on global similarity between items, which is based on all or most of the accessible attributes, regardless of their relevance for the decision. With holistic categorization, category members may be represented in memory as separate and specific exemplars or as unified and summarized prototypes (Alba and Hutchison 1987; Hutchison and Alba 1991; for a more complete discussion of categorization theories from a psychological perspective please see Murphy 2002).

Understanding how people categorize is important for marketers seeking to understand how consumers evaluate a new product and distinguish it from others. First, different strategies may categorize a product differently (e.g., Cohen and Basu 1987; Hutchison and Alba 1991). Second, if a rule exists, analytic categorization is much more efficient than holistic categorization, especially when category members have multiple attributes. Analytic categorization focuses attention on the most relevant information and reduces or eliminates the influence of seemingly important but actually irrelevant attributes.

Although categorization plays a central role in new product evaluation, most consumer research assumes that category structure knowledge (e.g., category rules, exemplars or stereotypes) preexists before a consumer's categorization decision is made (e.g., Broniarczyk and Alba 1994; Gregan-Paxton, Hoeffler, and Zhao 2005; Kreuzbauer and Malter 2005). Up to now, consumer research has devoted little attention to the issue of how consumers acquire relevant category knowledge. Category learning studies are therefore particularly important to cast light on consumers' category knowledge acquisition process.

The present study uses three experiments to investigate how prior expectations about categorization rules influence consumer category learning and how the effects of prior expectations interact with cognitive capacity. I find that prior expectations improve rule learning when the rule is consistent with expectations (Experiment 1). Cognitive constraints also affect rule learning, but the effect depends on the degree of consistency between prior expectations and the rule. Specifically, when prior expectations perfectly match the rule, that is, when the attribute that prior expectations anticipate to be the most relevant comprises a rule, cognitive constraints facilitate rule learning and the enhanced learning is not attributed to heuristic application of expectations (Experiment 2). But the positive effect of prior expectations on rule learning only holds when the expectations and the rule flawlessly match. When expectations depart from the rule, cognitive constraints tend to impede learning and attenuate the importance of the attribute that prior expectations assume to be highly relevant. This impeding effect is found when the attribute comprises a pseudorule for the task, which is not a perfect rule but is the most valid attribute in terms of predicting category membership (Experiment 2) and when the attribute combines with another highly relevant attribute to make a conjunctive rule (Experiment 3). Experiment 3 also tests whether constraints direct participants to focus on a smaller set of attributes at the beginning of the learning process, but does not find evidence for this proposition. Although attention does not favor relevant information over irrelevant information, evidence suggests that processing power is more likely to be allocated to relevant information under constraints. This may explain the positive effect of constraints on learning when prior expectations and the rule perfectly match.

Considerable previous research has shown that cognitive constraints impair performance on cognitive tasks (Drolet and Luce 2004; Hutchison and Alba 1991; Nowlis and Shiv 2005; Pontari and Schlenker 2000; Yzerbytm, Coull, and Rocher 1999). This research contributes to a more complete understanding of the effects of constraints on cognitive tasks and demonstrates that constraints can facilitate analytic categorization by reducing the influence of irrelevant attributes. Moreover, this research finds evidence that perceptual attention is not necessarily accompanied by sufficient information processing, and processing resources are primarily oriented toward the attribute that is expected to be the most important when cognitive resources are limited.

The reminder of this article is divided into five sections. First, I review literature in consumer categorization, rule learning, and effects of prior knowledge on concept acquisition, and develop the hypothesis about the effect of prior expectations on rule learning. Second, Experiment 1 is presented to test the first hypothesis. Third, I propose hypotheses regarding the effects of cognitive constraints on category learning and present Experiment 2 to test them. Fourth, two possible underlying mechanisms are proposed to explain how cognitive constraints influence category learning and Experiment 3 is tests for these mechanisms. Finally, I conclude with a summary of results and a discussion of marketing implications, limitations and avenues for future research.

THEORETICAL BACKGROUND

Definitions

First I provide definitions for some terms in this study. A rule is the definition of a category and it represents the necessary and sufficient condition to judge category membership. A single-attribute-based rule is comprised of an attribute which distinguishes the category from other categories. In this study, a pseudorule is not perfectly associated with category membership but is comprised of the most valid attribute in terms of predicting category membership; a conjunctive rule is based on two attributes and all category members have the same values for each of the two attributes. When categorization decisions are made according to a rule, an item is either in or not in the category, with no in-between cases, and all category members are as good as each other. Nevertheless, when categorization decisions are based on overall similarity between the new item and category exemplars or stereotypes, categorization results become probabilistic and the probability of an item being placed into a category depends on the overall similarity (e.g., Nosofsky (1992) presented the Generalized Context Model to show how to calculate a probability score based on overall similarity).

Analytic Categorization versus Holistic Categorization

Analytic categorization and holistic categorization represent two basic categorization strategies. Research on brand extension provides evidence that consumers use these two strategies to understand new products on the basis of their category knowledge. Broniarczyk and Alba (1994) demonstrated that a brand-specific association, which refers to an attribute or benefit that differentiates a brand from competing brands, is more important for consumers to evaluate a brand extension than overall similarity between the new product and the brand category. This shows an example of consumers' analytic categorization.

Consumers also perceive and identify new products through holistic categorization. Warlop and Alba (2004) found that a copycat brand, which had an identical product package with the leading brand except the brand name, was evaluated significantly higher than a differentiated brand when the copycat brand was priced lower than the leader. Kreuzbauer and Malter (2005) showed a leading European off-road motorbike brand (KTM) successfully extended into the street motorbike segment by gradually introducing models containing an increasing number of elements of street motorbikes over a period of several years. Gregan-Paxton, Hoeffler, and Zhao (2005) also demonstrated that when a new product was perceptually presented as a category member while conceptually labeled as a member of another category, the perceptually presented category information was more important than the conceptually presented category information in product evaluation if individuals had higher familiarity with the former category.

The above studies illustrate that both analytic and holistic strategies can be employed for new product categorization. However, despite its fundamental importance, little is known about how category structure knowledge (e.g., category rules, exemplars or stereotypes) is acquired. Category learning studies can cast light on the knowledge acquisition process. A typical category learning task has two phases. During the learning phase, learning stimuli are shown and their category membership is specified; in the test phase, participants are asked to judge category membership for each of a number of test stimuli (e.g., Allen and Brooks 1991; Cohen and Basu 1987; Hutchison and Alba 1991; Pazzani 1991; Nosofsky 1991).

An individual's intention of category learning is an important factor for the occurrence of analytic categorization. Holistic categorization is the default strategy when individuals learn categories incidentally; that is, when the focus is not on categorization. For example, participants may be told that they are to evaluate the products, but later they are unexpectedly asked to sort them into categories. By contrast, when the focal task is to learn about the category structure so that they can make predictions about category membership, participants seek a rule and if the rule is identified, they will engage in analytic categorization to make decisions (Hutchison and Alba 1991; Kemler Nelson 1984; van Osselaer, Janiszewski, and Cunha 2004).

Other factors also influence the adoption of categorization strategies. First, the availability of a rule makes a difference. When a category is not defined by a rule or the rule is too difficult to identify, participants have to rely upon exemplars or stereotypes (e.g., Juslin, Olsson, and Olsson 2003; Nosofsky 1991; Nosofsky, Clark, and Shin 1989). Second, cognitive capacity plays an important role in category learning. Rule identification is a complicated process that requires cognitive effort while the retrieval of exemplars and stereotypes can be passive and relatively effortless. Previous research found that young, retarded, and impulsive children produced more holistic categorization compared to adult participants, probably due to their immature cognition (Kemler Nelson 1982; Kemler Nelson and Smith 1989; Smith and Kemler Nelson 1988). Adults became more holistic when a concurrent cognitive load was imposed (Hutchison and Alba 1991; Justin et al. 2003; Smith and Kemler Nelson 1984). In addition, Smith, Tracy, and Murray (1993) showed that depression impaired analytic categorization and depressed people tended to be more holistic. Taken together, these findings suggest that holistic categorization may serve as a fallback mode when analytic categorization cannot be successfully performed.

Category Rule Learning

Rule identification requires adequate cognitive resources because it involves a systematic hypothesis testing process (Levine 1975; Restle 1962). When entering a category learning context, participants generate hypotheses with regard to how the attributes combine to determine the categories. The hypothesized rule will be retained as long as it successfully predicts the categories. Once it is proved to be wrong, participants will form a new rule taking into account both the previous rule and the retrieved information about category members. So hypothesis testing integrates a series of cognitive activities: flexible shifting of attention among attributes, attribute memorization, and comparison between category members.

Bruner and his colleagues conducted a series of studies to investigate the hypothesis testing process in the learning of unfamiliar categories (Bruner, Goodnow, and Austin 1956, 126-155). They found people tended to base their initial hypotheses on the entire set of attributes if they could not judge the relevance of attributes. If the category member is described by four binary-valued attributes, for example, and the first learning stimulus is 0110 from Category A, a participant generates her first hypothesis that the rule for Category A is exactly 0110. When the second learning trial is presented, and it is another stimulus from Category A: 1111, the participant then recognizes the irrelevance of the first and the last attributes, because the two attributes can have both values of 0 and 1 for the same category. By the end of the first two learning trials, the hypothesized rule for Category A may be updated to x11x where x means that attribute can be either possible value because it is not associated with category membership.

The approach described by Bruner and his colleagues (1956) suggests people tend to take a conservative and confirmatory approach in hypothesis testing when they learn categories. This approach might inhibit the learning of a conjunctive or disjunctive rule. A category is defined by a conjunctive rule when all category members have specific values for each one of two or more attributes; e.g., all members of the category "cell phone" are wireless and enable voice communication at long distances. A category is defined by a disjunctive rule when an item is defined as a category member because it contains any one or any combination of the specified values on the discriminating attributes. In addition, Meyer (1987) found a positive valence bias in the learning process: people were able to learn the attributes associated with items from a good category (i.e., a strong alloy) more rapidly and with greater accuracy than those associated with items from a bad category (i.e., a weak alloy). All these findings suggest it is difficult for consumers to learn from multi-attribute information (e.g., Meyer 1987; Tellis and Gaeth 1990).

Because rule identification consists of hypothesis generation, testing and updating, correct initial focus is important for finding the right rule within limited learning opportunities. Previous studies showed that people generated their initial hypotheses based on all of the attributes (Bruner et al. 1956, 126-155; Meyer 1987). This might be because the categories in these studies are either artificial categories (Bruner et al. 1956) or a product with which participants have little prior familiarity (Meyer 1987). In such cases, participants begin the learning process with little idea about the relevance of the attributes. However, in the real world, most consumers can draw upon previous experience with similar products when they try to understand a brand new product. As in the opening example, when trying to distinguish between crisp and soft varieties of an unfamiliar fruit, one might first compare skin color and size because these attributes might be most relevant based on one's experience with similar fruits.

Effects of Prior Knowledge on Category Learning

Prior knowledge influences concept acquisition. Murphy and Wisniewski (1989) demonstrated that a concept's content influenced how easy the concept was to learn. For example, when participants learned a coherent category in which category members were described by sensibly related attributes (e.g., lives in water, eats fish, has many offspring, and is small), they learned the category better than when they learned an incoherent category where the attributes did not make sense together (e.g., lives in water, eats wheat, has a flat end, and is used for stabbing bugs). Murphy and Allopenna (1994) further showed that knowledge aids learning by highlighting relationships among the attributes in the category, rather than through the properties of the attributes themselves. For instance, when the attributes were connected by a theme (e.g., a vehicle category: made in Norway, heavily insulated, white, drives on glaciers and has treads), it was easier to learn compared to a category without a theme (e.g., a vehicle category: white, automatic transmission, non-radial tires, automatic seat belts and cloth seats).

In addition, prior knowledge directs attention to more relevant attributes. Pazzani (1991) showed that people could learn a disjunctive rule better than a conjunctive rule when prior knowledge was consistent with the disjunctive rule. The author used picture stimuli which showed an adult or child doing an action on an inflated balloon that was either large or small and either yellow or purple. The conjunctive rule was "the color must be yellow and the balloon must be small" and the disjunctive rule was "the person must be an adult or the action must be stretching the balloon." Participants were instructed either to learn Category Alpha or to identify which balloons will inflate. It was found that under the inflate instruction condition, i.e. the condition that is more likely to evoke prior knowledge, participants identified the disjunctive rule much sooner than the conjunctive rule and they were less likely to request to see the color attribute.

Moreover, prior expectations help to identify the importance of attributes and influence which attributes are attended to. In a study where participants learned about a tool in a foreign country (Lin and Murphy 1997), the same learning stimuli were used across conditions but different explanations about the functions of the objects were provided to generate different background knowledge about the tool. The object descriptions were designed so that the most important part in one description was relatively unimportant in the other description. Later participants were presented with test stimuli lacking different parts and judged if each stimulus belonged to the tool category. Their judgments depended on the descriptions received during the learning phase because the importance of a missing part differed in different descriptions. When the descriptions suggested the missing part was important, participants tended to think the test stimulus was not in the category, and when the missing part was unimportant, participants tended to view it as the category member. Heit (1998) also found that when people encountered information that was incongruent with their prior knowledge (e.g., a shy person attends parties often), they tended to spend more time thinking about it compared to when they receive congruent information (e.g., a shy person does not attend parties often).

Research on covariation judgment provides converging evidence for the effect of prior expectations. Prior expectations increased covariation judgment accuracy by guiding hypothesis testing in the assessment of covariation (Baumgartner 1995; Wright and Murphy 1984). The covariation judgment was more accurate for the participants who knew that they were to judge price and quality than for those who were told that the two variables were simply X and Y. More important, Baumgartner (1995) demonstrated that the hypothesis testing process involved an active, expectation-guided examination of the data rather than a heuristic application of prior expectations, because labeling the attributes as price and quality increased the judgment accuracy even when the actual correlations between the two variables were negative. Spalding and Murphy (1999) also showed that the usage of prior knowledge in performing a category learning task did not inhibit the learning of the details of a category's attributes. So when prior expectations aid category learning, they do not overwhelm the learning task. Rather, people actively engage in the learning process when prior knowledge is applied.

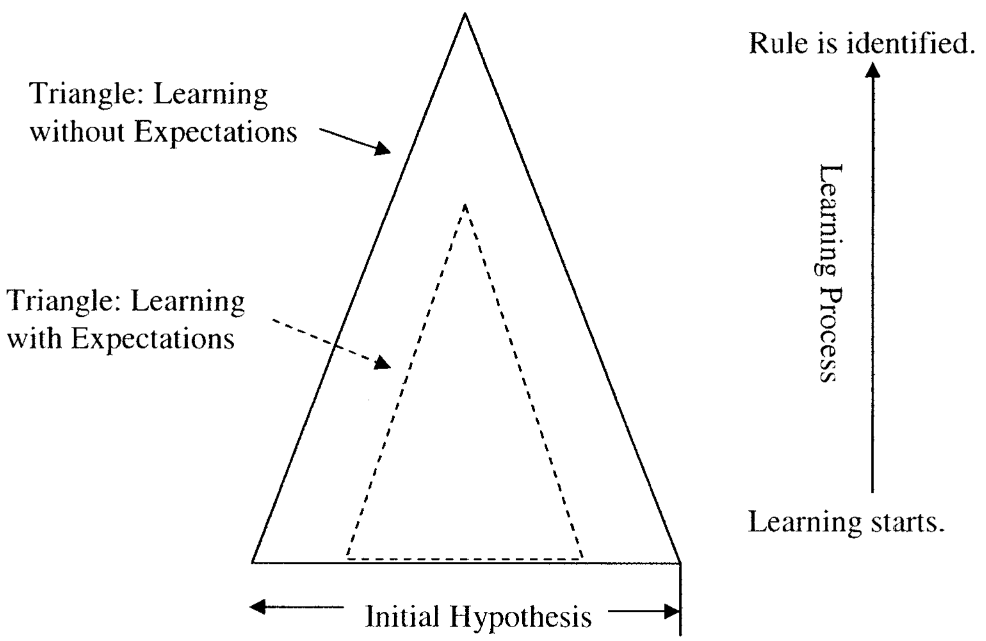
Hypothesis Development

I propose that when consumers have prior expectations about categories, their attention is directed to fewer, more relevant attributes and they have a more focused initial hypothesis. The process of hypothesis testing is illustrated in Figure 1. The solid-line triangle represents the hypothesis testing process without prior expectations and the dashed-line triangle represents the process with prior expectations. The length of the baseline of a triangle represents the number of attributes that are considered when the initial hypothesis is generated. When there are no prior expectations, the entire set of attributes is relevant and all of them are taken into consideration. When prior expectations exist, the initial hypothesis is based on a smaller set of more relevant attributes.

The steepness of the other two sides of the triangle represents the learning rate, or the speed of hypothesis updating. It is assumed to be positively related to the cognitive resources that are available. The hypothesis is narrowed down as disconfirmations about attributes are encountered, and the learning rate is also related to the strictness of the criterion for rejecting irrelevant attributes after they are disconfirmed. The strictest criterion will reject a hypothesis after a single disconfirmation, but decision makers may be willing to retain a hypothesis after two or even more disconfirmations if no hypotheses receive perfect support. The strictness of the criterion may also be related to the cognitive resources that are available. Generally speaking, as cognitive resources decrease, the learning rate will decrease because information processing and updating will slow down. When cognitive resources are not constrained, the learning speed of updating hypotheses is assumed to be equal across the two triangles. As may be seen in Figure 1, individuals in the condition with correct prior expectations can identify the rule sooner than those without prior expectations because they have a better initial focus.

Figure 1

Rule Learning Process without Cognitive Constraints



H1: Prior expectations that are consistent with categorization rules increase the usage of analytic categorization.

EXPERIMENT 1

Experiment 1 was designed to test Hypothesis 1 and to establish the effect of prior expectations on category learning. The category membership rule was based on a single attribute. Between the two conditions of this one-factor between subjects design, the attribute that comprised the rule was either highly consistent or highly inconsistent with research participants' prior expectations, as determined through pretesting. The task was to learn about another person's tastes in wine in order to select a wine for this person as a gift. Participants saw a series of wines and were told whether each wine was liked or disliked. Then two new wines were presented and participants judged which one would be liked.

The Stimuli

The stimuli design, illustrated in Table 1, follows the paradigm suggested by Cohen and Basu (1987). A wine was described by four binary-valued attributes: wine type (red or white), fermentation container (wooded or unwooded), vineyard (estate or boutique) and region (Canada or France). I constructed four wines for both liked and disliked categories and participants saw 16 learning trials – two randomized repetitions of the eight wines. The presentation order was the same for all participants. Barsalou, Huttenlocher, and Lamberts (1998) showed that when the exact same stimuli were presented for learning, whether participants thought that each stimulus was unique or they thought some stimuli were presented multiple times had virtually no effect on category learning results.

Table 1

Stimuli for Experiment 1

Learning Stimuli				
Category	*Attribute 1*	*Attribute 2*	*Attribute 3*	*Attribute 4*
	0	0	0	0
Liked	0	1	0	0
Wines	0	0	1	0
	0	0	0	1
	1	1	1	1
Disliked	1	0	1	1
Wines	1	1	0	1
	1	1	1	0

Test Stimuli				
	Attribute 1	*Attribute 2*	*Attribute 3*	*Attribute 4*
Wine A	0	1	1	1
Wine B	1	0	0	0

Learning Stimuli with the Presentation Order					
Category	*Attribute 1*	*Attribute2*	*Attribute3*	*Attribute 4*	*Order*
Liked	0	0	0	0	1
Disliked	1	1	0	1	2
Liked	0	1	0	0	3
Disliked	1	1	1	0	4
Disliked	1	1	1	1	5
Liked	0	1	0	0	6
Disliked	1	1	0	1	7
Liked	0	0	1	0	8
Liked	0	0	0	1	9
Disliked	1	1	1	0	10
Disliked	1	0	1	1	11
Liked	0	0	0	0	12
Disliked	1	1	1	1	13
Disliked	1	0	1	1	14
Liked	0	0	0	1	15
Liked	0	0	1	0	16

As shown in Table 1, the first attribute is the discriminating attribute, because all liked wines have the attribute level of 0 and all disliked wines have the level of 1. For the other three attributes, although they are not perfectly discriminating, liked wines tend to have the attribute level of 0 for these attributes and disliked wines tend to have 1. Based on overall similarity, category stereotype for liked wines is 0000 and for disliked wines 1111.

When making judgments about the two new wines, participants who use analytic categorization will rely on the first attribute and predict Wine A to be liked. In contrast, participants using holistic categorization will base their decisions on overall similarity and predict Wine B to be liked. Based on this stimulus design, inferences can be made from judgment results about categorization strategies that are used to make decisions.

Participants' expectations were pretested concerning which attribute was the most likely to discriminate between liked and disliked wines (see Appendix A-1 for the pretest questionnaire). Thirty-eight students from the same participant pool participated in the pretest. They ranked the four attributes in terms of their likelihoods of distinguishing the two kinds of wines. Responses from two participants were excluded from the analysis because one of them ranked "taste" which was not on the list and the other participant ranked "region" twice. Thirty-six participants ranked wine type as more likely than vineyard to be the discriminating feature. Twenty-three participants rated the wine type as the most likely discriminating feature, seven rated it as the second most likely, one rated it as the third most likely and five rated it as the least likely. The frequencies for the vineyard (from most likely to least likely) were 1, 6, 18 and 11 respectively. A chi-square test showed the association between the rank order and the feature was significant ($\chi^2(9) = 77.11$, $p < .01$, see Appendix A-3 for the test output). So wine type was assigned to be the first attribute for the condition where the rule was highly consistent with prior expectations and vineyard was the first attribute for the rule-inconsistent condition.

It was predicted that when the rule is consistent with prior expectations, the rule is easier to identify and analytic categorization will be used; when the rule is not consistent with expectations, decisions will be based on overall similarity. These predictions are contrary to the findings of previous research which assumes that individuals take all attributes into account when they form their initial hypotheses (Bruner et al. 1956; Meyer 1987). If that is true, participants should be able to identify the rule equally well across the two conditions, because the stimuli are designed in an identical way except that wine type and vineyard exchange their roles under different conditions. But this is not likely to happen when participants have prior expectations, because expectations will direct more attention to some attributes than to others and so the first hypothesis will be based on the most relevant attributes.

Procedure

Fifty-one undergraduate students from the University of Alberta participated. After signing consent forms, participants were told that their task was to predict another person's tastes in wine and they would select a wine as a gift for this person. Then they focused their attention on a computer screen where the instructions and all the stimuli were presented in sequence. In each trial, the description of a wine was presented for 10 seconds, followed by a screen asking participants to judge whether the wine would be liked or disliked. After six seconds, the answer was provided. Five seconds later, a new learning trial started. Across the learning stimuli, the discriminating attribute (i.e., wine type or vineyard) was always presented in the second place in the wine description. After the learning phase, participants saw two new wines and judged which one would be liked by the other person. See Appendix A-2 for task instructions and Appendices A-3 and A-4 for the screen shots presented during the learning phase and the test phase, respectively.

The reason participants needed to make judgments during the learning phase was that if category membership was provided together with a wine description, participants might easily detect the difference between adjacent trials and quickly locate the discriminating attribute, rather than developing hypotheses based on their prior expectations. For example, if category membership was provided, the first two trials for the wine type condition were: Liked Wine, Canada, Red, Unwooded, Boutique and Liked Wine, Canada, Red, Oak, Boutique. Participants would notice the irrelevance of the fermentation attribute and quickly narrow down to the other three attributes. Consequently the discriminating attribute could be quickly learned and participants would not need to rely on prior expectations. But if they were asked to judge category membership first, participants would need to develop the hypotheses themselves.

The participants took part in the study on two different days. For those who participated earlier (24 in total, 10 for the wine type condition and 14 for the vineyard condition), the collected data only included their final judgments about the test stimuli and their judgments about each learning stimulus. In order to obtain more information about the underlying categorization process, post-decision questions were added for those participants who took the study later (27 in total, 12 for the wine type condition and 15 for the vineyard condition). They were first asked if they thought there was a single key attribute determining the wines. If the answer was yes, they needed to specify the key attribute and explain how they made the judgments. For those who thought there were no key attributes, they also explained how they had reached their decisions. See Appendix A-5 for the post-decision questionnaire.

Results

The results supported hypothesis 1. Out of 22 participants in the condition where the wine type was the rule, 19 participants judged Wine A to be liked and only three participants judged Wine B to be liked. In the other condition where the rule was the vineyard, 11 participants chose Wine A and the other 18 chose Wine B. A Fisher's Exact Test revealed a significant difference (86% vs. 34%, $p < .01$). The statistical test outputs are attached in Appendix A-6.

As discussed previously, the categorization strategies can be inferred from the wine judgments: judging Wine A to be liked implies analytic categorization and Wine B implies holistic categorization. To certify this, the responses to the post-decision questions were analyzed (see Table 2 for a summary). Among the 12 participants who provided responses in the wine type condition, 11 of them, who were the same as those who selected Wine A, reported that they believed there was a key attribute and the attribute was the wine type. They also reported they identified it during the learning phase rather than knowing it from the beginning. The only participant who categorized Wine B as a liked wine said that she based the decision on the fermentation and she knew it was not the key attribute. Among the 15 participants who answered post-decision questions in the vineyard condition, eight of them selected Wine B and they all reported strategies based on multiple attributes, like "based on combined attribute information", "combined attributes: white + boutique + wooded", and one of them said "it seems a perfect combination would be Canada, boutique, oak, and red. So I chose the most similar one". The other seven participants in the vineyard condition selected Wine A. Six of them reported they had identified vineyard as the key attribute and one said she just "guessed it". The above analysis suggested that the judgments of the test wines were quite consistent with the self-reported categorization strategies.

Table 2

Self Reports' Results in Experiment 1

The wine type condition (12 participants)		The vineyard condition (15 participants)		
11 participants chose Wine A.	One participant chose Wine B.	Seven participants chose Wine A.		Eight participants chose Wine B.
All the 11 participants identified the wine type as the rule.	The participant based the decision on the fermentation.	Six participants identified the vineyard as the rule.	One participant guessed it.	All participants based the decisions on multiple attributes.

Discussion

It might be argued that judgment results do not necessarily correspond to the claimed strategies in the stimuli design. For example, a participant might fail to identify the rule and choose to base the decision on one of the other three non-discriminating attributes. This certainly is not a holistic strategy. In fact, it shows an analytic way of thinking: any of the other three attributes is a fairly good predictor which can provide correct category membership three out of every four trials. Here the non-discriminating attribute works as a "pseudorule". If the usage of a pseudorule ever occurs in Experiment 1, it is most likely to occur under the vineyard condition, because the perfect predictor is inconsistent with prior expectations.

The usage of pseudorules is further investigated in Experiment 2, and it is found that only a small portion of participants (28%) use pseudorules. Moreover, it is important to note that the pseudorule in Experiment 2 is more likely to be used as a predictor than a non-discriminating attribute in Experiment 1, because in Experiment 2 there are no perfect predictors and the pseudorule is the best predictor for the task. Therefore, it seems unlikely that pseudorule usage can account for the results of Experiment 1. Furthermore, the above analysis of self reports clearly demonstrates that under the vineyard condition, among the participants who chose Wine B and reported their strategies, none of them based the decisions on a single attribute. Therefore, both self reports in Experiment 1 and the judgment findings in Experiment 2 are more consistent with the original analysis and explanation than with the pseudorule explanation.

When investigating the effects of prior expectations in category learning, previous research has tended to focus on general coherence of a category or the correlations between attributes (e.g., Heit 1998; Murphy and Allopenna 1984; Murphy and Wisniewski 1989; Pazzani 1991). This experiment contributes to this literature by showing that people not only have expectations about the relationships between attributes but also expectations about how the category should be organized (i.e., which attribute should be discriminating).

This experiment studies a situation where the actual rule and prior expectations are perfectly matched: the rule is based on the single attribute which is expected to be the most likely discriminating attribute. But in the real world, chances are that the rule departs from prior expectations in one way or another.

Moreover, modern consumers are bombarded with a rapidly increasing amount of information and a lot of information is received and processed when consumers are cognitively busy. But relatively little research has been devoted to analyzing how cognitive resources influence category learning. The following two experiments attempt to advance our understanding of how prior expectations affect category learning when the rule departs from expectations and of how cognitive resources influence category learning.

EXPERIMENT 2

Hypothesis Development

It is proposed that the beneficial effect of prior expectations on analytic categorization will be more pronounced when category learning occurs under cognitive constraints.

Cognitive constraints tend to reduce the amount of information that is processed and impair the performance on cognitive tasks. Constraints inhibit people from considering the full set of relevant information (Drolet and Luce 2004; Nowlis and Shiv 2005), disrupt self-presentation behaviors (Pontari and Schlenker 2000), impair the ability to integrate incongruent information (Yzerbytm, Coull, and Rocher 1999), and inhibit analytic categorization (Hutchison and Alba 1991).

However, in a category learning task where the rule is matched with prior expectations, prior expectations will direct participants to focus on relevant attributes at the very beginning, and attention will stay with those attributes as long as they can predict categories correctly. So the presence of constraints will only decrease the processing of irrelevant information and thus they will enhance rule learning.

H2: When a category has a rule and it is comprised of the attribute that prior expectations anticipate to be the most relevant, cognitive constraints increase the usage of analytic categorization.

When prior expectations depart from the rule, for instance, when the attribute that prior expectations expect to be the most relevant comprises a pseudorule, constraints impede pseudorule learning. The usage of pseudorules has been a focus of research by itself. Many real-world categories lack precise definitions and people often make smart decisions by using simple heuristics (Gigerenzer et al. 1999). When a perfect rule is not available, usage of a pseudorule is in essence an analytic approach to solve the problem and is more efficient than holistic categorization (Hutchison and Alba 1991). Although some research has been conducted regarding the usage of pseudorules in categorization tasks (Hutchison and Alba 1991; Juslin et al. 2003; Rouder and Ratcliff 2004), many issues remain unresolved.

It is possible for cognitive constraints to increase the usage of pseudorules if the threshold for an acceptable solution is lowered because of constraints. Arkes, Dawes, and Christensen (1986) found that people were reluctant to use a decision rule that was 80% accurate even when they were told it was the best solution available. Their results suggest that people believe better decisions can be made if more factors are taken into consideration. But because the ability to process information is reduced under cognitive constraints, constrained people might lower their requirements for accuracy rates and want to use a pseudorule if the pseudorule is available.

Although cognitive constraints might lower the standard for an acceptable rule, constraints may be associated with less pseudorule usage after all, because pseudorules are more difficult to identify under constraints. A perfect rule is relatively easy to identify because even one disconfirmation of a candidate hypothesis is sufficient to definitively reject it. So the number of candidate hypotheses is reduced very quickly as disconfirmations are encountered. The identification of a pseudorule is more difficult because every hypothesis has to be disconfirmed at least once and the pseudorule cannot be identified until it is recognized that one attribute is disconfirmed much less often than the others. For a pseudorule to be found, all possible hypotheses must be held in memory, along with a tally of disconfirmations, until all the trials have been processed. Since the additional memory capacity that is required to identify a pseudorule is not available under cognitive constraints, constrained people are less likely to identify the pseudorule.

Taken together, when constrained, people might tend to use a pseudorule if the pseudorule is available, but they are less likely to identify a pseudorule by themselves. In related literature very little evidence has been found for the pseudorule usage in a category-learning task, even when high information load was imposed (Hutchison and Alba 1991) or when the decisions were made under time pressure (Juslin et al. 2003). In this experiment, although prior expectations highlight the most valid attribute initially, participants are predicted to consider other attributes and test other hypotheses after the focal attribute is disconfirmed and, as a result, it is difficult for them to learn the most valid attribute.

H3: When a category is constructed according to a pseudorule and it is comprised of the attribute that prior expectations anticipate to be the most relevant, cognitive constraints reduce the usage of analytic categorization.

In previous hypotheses, the primary dependent variable is the percentage of participants who use analytic categorization under different conditions. In addition to this, the weight of the focal attribute that comprises the (pseudo-)rule also sheds important light on how well the category is learned. There are three possible learning results. First, the rule is successfully identified so participants put a significant weight on the focal attribute and only on that attribute. Second, the importance of the focal attribute is recognized, but participants view other irrelevant attributes as relevant too and therefore put significant weight on the focal attribute as well as on other attributes. Third, participants only put significant weights on the actually irrelevant attributes. Since difference exists in these three cases in terms of how the category is learned, measures are needed to distinguish them. The percentage of analytic categorization usage can distinguish the first case from the other two but cannot detect the difference between the second and the third cases, where the weight that a participant puts on the focal attribute can provide insights. Therefore in Experiments 2 and 3 participants rated the probability of each test stimulus being in a category. This allows for a direct estimate of the degree to which people rely on each attribute, as measured by the attribute's coefficient in the linear regression model.

It is hypothesized that the effect of cognitive constraints on the weight of the focal attribute depends on whether the rule is perfect or pseudo. The focal attribute is the initial focus of attention regardless of cognitive constraints. If the attribute is perfectly associated with the category, constraints will not affect the attribute weight. The focal attribute is attended to from the start and as it does not have a single disconfirmation throughout the learning phase, a participant will recognize its importance whether or not they think other attributes are relevant. On the other hand, when the attribute comprises a pseudorule, cognitive constraints will decrease the weight of the focal attribute. After a disconfirmation is encountered, participants start to check on other attributes or at least take other attributes into account and so cognitive constraints consequently prevent the identification of the most valid attribute.

H4: Cognitive constraints decrease the weight of the attribute that prior expectations anticipate to be highly relevant if the attribute comprises a pseudorule, but constraints do not affect the attribute weight under the rule condition.

Design and the Stimuli

Experiment 2 employed a 2 (cognitive constraints: yes vs. no) X 2 (rule: rule vs. pseudorule) between subjects design. I manipulated cognitive constraints by asking half of the participants to memorize a letter string composed of 10 letters (Deshon, Brown, and Greenis 1996). Before the learning phase started, participants saw a letter string and memorized it. They needed to hold that string in mind until the string was recalled at the end of the learning phase. This extra cognitive task was expected to reduce the amount of information processed in learning.

The task was to identify two brands of electronic products based on their marketing strategies. Participants were told that there were two brands in the electronics market: Brand A and Brand B. Each brand offered a variety of electronic products and participants were to learn how to distinguish the two brands. Each product was described by five binary-valued attributes: price (high or low), quality (good or bad), advertising budgets (high or low), targeted consumers (college students or young professionals) and distribution outlets (electronic stores only or electronic stores and department stores). Brief explanations of the attributes were provided. The task instructions are attached in Appendix B-2.

Table 3 shows the learning stimulus design for the condition with a pseudorule. I constructed the learning stimuli using the following procedure: six different learning stimuli were generated for each category, then four stimuli were chosen from the original six and these four stimuli were presented twice yielding eight stimuli; these eight stimuli, plus the two which were in the original six but were presented only once, made 10 learning trials for each category. In this design, the first attribute comprises the pseudorule or the rule (in parentheses), and the other four attributes are randomly associated with the two brands. The pseudorule has significantly better diagnosticity than other attributes, providing 80% correct predictions, compared to only 50% for each of the other attributes. The same 20 learning stimuli were presented in a fixed order to all participants.

The order of the 20 learning trials was randomized except that the appearance of disconfirming trials was delayed under the pseudorule condition. Previous studies suggest that people seldom use pseudorules in a category learning task (Hutchison and Alba 1991; Juslin et al. 2003). I expected that late appearance of disconfirming trials might increase the chance of pseudorule usage, because if there were only few learning trials left after the first disconfirming trial was encountered, participants might want to stick with the pseudorule as it was more efficient than testing a new hypothesis. In this experiment the disconfirming trials appeared at the 15th, 17th, 19th, and 20th trial.

Table 3

Learning Stimuli (Experiment 2)

Category	*Quality*	*Advertising*	*Price*	*Targeted*	*Outlets*	*Order*
	0 (1)	1	1	0	1	15
	0 (1)	1	1	0	1	19
	1	1	0	0	1	2
	1	1	0	1	0	10
Brand A	1	1	0	1	0	18
	1	0	1	1	0	1
	1	0	1	0	0	7
	1	0	1	0	0	13
	1	0	0	1	1	5
	1	0	0	1	1	9
	1 (0)	0	0	1	0	17
	1 (0)	0	0	1	0	20
	0	0	1	1	0	4
	0	0	1	0	1	8
Brand B	0	0	1	0	1	14
	0	1	0	0	1	3
	0	1	0	1	1	6
	0	1	0	1	1	11
	0	1	1	0	0	12
	0	1	1	0	0	16

Note. Some abbreviated attribute names are used in the table. Advertising is abbreviated for advertising budgets, targeted for targeted consumers, and outlets for distribution outlets. Quality comprises a pseudorule or a rule (in parentheses) under difference conditions.

Prior expectations about the attributes were pretested (see Appendix B-1 for the pretest questionnaire). Twenty students from the same participant pool rated each attribute on a scale of 0-10 in terms of the likelihood it could distinguish between the two brands. The mean ratings for price, quality, advertising budgets, targeted consumers and distribution outlets were 7.20, 6.90, 5.15, 5.25 and 4.40 respectively. A MANOVA analysis showed a significant difference among the attributes: F (4, 76) = 6.27, $p < .01$. The ratings of price and quality were the highest and among the other three attributes, targeted consumers had the highest rating. Paired-samples T tests compared means of price, quality, and targeted consumers. Both price and quality were rated higher than targeted consumers (price vs. targeted consumers: t (19) = 3.90, $p < .01$; quality vs. targeted consumers: t (19) = 2.32, $p = .03$) and the ratings for price and quality were not different (t (19) = 0.44, $p = .66$). Please refer to Appendix B-5 for the test outputs. These results indicated that participants expected price and quality are much more likely than the other attributes to be the discriminating attribute. I used quality to comprise the rule or the pseudorule in case participants might assume high correlations between price and other attributes.

In order to obtain more information about categorization strategies, a couple of changes were made to the dependent variables. First, 16 test stimuli were generated according to a 2^5 fractional factorial design (Table 4). Second, after a participant provided judgments about the brands for the 16 test products, the products were presented again, one by one, along with the brand judgment made for each of them, and the participant indicated the probability of each product belonging to its brand on a range of 1-100. Based on these responses, a linear regression model including all attributes and all two-way interactions can be estimated for each participant to obtain the weight that is placed on each attribute and on each two-way interaction.

Table 4

Test Stimuli (Experiment 2)

	Quality	*Advertising*	*Price*	*Targeted*	*Outlets*	*Order*
1	0	0	0	1	1	8
2	0	0	0	0	0	3
3	0	0	1	0	1	2
4	0	0	1	1	0	12
5	0	1	0	0	1	14
6	0	1	0	1	0	9
7	0	1	1	0	0	7
8	0	1	1	1	1	11
9	1	0	0	1	0	1
10	1	0	0	0	1	13
11	1	0	1	1	1	6
12	1	0	1	0	0	16
13	1	1	0	0	0	15
14	1	1	0	1	1	5
15	1	1	1	0	1	10
16	1	1	1	1	0	4

Note. Some abbreviated attribute names are used in the table. Advertising is abbreviated for advertising budgets, targeted for targeted consumers, and outlets for distribution outlets.

Procedure

Experiment 2 was computer-based. The procedure of the experiment was based on that of Experiment 1 but incorporated the following changes. First, participants in the cognitive constraint condition memorized a letter string which was shown for 60 seconds before the learning phase started and recalled it at the end of the learning phase. Second, in each learning trial, the product description and its brand label were presented on the same screen for 10 seconds. In Experiment 1 a participant needed to make her judgment about a wine before the feedback was provided, because the wine stimulus was described by four attributes and it might be possible for participants to memorize and compare adjacent learning stimuli. If so, participants could quickly learn the discriminating rule and did not need to develop hypotheses by themselves. But this is less likely to happen in Experiment 2, because the stimulus in Experiment 2 was described by five attributes and it is more difficult to memorize and make comparisons on all of the five attributes. Third, the test phase had two dependent variables: the judgments made for the 16 test products and the probabilities provided for each judgment. Fourth, there was a time constraint during the test phase for all participants. When judging whether a product was Brand A or Brand B, participants needed to make their decisions within 10 seconds. Finally, to encourage participants to take the task seriously, a small prize (i.e., a candy bar with the value of $0.40) was provided. Participants were told that they could win the prize if the accuracy rate of brand judgments was good. Eventually every participant received the candy bar. Post-decision questions were answered at the end of the experiment. See Appendix B-3 and B-4 for the screen shots during the learning phase and the test phase, and B-5 for the post-decision questionnaire.

Results

Participants were 102 students from the University of Alberta, with 24, 25, 25 and 28 participants for the four conditions. The statistical test outputs are attached in Appendix B-6.

Percentage of analytic categorization. To test Hypothesis 2 and Hypothesis 3, the number of participants who used analytic categorization was analyzed. Multiple measures were used in a sequence to identify (pseudo-)rule users. The first measure was the number of correct judgments. For both rule and pseudorule conditions, the correct brand of a test product was determined by the attribute value of quality. A participant who used analytic categorization should make 16 correct judgments. The number of participants who made 16 correct judgments for each condition was counted: 16 out of 28 under the rule-unconstrained condition, 17 out of 24 under the rule-constrained condition, nine out of 25 under the pseudorule-unconstrained condition, and four out of 25 under the pseudorule-constrained condition.

However, making 16 correct judgments does not necessarily mean the participant used a rule or a pseudorule. First, it is possible for a participant to base her decisions on quality because she expected the two brands to be distinguished by quality and she might have simply relied on this prior expectation. Second, when the rule was a pseudorule, it is possible that a participant missed the disconfirming trials and consequently identified quality as a perfect rule. In this case, the participant actually was not a pseudorule user because she did not process information correctly.

In order to rule out the above possibilities and correctly identify rule or pseudorule users, the second measure was examined: the answer to the post-decision question "based on the information provided during the learning process, do you think there is one single product feature that always predicts that a product is Brand A or Brand B? Put in another way, whether a product is of Brand A or Brand B can be solely based on this one feature, without the need to consider other features (yes, no, I don't know)?" In addition, the third measure was also checked: the responses to the open-ended post-decision question "please explain how you decided whether a product is of Brand A or Brand B?" It was expected that under the rule condition, rule users should correctly identify quality as the discriminating attribute but under the pseudorule condition, pseudorule users should recognize there were no perfectly predictive attributes but they still based their decisions solely on quality.

Examination of the second and third measures showed that not all participants who made 16 correct judgments were truly the rule or pseudorule users. Among the 16 participants making 16 correct judgments under the rule-unconstrained condition, only 10 of them correctly identified quality as the discriminating attribute and used quality to make decisions. Under the rule-constrained condition, 16 out of the 17 participants making all correct decisions successfully identified quality and based their decision on quality. Under the pseudorule-unconstrained condition, among the nine participants making all correct decisions, one reported quality was perfectly predictive, indicating she missed disconfirming trials and did not learn the pseudorule. The other eight participants did not think there was a rule, but one of them used multiple attributes and she described her strategy as "primarily quality, and then price and amount of advertising. Sales channel has no influence on my decisions." So in total there were seven participants under the pseudorule-unconstrained condition who used analytic categorization. Finally, under the pseudorule-constrained condition, the four participants who made all correct decisions did not think there was a rule but two of them reported that they had used multiple attributes to make decisions. For instance, one participant said "(it) seemed to be lower price, better quality and more targeted towards a younger crowd in brand A". Table 5 illustrates the identification procedure described above.

Table 5

Identification Procedure of Analytic Categorization Users

The rule-unconstrained condition (28 participants):

Measure 1: 16 correct brand judgments	16 participants made 16 correct judgments.			
Measure 2: answers to the question of whether was a discriminating attribute	10 participants reported that quality was the discriminating attribute.	Two participants did not know whether there was a discriminating attribute.	Three participants thought there were no discriminating attributes.	One participant thought price was the discriminating attribute.
Measure 3: self-reported strategies	10 participants reported that they based their decisions on quality.			

The rule-constrained condition (24 participants):

Measure 1: 16 correct brand judgments	17 participants made 16 correct judgments.	
Measure 2: answers to the question of whether was a discriminating attribute	16 participants reported that quality was the discriminating attribute.	One participant did not know whether there was a discriminating attribute.
Measure 3: self-reported strategies	16 participants reported that they based their decisions on quality.	

The pseudorule-unconstrained condition (25 participants):

Measure 1: 16 correct brand judgments	Nine participants made 16 correct judgments.	
Measure 2: answers to the question of whether was a discriminating attribute	Eight participants thought there were no discriminating attributes.	One participant thought quality was perfectly discriminating.
Measure 3: self-reported strategies	Seven participants reported that they based their decisions on quality.	One participant used multiple attributes to make categorization judgments.

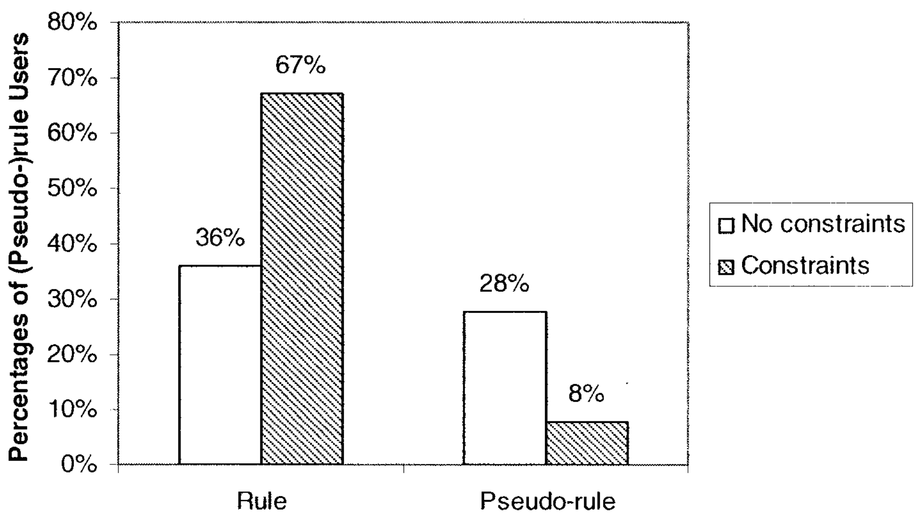
The pseudorule-constrained condition (25 participants):

Measure 1: 16 correct brand judgments	Four participants made 16 correct judgments.	
Measure 2: answers to the question of whether was a discriminating attribute	Four participants thought there were no discriminating attributes.	
Measure 3: self-reported strategies	Two participants reported that they based their decisions on quality.	Two participants used multiple attributes to make categorization judgments.

In summary, 10 out of 28 participants (36%) used analytic categorization under the rule-unconstrained condition and 16 out of 24 participants (67%) under the rule-constrained condition. Hypothesis 2 is supported; i.e. the percentage of rule users was greater under cognitive constraints (Fisher's Exact Test: p (1-sided) = .02), as shown in Figure 2. When quality comprised a pseudorule, 7 out of 25 unconstrained participants (28%) used analytic categorization compared to only 2 out of 25 constrained participants (8%). This difference was marginally significant (Fisher's Exact Test: p (1-sided) = .07). Hypothesis 3 received qualified support.

Figure 2

Percentages of (Pseudo)Rule Users (Experiment 2)



The three measures that were used to identify analytic categorization users included both behavioral measures (i.e., the accuracy rate of the judgment set) and self reports. If the criterion is only based upon behavioral measures, the percentages of analytic categorization usage for the four conditions were 57% (the rule-unconstrained condition), 71% (the rule-constrained condition), 36% (the pseudorule-unconstrained condition), and 16% (the pseudorule-unconstrained condition) respectively. The effect of cognitive constraints was not significant for the rule condition (Fisher's Exact Test: p (1-sided) = .23) and was still marginally significant for the pseudorule condition (Fisher's Exact Test: p (1-sided) = .10).

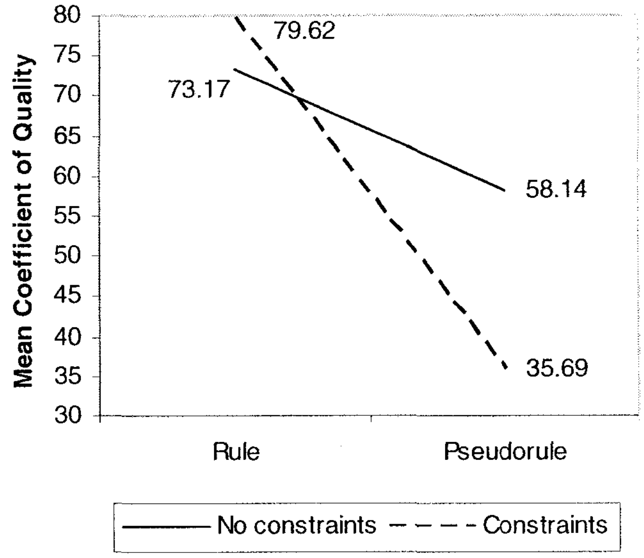
On the other hand, if the criterion regarding whether a participant used a (pseudo-)rule was based on self-reported strategies alone, the percentages of analytic categorization usage under different conditions also changed. This is because there might be some participants who used analytic categorization strategies but did not make 16 correct judgments, probably due to careless mistakes. After examining the self-reports of all participants, I found there was one participant under the pseudorule-unconstrained condition who made 14 correct judgments, did not think there was a rule but chose to base the decisions solely on quality. If this participant is classified as an analytic categorization user, the percentage under this condition changes to 32% (8 out of 25 participants). For all the other conditions, the percentages remained unchanged because the participants who made 14 or 15 correct judgments did not provide self-reports that were consistent with the analytic categorization strategy. So the percentages for the four conditions were 36% (the rule-unconstrained condition), 67% (the rule-constrained condition), 32% (the pseudorule-unconstrained condition), and 8% (the pseudorule-unconstrained condition) respectively. The effect of cognitive constraints became significant for both the rule condition (Fisher's Exact Test: p (1-sided) = .02) and the pseudorule condition (Fisher's Exact Test: p (1-sided) = .04).

Weight of the focal attribute. Next the weight of quality was analyzed to test hypothesis 4. As discussed before, the weight of quality indicates the importance of quality in the category judgments and it is an important indicator of how well the category structure is learned. Based on the 16 probabilities that a participant provided for the test products, a linear regression model was estimated for each participant with probability as the dependent variable and the five attribute values and their two-way interactions as independent variables. The coefficient estimates for the regression model indicated the weights that a participant put on the five attributes and on their two-way interactions. A 2 (constraints) X 2 (rule) ANOVA analysis of the coefficients of quality showed a significant main effect of rule ($F_{(1, 98)} = 23.21$, $p < .01$), suggesting the weight of quality was significantly lower when quality was a pseudorule compared to when quality was a rule. Follow-up comparisons showed the rule effect was significant for both the unconstrained group ($t_{(51)} = -1.82$, $p = .08$) and the constrained group ($t_{(47)} = -4.85$, $p < .01$). Moreover, the interaction between constraints and rule was also significant ($F_{(1, 98)} = 5.57$, $p = .02$).[1] Hypothesis 4 was supported. When quality was a rule, cognitive constraints did not increase its weight or importance in decision making (constrained group = 79.62, unconstrained group = 73.17, $t_{(50)} = -0.78$, $p = .44$). When quality was the pseudorule, as expected, constraints decreased the weight of quality (constrained group = 35.69, unconstrained group = 58.14, $t_{(48)} = 2.49$, $p = .02$). The mean coefficients of quality are shown in Figure 3.

[1] One sample Kolmogorov-Smirnov test showed the coefficient of quality was not normally distributed ($p = 0.046$). But Levene's test of equality of error variances was not significant: $F_{(3, 98)} = 0.72$, $p = 0.54$. The results of ANOVA analysis are therefore reported. Mann-Whitney test, which is a nonparametric test often used as an alternative to an F test when the data are not normally distributed, showed similar results as the ANOVA analysis.

Figure 3

Mean Coefficients of Quality (Experiment 2)



Percentage correct. In addition to the most relevant dependent variables, the percentage of correct judgments was also analyzed. Percentage correct is not directly related to the categorization strategy, because for a particular test stimulus, there could be multiple reasons for it being judged correctly, such as by using the discriminating attribute, by using a non-discriminating attribute, by using multiple attributes or simply by guessing. So a true usage of analytic categorization should lead to an entire set of correct judgments assuming there are no careless mistakes. But percentage correct might be an important variable itself because it shows learning consequences and to some extent demonstrates how well the category is learned. Many previous studies use this variable as one of the primary dependent variables (e.g., Allen and Brooks 1991; Juslin et al. 2003; Murphy and Allopenna 1994; Smith and Shapiro 1989). Note that in this experiment, the criterion about the correctness of a judgment is based on the usage of analytic categorization, so it is arbitrary for the pseudorule condition since quality is not perfectly predictive in this case.

A 2 (constraints) X 2 (rule) ANOVA analysis of percentage correct showed a significant main effect of rule (rule group = 91%, pseudorule group = 80%, $F_{(1, 98)} = 11.92$, $p < .01$) and a marginally significant interaction between constraints and rule ($F_{(1, 98)} = 3.72$, $p = .06$).[2] It suggested that participants in the rule condition made significantly more correct judgments than the pseudorule condition. But again, the criterion used for judging the correctness of a judgment was arbitrary for the pseudorule condition. For the rule condition, cognitive constraints did not affect percentage correct (constrained group = 92%, unconstrained group = 90%, $t_{(50)} = -0.42$, $p = .67$), while for the pseudorule condition, constraints decreased percentage correct (constrained group = 74%, unconstrained group = 85%, $t_{(48)} = 2.12$, $p = .04$). These results might be explained by the effects of constraints on weight of quality under different conditions. As quality was the most important attribute under all conditions, the importance of quality in decision making was closely associated with the correctness of a judgment. Previous analysis showed constraints did not change weight of quality under the rule condition but decreased the weight under the pseudorule condition, showing a consistent pattern with the effects of constraints on percentage correct.

[2] One sample Kolmogorov-Smirnov test showed percentage correct was not normally distributed ($p <.01$). Levene's test of equality of error variances was not significant: $F_{(3, 98)} = 2.63$, $p = .054$. The Mann-Whitney test showed similar results as the ANOVA analysis.

Discussion

To summarize, Experiment 2 provides supporting evidence for Hypotheses 2, 3 and 4. Cognitive constraints enhance analytic categorization when the rule is perfectly matched with prior expectations. This finding identifies a boundary condition for the well-established impairing effect of cognitive constraints on cognitive tasks (Drolet and Luce 2004; Hutchison and Alba 1991; Nowlis and Shiv 2005; Pontari and Schlenker 2000; Yzerbytm, Coull, and Rocher 1999).

An alternative explanation for constraints improving rule learning might be that under cognitive constraints, participants rely more heavily on their prior expectations. Because the rule in this experiment is consistent with the expectations, more reliance on expectations leads to a higher percentage of rule usage. However, evidence disapproves this explanation. First, when quality is the rule, the weights that participants put on quality are independent of the presence of cognitive constraints, suggesting the importance of quality is equally well recognized across the two conditions. So for unconstrained participants, some of them failed to identify the rule not because they did not learn the importance of quality but rather because they considered other attributes to be relevant. In other words, improved analytic categorization is accompanied by attenuated influence of irrelevant attributes rather than by accentuated importance of relevant attributes. Second, the pretest shows that quality and price are equivalent in terms of their likelihood to be the rule. So participants have to learn actively in order to identify quality, and not price, as the rule. Therefore the increased usage of analytic categorization under cognitive constraints cannot be attributed to heuristic application of prior expectations.

The positive effect of cognitive constraints on analytic categorization only holds when the rule and prior expectations flawlessly match. When the most relevant attribute comprises a pseudorule, cognitive constraints significantly decrease the importance of this attribute and the percentage of pseudorule users also tends to decrease. This finding is consistent with previous studies which observed little evidence for the usage of a pseudorule in category learning (Hutchison and Alba, 1991; Justin et al. 2003). The authors manipulated cognitive constraints by increasing the complexity of the learning stimulus (Hutchison and Alba, 1991) or by imposing time pressure (Justin et al. 2003), which was different from the manipulation in this experiment. Moreover, in this experiment the disconfirming trials for quality did not appear until the last five trials, but still most participants learned the disconfirming information and many of them changed their strategies. This suggests people are reluctant to use a pseudorule, and they tend to believe taking more attributes into account will yield better decisions (Arkes et al. 1986). It is also suggested that constraints decrease the usage of a pseudorule because a pseudorule is more difficult to identify than a rule. After an attribute is disconfirmed, participants start to attend to other attributes and test new hypotheses, which makes it difficult to find out which attribute is the most valid predictor.

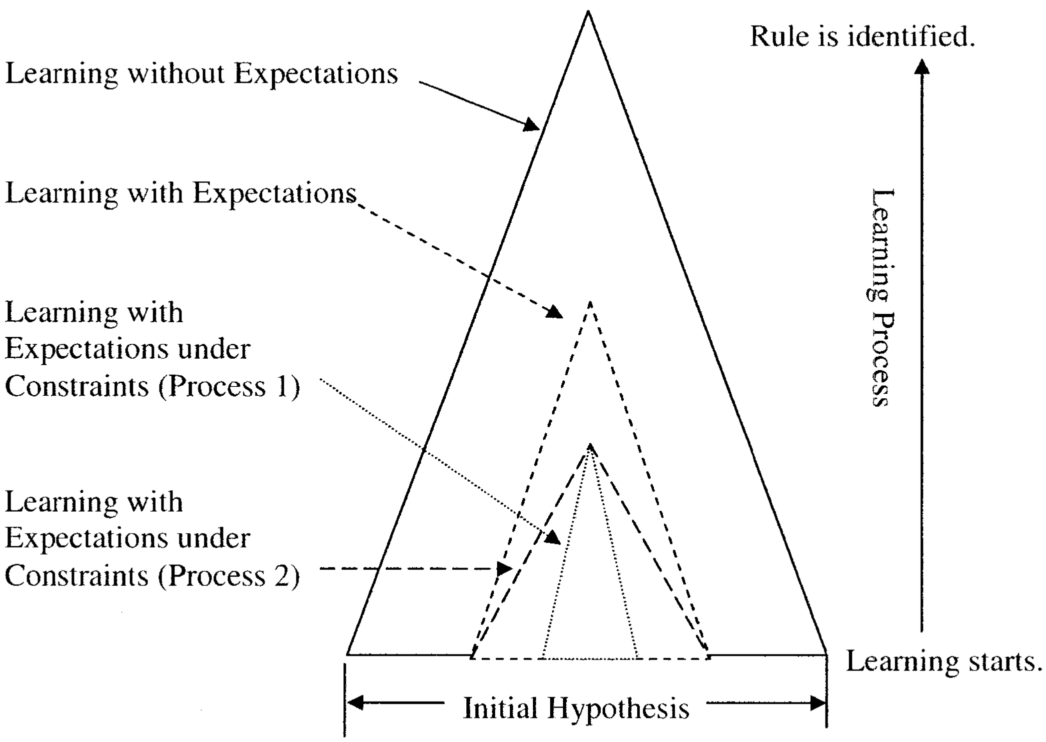
This experiment suggests constraints facilitate rule learning by reducing the influence of irrelevant attributes. However, it does not clearly show exactly how constraints reduce the effect of irrelevant information. Experiment 3 was conducted to address this question.

EXPERIMENT 3

There are at least two ways for cognitive constraints to exhibit a positive effect on rule learning when the rule is consistent with prior expectations. First, cognitive constraints might cause participants to further narrow down their initial hypotheses (Process 1 in Figure 4). Second, cognitive constraints might somehow increase the learning rate and make participants update their hypotheses more efficiently (Process 2 in Figure 4). These two processes either separately or together.

Figure 4

Rule Learning Process with and without Cognitive Constraints



Cognitive constraints may influence the generation of the first hypothesis by reducing the number of attributes in the initial hypothesis. Take the stimulus in Experiment 2 as an example. Constrained participants might choose to focus their attention only on price and quality during the first few learning trials, because the two attributes are the most relevant according to their prior expectations. Unconstrained participants, on the other hand, certainly would pay attention to price and quality, but they are also likely to attend to other attributes because they have additional cognitive resources to do so. Because quality receives consistent confirmations and all other attributes simply add noise to the task, it would be easier for the participants with a more focused initial hypothesis to identify the rule. As to the learning rate of this process, participants with a better initial focus can update information either more quickly or more slowly. Hypothesis updating can be slowed down because of the constraints, but the updating rate can also increase because the attention is focused on fewer attributes. If hypothesis testing is slowed down, the benefits from a more focused initial hypothesis must outweigh the reduction in learning rate in order for a positive effect of constraints on analytic categorization to be observed.

Alternatively, cognitive constraints may increase the efficiency of hypothesis testing. As discussed above, constrained participants might be able to update information more rapidly when they focus on a smaller number of attributes. If the number of attributes in the hypothesis does change under constraints, constrained participants can still update information more quickly by adopting a more aggressive approach in hypothesis testing. The aggressiveness in hypothesis updating is related to the criterion that participants use to reject disconfirmed attributes. When they have adequate cognitive resources, participants might choose to keep attending to an attribute after it is disconfirmed to further test it or test the combination of this attribute with other attributes. But when cognitive resources are limited, participants might become more aggressive and tend to drop a disconfirmed attribute much sooner so that the hypotheses can be rapidly narrowed down. This aggressive approach particularly favors the situation where the rule is based on a single attribute, because all irrelevant attributes can be quickly rejected and the rule is easy to identify. However, when the rule is conjunctive, which means category membership is based on multiple attributes, the aggressive approach will hurt rule learning. This is because in the conjunctive rule case, all attributes have at least one disconfirmation, and if participants quickly reject attributes after one or two disconfirming trails, they will not be able to test a conjunctive rule until all attributes are disconfirmed.

Design

Experiment 3 used a 2 (cognitive constraints: yes vs. no) X 2 (rule: single-attribute-based rule vs. conjunctive rule) between-subjects design. There were two reasons for using the conjunctive-rule condition. One was to test whether constrained participants stop considering a disconfirmed attribute sooner than unconstrained participants. If so, constraints would inhibit the identification of a conjunctive rule. In addition, a conjunctive rule also represents another condition where prior expectations and rules do not flawlessly match. Previous research suggests that in a category learning task, participants tend to look for a single-attribute-based rule (Nosofsky, Palmeri, and Mckinley 1994). A conjunctive rule departs from prior expectations in that the rule is based on multiple attributes rather than on the most relevant attribute according to prior expectations.

Unlike Experiments 1 and 2, this experiment employed an Information Display Board procedure, in which attribute values were hidden under buttons and a participant needed to click on each button to read the information. When the participant released the mouse or removed the mouse from the button, the information was hidden again. In each learning trial the following variables were measured: which buttons were clicked, the order the buttons were clicked, the time that was spent on reading each button, and the time that was spent on each trial. These process measures provided behavioral information in each learning trial.

Two additional design features differed from Experiment 2. First, this experiment manipulated prior expectations in order to obtain clear-cut and consistent prior expectations across all participants. Second, cognitive constraints were manipulated in a different way. Participants needed to memorize an item before each learning trial and to recall it after that trial. By doing so, participants had a constant amount of cognitive load for each learning trial. Because participants needed to memorize a new item for each trial, a 6-digit number was used instead of a letter string to make the task easier. Number memorization has been widely used in the literature as a manipulation of cognitive constraints (e.g., Nowlis and Shiv 2005; Trope and Alfieri 1997). Each number was shown for 10 seconds before each learning trial.

In case a participant might click on all buttons throughout the phase just out of curiosity, participants were asked to click on buttons that were necessary or helpful. As in Experiment 2, a small prize (i.e., a candy bar) was provided to make participants more involved in the task. Participants were told that winning the prize depended on their performance, which was positively related to the number of accurate judgments made during the test phase and negatively related to the number of button clicks. For the participants under cognitive constraints, their performance was also positively related to accurate recall of the numbers. At the end of the experiment, every participant received the candy bar.

The Stimuli and Procedure

The product category was the sailboat. All sailboats in the world were described as either Type A or Type B and participants learned how to distinguish between the two types. It was assumed that participants were not familiar with sailboats, and to test this, participants were asked to provide familiarity and knowledge ratings at the end of the experiment. Each sailboat was described by five binary-valued attributes: bottom of hull (round or V-shaped), hull coating (polyurethane or neoprene), keel type (full keel or fin keel), shape of sail (square or triangular) and material of sail (tyvek or dacron). Participants saw pictures of different types of hulls, keels, and sails to understand these attributes. The different kinds of hull coatings and materials of sail were described as the most commonly used materials. See Appendix C-1 for task instructions.

To manipulate prior expectations, participants read a survey about sailboat types. The survey was said to have been conducted by a sports magazine among its subscribers. In the survey one question was "how important is it to know the value of XXX (an attribute specified here) to predict a sailboat's type". The survey found that 70% of respondents thought the information about a boat's bottom of hull to be important; 51% thought the keel type was important, and for the hull coating, the shape of sail and the material of sail, the percentages were 12%, 18%, and 15% respectively. It was expected that the survey report would lead participants to think that the bottom of hull and the keel type were the two most important attributes in determining boat types. In order to check this, participants rated each attribute in terms of its importance in predicting boat types on a scale of 0-10 immediately after the survey information was presented.

Table 6 showed the learning stimuli for the two rule conditions. When the rule was based on a single attribute (on the left of the table), the bottom of hull distinguished between the two categories; when the rule was conjunctive (on the right of the table), a boat needed to have particular attribute values for both the bottom of hull and the keel type to be a particular type. The other attributes were held constant across conditions and they were randomly associated with the categories. The order of the 18 learning trials was randomized. In the conjunctive-rule condition, both the bottom of hull and the keel type had four disconfirming trials to show that the single attribute was not perfectly predictive. Disconfirming trials for the bottom of hull were at the 4^{th}, 6^{th}, 11^{th}, and 13^{th} trials and for the keel type the 8^{th}, 10^{th}, 15^{th}, and 18^{th} trials. The test stimuli were generated in the same way as in Experiment 2: 16 stimuli based on a 2^5 fractional factorial design.

Table 6

Learning Stimuli (Experiment 3)

SINGLE-ATTRIBUTE-BASED RULE							CONJUNCTIVE RULE					
	H	C	K	S	M	O	H	C	K	S	M	
Type A	1	1	0	1	0	1	1	1	1	1	0	Type A
	1	1	0	0	0	2	1	1	1	0	0	
	1	0	1	0	1	3	1	0	1	0	1	
	1	0	1	1	1	5	1	0	1	1	1	
	1	0	1	1	0	7	1	0	1	1	0	
	1	1	0	0	1	9	1	1	1	0	1	
	1	0	1	0	1	12	1	0	1	0	1	
	1	1	0	0	0	14	1	1	1	0	0	
	1	0	1	1	1	16	1	0	1	1	1	
	1	1	0	1	0	17	1	1	1	1	0	
Type B	0	0	0	0	1	4	1	0	0	0	1	Type B
	0	1	0	0	0	6	1	1	0	0	0	
	0	1	1	1	0	8	0	1	1	1	0	
	0	1	1	0	1	10	0	1	1	0	1	
	0	0	0	0	1	11	1	0	0	0	1	
	0	0	0	1	0	13	1	0	0	1	0	
	0	0	1	1	1	15	0	0	1	1	1	
	0	1	1	1	0	18	0	1	1	1	0	

Note. Abbreviated attribute names are used in the table. H is abbreviated for bottom of hull, C for hull coating, K for keel type, S for shape of sail, and M for material of sail. O is abbreviated for presentation order. Under the single-attribute-based rule condition, the bottom of hull comprises the rule, and under the conjunctive-rule condition, the bottom of hull and the keel type combine to determine a boat's type.

The experimental procedure was similar to that used in Experiment 2 with a few changes. After reading the task instructions and the survey report, participants rated each attribute's importance for the manipulation check, followed by three practice trials and the learning phase. During the learning phase, the participants in the cognitive constraints condition memorized a new number before each learning trial and recalled the number after that trial. Then participants made judgments in the test phase and answered post-decision questions. Finally participants provided familiarity and knowledge ratings about sailboats and answered some demographic questions (see Appendix C-5 for the post-decision questionnaire). An important change in the procedure was that both learning phase and test phase were self-paced in this experiment. For the learning phase, as participants needed to memorize a new number for each learning trial, additional time constraints might make the learning task somewhat intimidating for the constrained group, so the time constraints for the learning phase were removed. With regard to the test phase, results in Experiment 2 showed that 94.6% brand judgments were made within 10 seconds, so the 10-second time limit was also removed for the test phase. See Appendix C-2, C-3 and C-4 for the screen shots during the learning phase under different conditions and the screen shots for the test phase.

Predictions

Experiment 3 had two purposes. One was to measure the information processing behavior and explore if constraints would lead to a more focused initial hypothesis and/or a more aggressive hypothesis testing approach. Process measures were employed to provide evidence for these two processes. For example, if constraints result in a more focused initial hypothesis, the number of attributes that were clicked in the first few learning trials should decrease.

The other purpose was to investigate the effects of cognitive constraints on analytic categorization in another situation where the rule departs from prior expectations: the conjunctive-rule condition. When the rule is based on a single attribute, percentage of analytic categorization will increase under cognitive constraints, and this occurs whether constraints reduce the number of attributes in the initial hypothesis or generate a more aggressive information updating process. When the rule is conjunctive, however, the effects of constraints will depend on the underlying mechanism. If constraints yield a more aggressive approach in hypothesis testing, percentage of analytic categorization will decrease under constraints; if constraints only lead to a more focused initial hypothesis and do not affect the criterion of rejecting a disconfirmed attribute, it is uncertain how constraints will affect percentage of analytic categorization. Constraints might increase the percentage because the conjunctive rule is based on the two most relevant attributes and the learning rate might increase with less information being processed. But constraints can also impair the learning of a conjunctive rule because identifying a conjunctive rule typically requires more cognitive efforts than identifying a single-attribute-based rule.

In addition, the weight of the bottom of hull and the weight of the keel type are also important indicators of how well the category structure is learned. When the rule is comprised of a single attribute, as when the bottom of hull is the rule and the keel type is randomly associated with the boat types, it is easy to learn the importance of the bottom of hull and the irrelevance of the keel type, so cognitive constraints will not change the weight of either attribute. When the rule is conjunctive, neither attribute is perfectly predictive; thus, both weights will be decreased and their importance will be less recognized under cognitive constraints.

Results

There were 112 participants in total. Five of them were excluded because they clicked on buttons in only one trial or did not click at all, leaving 107 participants for data analysis. Self-reported familiarity and knowledge had mean ratings of 1.27 and 1.14 on a 0-10 scale, indicating it was unlikely for participants to generate expectations based on their own knowledge. The statistical outputs are attached in Appendix C-5.

Manipulation check. The manipulation of prior expectations worked as anticipated. The mean importance ratings for the five attributes, bottom of hull, hull coating, keel type, shape of sail and material of sail, were 8.07, 3.75, 7.12, 5.78, and 3.89 respectively. A MANOVA analysis showed significant difference among the five attributes ($F_{(3, 307)} = 126.34$, $p < .01$). The bottom of hull and the keel type had the two highest ratings and the shape of sail had the highest among the remaining three attributes. A comparison of ratings between the shape of sail and the bottom of hull showed a significant significance ($t_{(106)} = 8.81$, $p < .01$). The rating difference between the shape of sail and the keel type was also significant ($t_{(106)} = 6.54$, $p < .01$) and so was the difference between the bottom of hull and the keel type ($t_{(106)} = 5.7$, $p < .01$). These results suggested participants expected the bottom of hull to be the most important attribute for predicting sailboat types and the keel type to be the second most important attribute. Both of them were significantly more important than the other three attributes.

Percentage of analytic categorization usage. Following Experiment 2, I used three measures in sequence to identify the participants who used analytic categorization: 16 correct judgments, correct identification of the rule, and self-reported reliance on the rule. Among the 28 participants under the single-attribute-based rule, unconstrained condition, 19 of them made 16 correct judgments and three of the 19 did not think there was a rule, so 16 participants (57%) were identified as rule users. These 16 participants all reported that their decisions were solely based on the bottom of hull. Under the single-attribute-based rule, constrained condition, 18 out of 26 participants made all correct judgments. Two of the 18 did not know there was a rule and reported that they had used other attributes, and the other 16 participants based their decisions on the bottom of hull. So these 16 participants used the rule to make decisions (62%). A chi-square test showed cognitive constraints did not affect the percentage of analytic categorization when the rule was based on a single attribute (constrained group = 62%, unconstrained group = 57%, Fisher's Exact Test: p (1-sided) = .48).

Unexpectedly there seemed to have a floor effect in rule usage when the rule was a conjunctive rule. Under the conjunctive-rule, unconstrained condition, only four out of 29 participants made 16 correct judgments and all of them correctly identified the rule (14%). Among the 24 participants under the conjunctive-rule, constrained condition, three participants met all the criteria and were identified as the users of analytic categorization (12%). Cognitive constraints did not affect the percentage for the conjunctive-rule condition either (constrained group = 12%, unconstrained group = 14%, Fisher's Exact Test: p (1-sided) = .61).

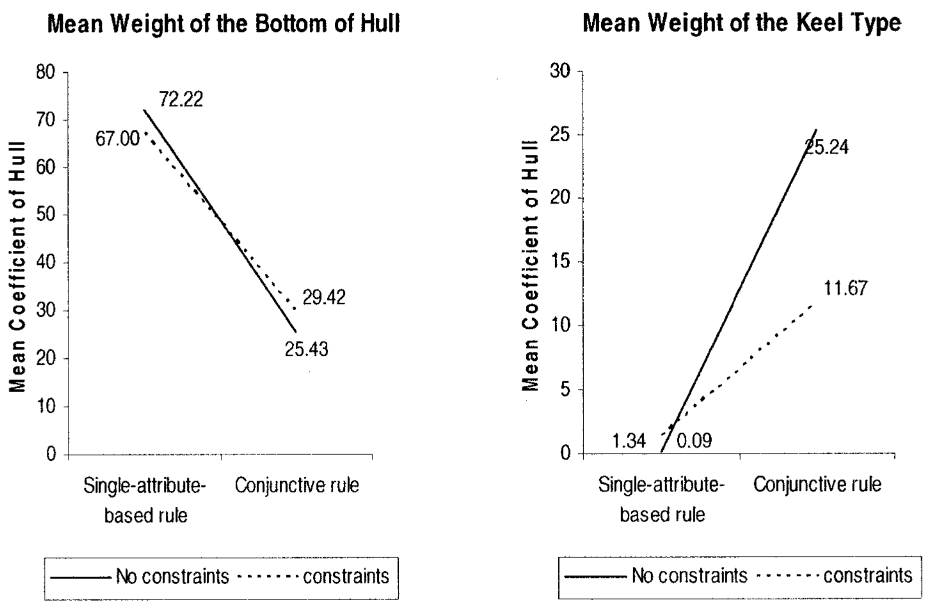
The main effect of rule type on percentages was significant. Under the conjunctive-rule condition, significantly fewer participants used analytic categorization compared to the single-attribute-based rule condition (conjunctive rule = 13%, single-attribute-based rule = 60%, Fisher's Exact Test: $p < .01$). Follow-up tests showed that this effect of rule type existed for both constrained group (12% vs. 62%, Fisher's Exact Test: p (1-sided) < .01) and unconstrained group (14% vs. 57%, Fisher's Exact Test: p (1-sided) < .01).

As in Experiment 2, I checked to see if some participants who used analytic categorization made one or two wrong judgments by mistake. Among all the participants who made 14 or 15 correct judgments, none of them used correct rules according to their responses to post-decision questions.

Attribute weight. Although cognitive constraints had no effects on the percentage of analytic categorization, it does not necessarily mean that constrained participants learned equally as well as unconstrained participants about the importance of attributes. The attribute weights might be more sensitive to the manipulation of cognitive constraints. As in Experiment 2, a linear regression model was estimated for each participant with the probability judgments for the 16 test boats as the dependent variable, and the five attributes as well as all two-way interactions as the independent variables. The coefficients for the bottom of hull and for the keel type were analyzed (Figure 5). [3]

Figure 5

Mean Weight for the Bottom of Hull and for the Keel Type
(Experiment 3)



ANOVA was not used for the coefficient analysis because the assumption of equality of error variances did not hold for the weight of the keel type (Levene's test: $F_{(3, 102)} = 13.48$, $p < .01$). A Mann-Whitney test was used instead. A Mann-Whitney test is often used as an alternative to a t test when the data are not normally distributed, and it ranks all the values from low to high and compares the mean ranks in the two groups. The effect of rule type was significant for both weights. The weight of the bottom of hull (hereafter referred

[3] One participant provided the same brand judgment and probability for all test boats. The linear regression model could not be estimated based on her data. So there were responses from 106 participants in the analysis of attribute weights.

to as weight of hull) was significantly higher when the rule was based on a single attribute than when the rule was conjunctive ($Z = -5.95$, $p < .01$), while the weight of the keel type (hereafter referred to weight of keel) was higher under the conjunctive-rule condition than under the single-attribute-based rule condition ($Z = -4.25$, $p < .01$). These findings suggested that most participants learned the basic structure of the categories.

As expected, cognitive constraints did not affect the weight of hull under the single-attribute-based rule condition ($Z = -0.31$, $p = .75$). When hull comprised the rule, its importance was recognized for both constrained and unconstrained participants. It was interesting to find that when the rule was conjunctive, constraints did not affect the weights of hull either ($Z = -0.46$, $p = .65$).

For the weight of keel, there seemed to be an interaction effect between constraints and rule type. When the rule was solely based on hull, participants knew keel was not important and constraints did not make a difference ($Z = -0.16$, $p = .87$); when the rule was conjunctive, a significantly higher weight was put on keel by unconstrained participants ($Z = -2.11$, $p = .03$), suggesting constraints impeded the recognition of the importance of keel in a conjunctive rule.

Some follow-up tests were conducted for the conjunctive-rule condition. For unconstrained participants, the bottom of hull and the keel type were viewed as equally important ($Z = -0.21$, $p = .83$), suggesting that participants with adequate cognitive resources were able to learn the importance of an attribute in a conjunctive rule fairly well regardless of whether the attribute was expected to be the most important or the second most important. For constrained participants, on the other hand, the weight of hull was significantly higher than the weight of keel ($Z = -2.15, p = .03$).

The main effect of rule type significantly influenced the weight of the interaction term hullXkeel ($Z = -2.23$, $p = .03$), suggesting the interaction term was more important under the conjunctive-rule condition than the single-attribute-based rule condition. Contraints and the constraintXrule interaction were not significantly related to hullXkeel.

Process measures. Next process measures were analyzed to understand the information processing behavior. First, in order to examine whether constraints led to a more focused hypothesis at the early stage of learning, the total number of clicks on the five attributes, the number of clicks on irrelevant attributes (i.e., hull coating, shape of sail and material of sail), and the number of clicks on relevant attributes (i.e., bottom of hull and keel type) were compared between constrained participants and unconstrained participants for the first three learning trials. Across the four conditions, the first two learning trials were identical, so the information processing behavior within the first three trials should only be influenced by the presence of cognitive constraints.

The following analysis was based on the data in first three learning trials. A Mann-Whitney test of the total number of clicks showed a significant effect of constraints ($Z = -2.34$, $p = .02$), indicating the constrained group made fewer total clicks than unconstrained group. The number of clicks on hull was significantly different between constrained and unconstrained groups ($Z = -2.24$, $p = .03$), as was the number of clicks on keel ($Z = -2.73, p < .01$). The effect of constraints on the number of clicks on the other three irrelevant attributes was also significant ($Z = -1.93, p = .05$). The ratio of the number of clicks on irrelevant attributes over the total clicks was not affected by cognitive constraints ($Z = -0.85, p = .40$). Since the number of clicks on irrelevant attributes decreased proportionally with the total number of clicks, the notion that constraints reduce attention to irrelevant attributes more than to relevant attributes is not supported.

For the entire learning phase, it was surprising that no difference was found between constrained and unconstrained groups in the total number of clicks ($Z = -1.34, p = .18$), the number of clicks on the two relevant attributes ($Z = -1.13, p = .26$), or the number of clicks on irrelevant attributes ($Z = -1.01, p = .31$). Only the effect of rule was significant (the total number of clicks: $Z = -3.48, p < .01$; the number of clicks on relevant attributes: $Z = -3.81, p < .01$; the number of clicks on irrelevant attributes: $Z = -2.98, p < .01$). Participants under the conjunctive-rule condition processed more information than unconstrained participants because the conjunctive rule was harder to identify.

Also, it was interesting to note that under the conjunctive rule condition, participants made the same number of clicks on the bottom of hull as on the keel type during the entire learning phase. The test for differences in the number of clicks between the two attributes was insignificant for either the constrained group ($Z = -0.40, p = .69$) or the unconstrained group ($Z = 0.90, p = .37$). This finding was particularly unexpected for the constrained group, because analysis of attribute weight showed that constrained participants placed significantly less weight on the keel type than on the bottom of hull.

As expected, constrained participants tended to skip more learning trials than unconstrained participants. I noticed that there were some trials where no buttons were ever clicked and I counted the number of trials where at least one button was clicked for each participant. A Mann-Whitney test showed a significant main effect of constraints: $Z = -2.36$, $p = .02$, indicating constrained participants requested information on fewer trials. But note that with fewer learning opportunities, constrained participants learned equally as well as unconstrained participants.

There was no difference between constrained and unconstrained participants in terms of whether they kept clicking on an attribute after it was disconfirmed. Across the two groups, most participants still clicked on hull and keel in their last learning trials. Some of them had stopped clicking on the bottom of hull (or the keel type) after one or two disconfirming trials but they started to check on this attribute again after a couple of trials.

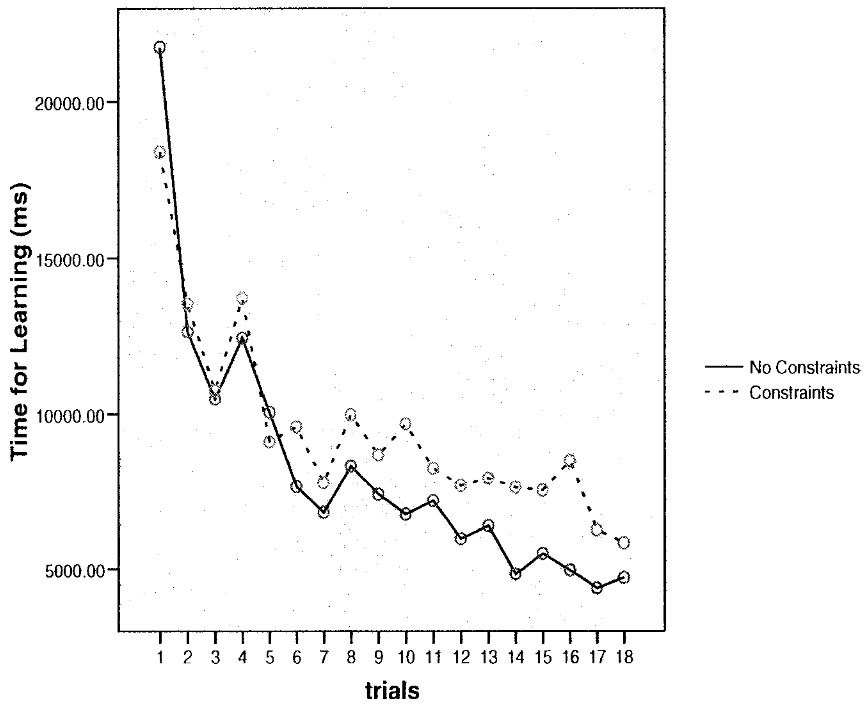
Learning time and percentage correct. The time that participants spent on the learning trials was also analyzed. A MANOVA model with the 18 learning trials as the within-subject factor, and rule type and constraints as the between-subjects factors, showed a significant effect of rule type ($F_{(1, 103)} = 10.80$, $p < .01$)[4]. Participants spent more time learning a conjunctive rule than a single-attribute-based rule. The main effect of trials was also significant ($F_{(7, 794)}$ =

[4] Box's test of equality of covariance matrices for learning time was significant: F (513, 215) = 1.92, $p < .01$.

46.56, $p < .01$), as was the interaction between trials and constraints ($F_{(7, 794)} = 2.10$, $p = .04$). As shown in Figure 6, participants spent less time on successive learning trials, but the decreasing rate appeared to be slower for constrained participants than for unconstrained participants. But the effect of constraints was not significant ($F_{(1, 103)} = 2.10$, $p = .15$), and a Mann-Whitney test showed similar results ($Z = -1.01$, $p = .31$).

Figure 6

Mean Time Spent on Learning Trials by Constrained and Unconstrained Participants (Experiment 3)



As in Experiment 2, percentage correct was analyzed. A 2 (cognitive constraints) X 2 (rule type) ANOVA analysis of percentage correct showed a significant effect of rule type (single-attribute-based rule = 89%, conjunctive rule = 68%, $F_{(1, 103)} = 23.82$, $p < .01$) and no other effects were significant[5].

Discussion

The effects of cognitive constraints on percentage of analytic categorization are not replicated in this experiment. Constraints do not change the likelihood of using analytic categorization. It might be attributed to the increased task difficulty during the learning phase which is caused by the Information Display Board procedure. In that procedure, attribute information is shown when the button is clicked on but is hidden again if the mouse is released or removed from the button. So at any particular point of time, a participant can only view one attribute value at most and has to hold the attribute information in mind when processing other attributes. This might cause a participant to make as few clicks as possible to decrease the memory load. So even under the unconstrained condition, a participant's memory capacity is actually constrained and the learning is affected by the constraints.

The attribute weights suggest that participants primarily focus their attention on the most important attribute under cognitive constraints. Under the conjunctive-rule condition, unconstrained participants do not show any difference in the weights between the bottom of hull and the keel type, suggesting they learn that the two attributes are equally important. However, cognitive constraints

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[5] Percentage correct was not normally distributed ($Z = .2.31$, $p < .01$) and Levene's test of equality of error variances was not significant: $F(3, 103) = 0.91$, $p = .44$.

decrease the weight of keel and do not affect the weight of hull. Note that in the conjunctive-rule condition, the bottom of hull and the keel type are associated with the two categories in the same pattern except that the disconfirming trials for the bottom of hull appear even earlier than those for the type of keel. So the effects of constraints on the attribute weights suggest that under constraints a participant's information processing is primarily oriented toward the attribute that is expected to be the most important.

In summary, these findings suggest that people tend to seek a single-attribute-based rule when they learn categories (Nosofsky et al. 1994), and that the effects of cognitive constraints on rule learning depend on the consistency between the rule and prior expectations. Constraints impede learning, except when the attribute that is expected to be the most important is indeed important. Moreover, participants tend to accept the information that is consistent with their expectations more readily under cognitive constraints (i.e., needing less learning trials).

Process measures reveal that constraints decrease the amount of information that is processed at the early stage of learning. However, the unchanged ratio of irrelevant clicks over total clicks suggests that constrained participants proportionally reduce the acquisition of relevant and irrelevant information. In other words, evidence is not observed for Process 1 which proposes that constraints lead to more focused initial hypotheses.

In addition, this experiment does not show evidence that constrained participants stop searching on a disconfirmed attribute sooner than unconstrained participants. This suggests that in general people are conservative in hypothesis testing and they do not easily reject an attribute if it seems to be relevant. More important, this behavior pattern remains unchanged under cognitive constraints.

The attribute weights show that constraints reduce the influence of irrelevant information, but the underlying mechanism remains a question to be answered. The process data offer some interesting insights in this regard. Constraints do not seem to influence the information acquisition behavior, at least during the early stage of learning. One explanation could be that a participant clicks on an irrelevant attribute in order to test whether it really is irrelevant. That is, it would be reasonable to look at Attribute 2 in order to test the hypothesis that Attribute 1 is the rule.

Another interpretation is that this information acquisition behavior is not followed by sufficient information processing. In fact evidence exists that the same information acquisition behavior leads to different processing results. Under the conjunctive rule condition, constrained participants put a significantly higher weight on the bottom of hull than on the keel type, but they made the same number of clicks on these two attributes. As shown in the stimuli design (Table 6), the bottom of hull and the keel type present their associations with the two categories in exactly the same way, so if the two attributes are acquired for the same number of times and the information is processed equally well, participants should be able to find out that the two attributes are equally important. However, the data suggests that the less important attribute (i.e., the keel type) is not processed as effectively as the most important attribute (i.e., the bottom of hull).

This observation is in accord with Sherman et al. (1998)'s finding. They found that when people process information about stereotypes under cognitive constraints, inconsistent information receives greater attention but consistent information is associated with significantly better conceptual encoding. So in this experiment, it seems likely that when cognitive resources are limited, participants choose to devote more processing resources (e.g, memory and encoding) to the information that is expected to be most important. This might explain why the influence of irrelevant information can still be reduced although the acquisition of this information is not changed under constraints: the information is acquired but not processed effectively. Certainly this mechanism does not only apply to the early stage of learning, but to the entire learning phase.

Learning rate might also contribute to the reduced influence of irrelevant information. Although the ratio does not change, the absolute amount of information that is acquired significantly decreases. So the learning rate can increase with the decreased information load, and participants are better able to learn which attributes are irrelevant.

Finally, although tracking of clicked attributes shows that most participants still seek information about the bottom of hull and the keel type in their hypotheses after the two attributes are disconfirmed, very few participants identify the conjunctive rule. It suggests that participants do not quite realize the possibility of a conjunctive rule for the task. After the two attributes are disconfirmed, participants start to bring other attributes into their hypotheses. But one possibility is that participants do not expect any relationship between the two attributes and tend to treat them separately. Future studies need be conducted to investigate factors that affect conjunctive rule learning under cognitive constraints.

GENERAL DISCUSSION

Summary and Contributions

In the era of web-enabled computers, consumers are bombarded with a rapidly increasing amount of information and multitasking has become routine. When a consumer is browsing product information online, she might be conducting Instant Messenger conversations and watching TV at the same time. This paper investigates how consumers under cognitive constraints (e.g., working on a secondary task) learn predictive relationships between product features and product categories or brands.

It is widely held in the literature that cognitive constraints generally impair the performance of the primary cognitive task (e.g., Drolet and Luce 2004; Nowlis and Shiv 2005; Pontari and Schlenker 2000; Yzerbytm, Coull, and Rocher 1999). In contrast, this paper provides evidence that cognitive constraints (i.e., an extra memorization task) do not necessarily hurt category learning. When the rule is perfectly matched with prior expectations, specifically, when the rule is based on the single attribute that prior expectations anticipate to be the most relevant for the categorization task, constrained participants can identify the rule better than (Experiment 2) or as well as (Experiment 3) unconstrained participants.

Meanwhile, evidence suggests that cognitive constraints may also impede the learning of important attributes. When the attribute that is anticipated to be the most relevant is an imperfect but still valid predictor, its importance in decision making is less recognized under constraints. This effect is even stronger if the attribute is anticipated to be less relevant.

This evidence that prior expectations and cognitive constraints influence category learning is consistent with the proposed model about how these factors affect the hypothesis testing process in rule learning. When constrained, participants tend to focus on the information that is expected to be most relevant and test hypotheses based on that information, so constraints can facilitate the learning of expectation-consistent rules by reducing the influence of irrelevant information. Constraints impede the learning of pseudorules because the inevitable disconfirmation of expected hypotheses means participants must shift to association learning, and constraints increase the difficulty of learning the associations between attributes and categories. It is important to note that constraints do not generate more focused initial hypotheses or draw attention only to relevant attributes, because the ratio of irrelevant information over the total amount of information does not change. Instead, the data suggest that participants exhibit different efficiency in processing the data that are acquired and more efficient processing is observed for the information that is expected to be most important.

While the results are generally consistent with our model, additional insights may be drawn by considering how these data may be explained by association learning. Association models use a continuous dependent variable that measures the association strength of each cue to the outcome. In order to apply such models to categorization, it is necessary to introduce an additional set of assumptions. When the cues have similar association strength, but are not perfectly associated with the outcome, categorizations are made based on multiple cues, namely, through holistic categorization. For the decision maker to switch from holistic to analytic categorization, an attribute should exhibit a strong association with the outcome. I propose that analytic categorization will occur when the strength of the association exceeds some threshold, and that the threshold will depend on various context factors.

Many of the results are consistent with the Mackintosh (1975) model of attention, a conditioned stimulus processing model which captures the influence of expectations in association learning. In the Mackintosh model, the updating of the strength of an association (s_{ij}) between a predictive cue i and an outcome j is a function of the discrepancy between the outcome level predicted by a specific cue and the experienced outcome level. More precisely:

$$\Delta s_{ij} = \alpha_i . \beta(q_j - s_{ij})$$

where q_j is the experienced outcome level, and s_{ij} is the outcome level predicted by the cue i, β and α_i are both learning-rate parameters.

The parameter β is specific to the task and does not vary across different cues or change over the course of learning. For instance, the presence of cognitive constraints is generally assumed to decrease β. The parameter α_i is specific to the cue i and it represents the difference in association strength updating between different cues as a result of the same outcome. This parameter varies according to (1) the physical characteristics, like the salience, of the cue; and (2) the learning history of the cue. The learning about the cue may have occurred before the start of a learning task (i.e., prior expectations), but α_i also is assumed to change during the course of the learning task.

$$\Delta\alpha_i^m > 0 \text{ when } |q_j^m - s_{ij}^{m-1}| < |q_j^m - s_X^{m-1}|$$

$$\Delta\alpha_i^m < 0 \text{ when } |q_j^m - s_{ij}^{m-1}| \geq |q_j^m - s_X^{m-1}|$$

where q_j is the experienced outcome level, s_{ij} is the outcome level predicted by the cue, s_X is the associative strength of all cues other than cue i, and m is the learning trial number. When cue i is a better predictor than the accompanying cues, the learning rate of cue i increases, which means the association strength updating of cue i is increasingly influenced by the outcome. When the accompanying cues are as effective, or more effective, than cue i at predicting the outcome, the learning rate of cue i decreases.

The Mackintosh model provides explanations for most of the findings in this paper through the two components of the learning rate: α_i and β. In Experiment 1, consistent prior expectations facilitate rule learning because expectations generate a higher initial α_i for the wine type than for the vineyard. Although both attributes are perfectly associated with the categories, the discriminating attribute with the higher α_i updates its association strength more rapidly with the outcome and thus it is easier for participants to identify the rule.

In Experiment 2 and 3, the fact that cognitive constraints do not impair the learning of the expected rules suggests that constraints have opposite effects on the two components of the learning rate: α_i and β. The presence of cognitive constraints tends to decrease β, but the initial α_i for the expected discriminating attribute (i.e., quality or the bottom of hull) might further increase under constraints, and consequently make the learning rate unchanged compared to unconstrained conditions. This would explain why constraints do not hurt the learning of the importance of quality or the bottom of hull when the attribute discriminates between the categories.

When participants learn about the attribute that is expected to be less important, e.g., the keel type in Experiment 3, constraints reduce the recognition of the attribute importance. This implies that for the keel type, the increase of α_i, if there is any, does not outweigh the decrease in β, and therefore this attribute's learning rate decreases under cognitive constraints and its association with the outcome is less well learned.

One finding that the Mackintosh model cannot explain is the inconsistent learning result for the pseudorule: the importance of quality decreases under constraints in Experiment 2; whereas, the importance of the bottom of hull is not influenced by constraints in Experiment 3. These two attributes are both expected to be the most likely discriminating attribute and they should show the same effect of constraints. When the two attributes are perfectly discriminating, constraints do affect the importance of either attribute, suggesting that the collective learning rate $\alpha_i\beta$ does not change after the introduction of the extra memorization task. It is hard to explain why the learning rate for quality seems to decrease under constraints when quality is the pseudorule.

This paper also contributes to the Mackintosh model by providing evidence that some specifications of the model might need to be reconsidered. First, Mackintosh specified α_i as a learning-rate parameter and it is equivalent to the attention that participants allocate toward the attribute. Experiment 3 provides clear evidence that α_i is not equivalent to attention. The process measures show that participants pay equal attention between the bottom of hull and the keel type, but the learned importance is significantly different between the two attributes. These findings suggest that α_i is a learning-rate parameter that represents the learning efficiency of the association updating. More precisely, it represents the responsiveness of the changes in association strength of an attribute to the outcomes.

Second, the results of Experiment 3 also imply that people have limited processing capacity and different attributes compete for this capacity. Mathematically it can be represented that the sum of α_i from all the attributes should be equal to 1. This idea is similar to the assumption in theories of selective attention that the probability of attending to one attribute is inversely related to the probability of attending to others (e.g., Sutherland and Mackintosh 1971). When there are no cognitive constraints, the importance of the bottom of hull and the importance of the keel type are equally well learned under the conjunctive condition; but the learning of the keel type is impeded under constraints. This suggests that when cognitive resources are limited, participants tend to allocate their resources (i.e., processing power) to the attribute that is expected to be the most important and reduce the resources allocated to the less important attribute.

In summary, the findings in this paper are reasonably consistent with the Mackintosh model. The attribute-specific learning-rate parameter α_i tends to increase for the attribute that is expected to be most important when cognitive resources are limited, and thus outweighs the decrease in the learning rate β due to the constraints. Evidence also suggests that α_i does not represent the attention that is allocated to an attribute; it represents the processing resources that are allocated to an attribute in order to efficiently update its association strength according to the outcomes. Moreover, cognitive resources tend to favor the information that is expected to be most important when resources are limited.

Marketing Implications

This study provides insights to marketing managers for developing better strategies in product positioning or brand extensions. It is wise for a brand to establish a single attribute that distinguishes itself from others, because consumers, especially modern multitasking consumers, seek a simple way to organize the world. When a brand is not perfectly consistent with the attribute, for instance, when a high-quality brand recalls products because of quality problems, or when a brand stands in the market based on multiple attributes (e.g., a conjunctive rule), this paper suggests that the importance of that attribute will decrease and consumers' decision making will be influenced by other less important attributes. Similarly, when a product is positioned in a particular category, the positioning will be most successful if the new product has the attribute (or attribute level) that consumers believe is the most important for this category, as consumers look for expectation-confirming evidence.

Moreover, this study highlights the importance of understanding consumers' prior expectations, and suggests that marketers should take every opportunity to influence or change consumers' expectations about categories. Every day consumers are bombarded with reams of new information and their views and opinions are constantly updated. Sometimes a simple change in store shelf display may alter product concepts in consumers' minds. For example, the shelves of yogurt in most stores are arranged by brands. If the products are sorted into fat-free yogurts versus regular yogurts, the category structure changes and consumer expectations about the most important attribute for a given variety of yogurts will change too. As a result, the sale of fat-free yogurts might be increased.

The findings about processing ability and attention also provide interesting insights. To catch the consumer's eye has become one of the most important objectives in marketing communications. However, this paper observes that especially in consumers' learning experience, attention is not necessarily accompanied by sufficient processing. This suggests that a goal that is more important than grabbing attention, especially in consumer education, is to obtain the processing resources from the multitasking audience.

Limitations and Future Research

One limitation of this research is the homogeneity assumption for prior expectations. Individual differences certainly exist regardless of whether the expectations are measured or manipulated. Moreover, a Mann-Whitney test is used to compare the weight of hull and the weight of keel in Experiment 3. One assumption of the Mann-Whitney test is sample independence, which is violated in the analysis because the weight measures are provided by the same participants. Furthermore, while process measures in Experiment 3 provide evidence for the occurrence of the two mechanisms, neither of the mechanisms is directly tested. Further research should be conducted to directly test the mechanisms and also to explore the possible interplays between them.

This paper calls for more future research to investigate how association learning turns into analytic rule usage in category learning. There are at least two criteria. One is the absolute criterion, which assumes that an attribute is used as a rule when it approaches a perfect association with the outcome. The other criterion is more relative and it assumes that the probability of an attribute being used as a rule is related to the difference in association strength between this attribute and other attributes. When the absolute association or the relative difference in associations exceeds a threshold, that attribute will be used as a rule. The hypothesis testing view in category leaning theories is more consistent with the absolute criterion than the relative one, but it is observed that people use a pseudorule knowing it is not perfectly associated with the categories. Additional research needs to further study the factors or conditions that influence criteria adoption.

Future studies are also necessary to further advance our understanding of the category learning area. First, our study primarily disrupts participants' memory capacity. Future research may investigate the effects of other constraints, like attention distractions, on category learning. Second, rules can depart from prior expectations in other ways. For instance, prior expectations might strongly suggest multiple attributes should be relevant but actually they are not. Research on how the learning of attribute irrelevance and how this learning is affected by constraints facilitate our understanding of the learning process. Third, this study suggests it is typically difficult to learn a pseudorule or a conjunctive rule. More research needs to be conducted to investigate how to improve the learning of these two rule types because both types are common in the real world. Finally, cultural difference has been found in cognitive processes (Nisbett et al. 2001). Eastern Asians tend to be holistic and rely less on rules while Westerns are more analytic. Culture difference in category learning warrants future research.

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Appendices

Appendix A: Materials for Experiment 1

1. Pretest questionnaire for Experiment 1[6].

Suppose we use four features (shown below) to describe a car. For each feature, a car can have either of two possible values.

The region of origin: North American or foreign (European / Asian)
The body type: sedan or SUV
The features package: sporty or luxury
The engine: Traditional Gas or Hybrid (Gas and Electric)

For example, a car could be described in this way: North American SUV, luxury model, with a traditional gas engine.

It is common that people like some cars and dislike others. Sometimes, ONLY ONE FEATURE can distinguish whether a person likes a car or not while none of the other three features matters. For example, if the region can distinguish preferences in this way, this means a person likes all North American cars (or foreign cars) but dislikes all foreign cars (or North American cars), and she/he doesn't care about whether the body is a sedan or an SUV, or whether it is a sports car or a luxury car, or if it has a gas or a hybrid engine.

Now, imagine that we were to describe wine according to the following four features:

The container of fermentation: wooded or unwooded
The vineyard: estate or boutique
The wine type: red or white
The region: Canada or France

For example, a wine could be described in this way: wooded fermentation container, produced by a boutique vineyard, red wine, and produced in France.

Now, if someone were to use a single feature to distinguish among wines, which one of these features would it be? There are no correct or incorrect answers. We are just interested in your opinion.
Based on your own judgment, among the four features, what feature do you think is the most likely single feature to distinguish whether a person likes a wine or not? What are the second most likely, the third most likely, and the least likely distinguishing features respectively? Please specify the four features in the order listed below.

The most likely feature to distinguish among wines:

[6] I randomized the order of the four attributes in the list, generated two versions of questionnaire with different orders and randomly assigned them among the participants.

The second most likely feature to distinguish among wines:
The third most likely feature to distinguish among wines:
The least likely feature to distinguish among wines:

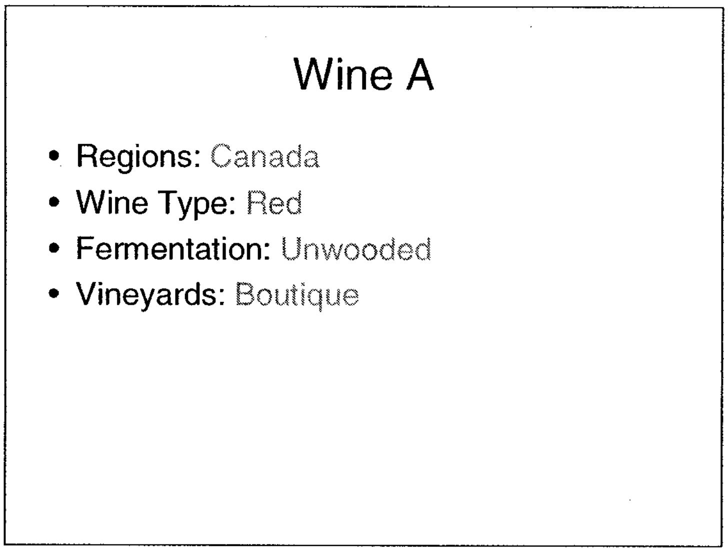
2. Task instructions for Experiment 1.

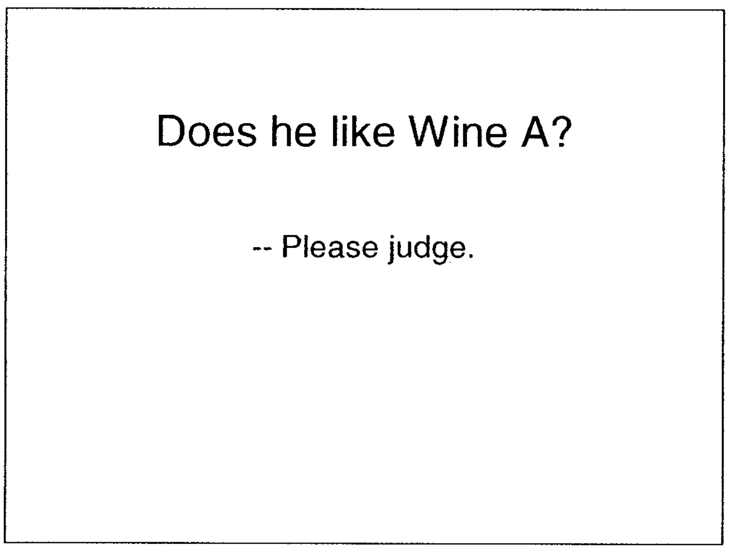
Screen 1:
Imagine that you are invited by your new supervisor to have a dinner at his home, for the first time. You know your supervisor is a wine lover, so you have decided to bring a wine.

Screen 2:
However, you don't know what kind of wine he likes. Fortunately, one colleague provides you with some information about the wines the supervisor likes and those he doesn't like (Eight wines for each type). Now it's your time to learn and judge.

Screen 3:
On the following screens, you will see wines described on four attributes (wine types, regions, fermentation container, and vineyards). You will be asked to judge first whether your supervisor likes the wine or not. Immediately afterwards, feedback will be given (whether he actually likes it or not). By the end of the study, you should be able to distinguish between wines that he likes and ones he dislikes.

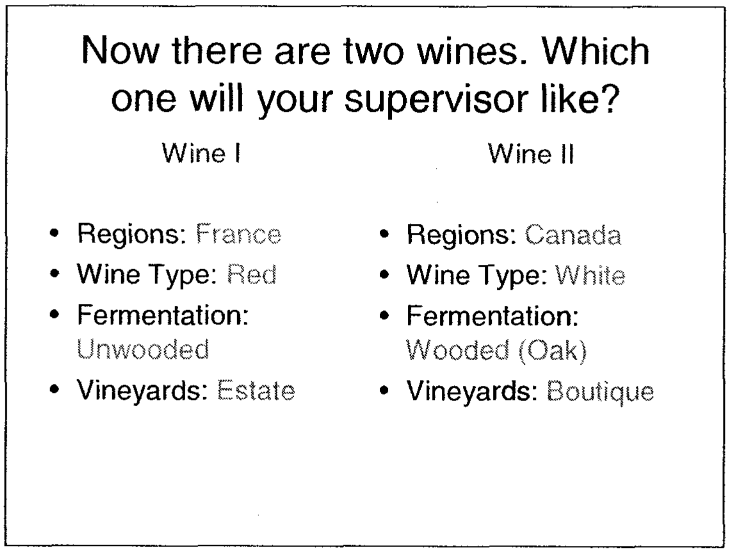
3. Screen shots for a learning trial in Experiment 1 (PPT slides were used to present information).





- Yes, he does like it!

4. Screen shots for the test phase in Experiment 1.



5. Post-decision questions for Experiment 1.
(The responses were collected by paper and pencil).

Q1. Do you think there is a KEY, SINGLE attribute that determines whether the supervisor would like the wine? (Please circle)
Yes (Go to Q2a, 2b, 2c and skip Q3) No (Go to Q3 and skip Q2)

Q2 (a). Did you believe there is a key, single attribute at the very beginning of the task or you became to realize that as you learned?

Q2 (b). Did you find the key, single attribute? If yes, how did you find it? If no, explain how did you judge whether your supervisor would like Wine I or Wine II.

Q2 (c). Specify the ORDER of four attributes (regions, wine types, fermentation and vineyard) that you planned to test to see if it determines the supervisor's liking the wine or not, supposing that you didn't find the right one until you tested on all.

Q3. Explain how did you judge whether your supervisor would like Wine I or Wine II?

6. Statistics for Experiment 1.

(1) Chi-square test for the pretest data in Experiment 1.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	77.111(a)	9	.000
Likelihood Ratio	81.917	9	.000
Linear-by-Linear Association	1.946	1	.163
N of Valid Cases	144		

a 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.00.

(2) Chi-square test for the data in Experiment 1.

1 = wineA, 0 = wineB * 1 = winetype, 2 = vineyard Crosstabulation

Count

		1 = winetype, 2 = vineyard		Total
		1	2	1
1 = wineA, 0 = wineB	0	3	18	21
	1	19	11	30
Total		22	29	51

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	12.115(b)	1	.001		
Continuity Correction(a)	10.198	1	.001		
Likelihood Ratio	13.083	1	.000		
Fisher's Exact Test				.001	.001
Linear-by-Linear Association	11.878	1	.001		
N of Valid Cases	51				

a Computed only for a 2x2 table
b 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.06.

Appendix B: Materials for Experiment 2

1. Pretest questionnaire for Experiment 2.

Suppose there are two brands in the electronics market: Brand P and Brand Q. Each brand offers a variety of electronic products, such as digital cameras, MP3 players, cell phones, TVs, DVD players, computers, etc. Competing in the same market, both brands want to distinguish themselves from each other by offering unique product features.

Each product can be described according to the following five product features:

Advertising: the amount of advertising about the product within one year after it is introduced to the market. It could be high or low, relative to the other brands;

Quality ratings: the product's quality rating according to Consumer Reports. Relative quality is reported to be "good" if the product's quality is better than the average of other products in the market or "bad" if it is worse than the market average;

Place of sale: the product may be sold at electronics stores only or at both electronics and department stores;

Targeted consumer segments: the consumer group that the product is targeted toward. For these brands, the target segment could be college students or young executives;

Price: the price level of the product in its market. It could be high or low. High price means: if this product is a digital camera, its price is above the average price level of digital cameras.

If there is only ONE feature that distinguishes the two brands from each other, which one of these features do you think it is most likely to be? There are no correct or incorrect answers. We are just interested in your opinion.

2. Task instructions for Experiment 2

Screen 1:
Please imagine there are two brands in the electronics market: Brand A and Brand B. Each brand offers a variety of electronic products, like digital cameras, MP3 players, cell phones, TVs, DVD players, computers, etc.
Competing in the same market, both brands want to distinguish themselves from each other by offering unique product features.

Screen 2:
We are going to show you some products from each brand. Each product will be described from the following five product features:
Price: the price level of the product in its market. It could be high or low. A high price means: if this product is a digital camera, its price is above the average price level of digital cameras;
Quality ratings: the product's quality rating according to Consumer Reports. Relative quality is reported to be "good" if the product's quality is better than the average of other products in the market or "bad" if it is worse than the market average;
Advertising: the amount of advertising about the product within one year after it is introduced to the market. It could be high or low;
Targeted consumer segments: the consumer group that the product is targeted toward. It could be college students or young executives;
Place of sale: the product may be sold at "electronics stores only" or "electronics and department stores".

Screen3 for unconstrained conditions:
Next you will see 10 different products from each brand, with one product on each screen. You don't need to think about what these 20 products are. Your task is to learn how to distinguish the two brands.
To facilitate your reading, products with Brand A will appear on the left of the screen and Brand B on the right. Please read the information about each product carefully.
Each product will be shown for 10 seconds.
After you learn about the 20 products, new products will be presented and you will be asked to state which brand offers each new product.
Note that you will have a chance to win a prize! If your score meets the criterion, you will receive the prize!
Beginning with the next page, you cannot take notes or return to the previous page.
If you have any questions about the instruction, please ask the administrator now. If not, click here to start the learning process.
(Instructions for unconstrained group end here.)

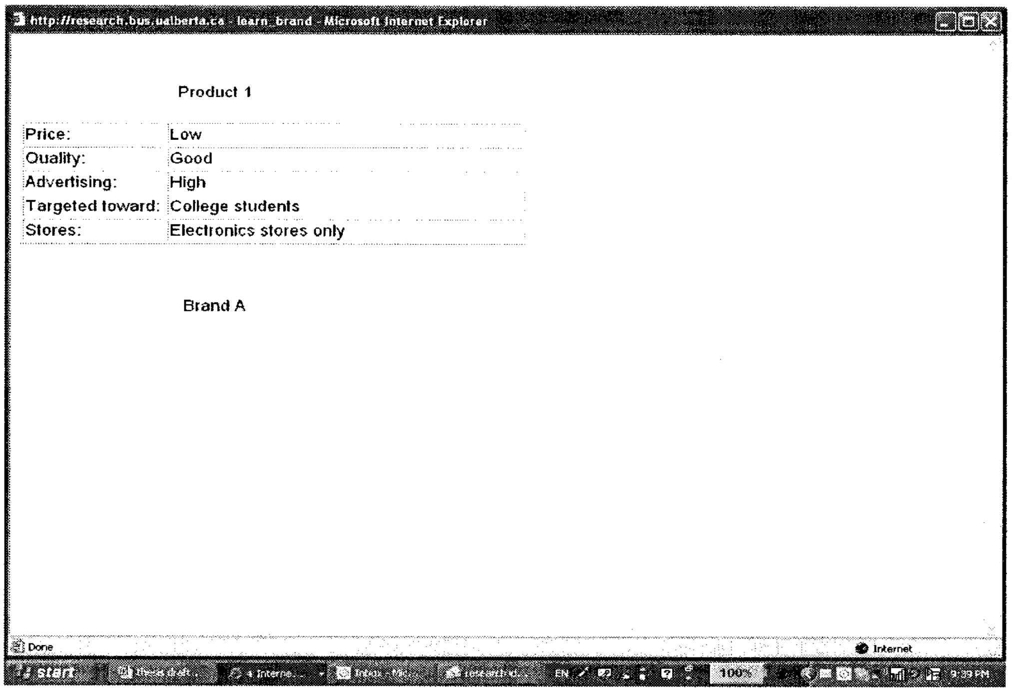
Screen3 for constrained conditions:
Next you will see 10 different products from each brand, with one product on each screen. You don't need to think about what these 20 products are. Your task is to learn how to distinguish the two brands.
To facilitate your reading, products with Brand A will appear on the left of the screen and Brand B on the right. Please read the information about each product carefully.
Each product will be shown for 10 seconds.
After you learn about the 20 products, new products will be presented and you will be asked to state which brand offers each new product.

Screen 4 for constrained conditions:
Before the 20 products are presented, we would like you to memorize a letter string, which will be shown on the next screen for 1 minute. Please try to memorize the letter string and you are not allowed to take any notes.
After the 20 products are presented, you will be asked to recall the letter string. Research shows that the best way to keep the letter string in mind is to keep rehearsing it.
Based on your overall performance (brand predictions and string memorization), you will have a chance to win a prize! If your score meets the criterion, you will receive the prize!
Beginning with the next page, you cannot return to the previous page. If you have any questions about the instruction, please ask the administrator now. If not, click here to see the letter string.
(Instructions for constrained group end here.)

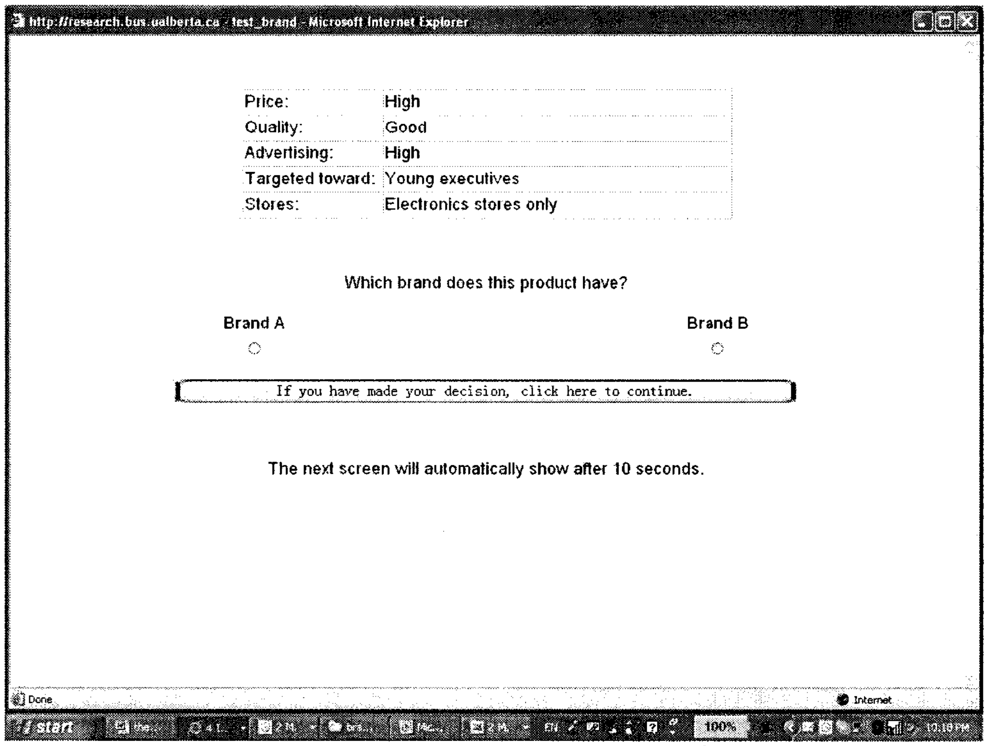
At the end of the learning phase, the instructions are shown for the test phase:

This is the end of the learning process. Have you figured out what kind of products tends to be offered by Brand A or Brand B? Beginning with the next screen, you will be shown some products and asked to state each product's brand. You need to make your judgments as soon as possible without sacrificing accuracy.
If you cannot make the decisions within 10 seconds, the next screen will automatically show up, where you can still make your judgment, based on the product description on the previous screen. If you can make decisions before that, you may click and go to the next screen.
Please note these judgments should be based entirely on what you have just learned, and not on any knowledge you had about the electronics market before you began this study.

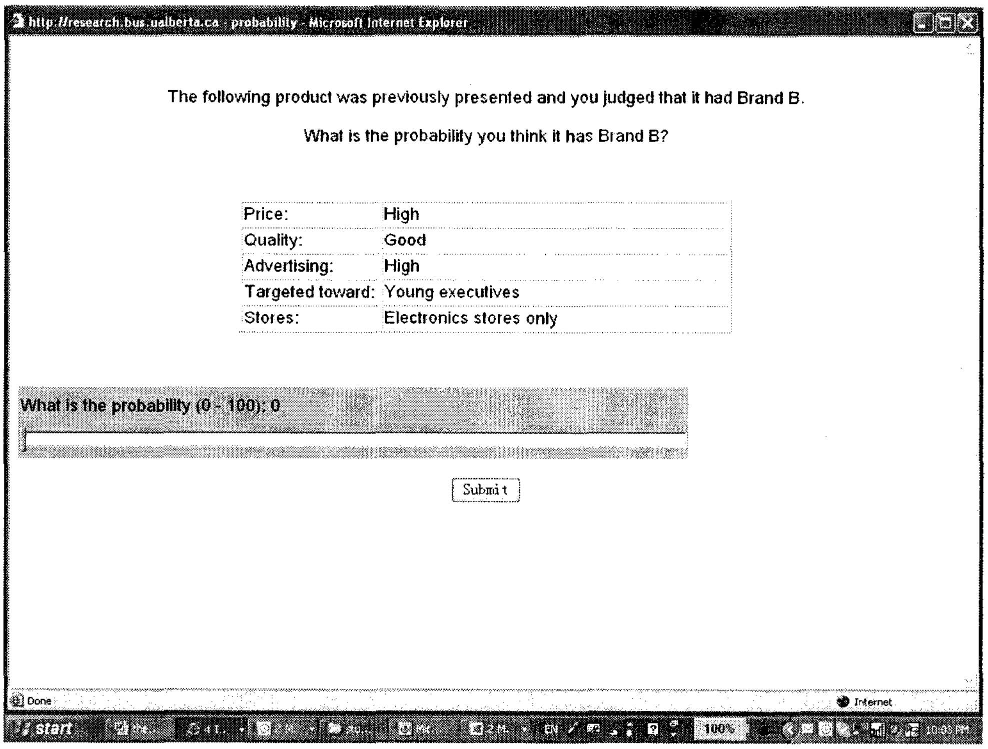
3. A screen shot for a learning trial in Experiment 2.



4. Screen shots for a test trial in Experiment 2.



After 16 brand judgments, the products are shown again for the probability responses.



5. Post-decision questions for Experiment 2.
(The responses were collected on computer.)

Q1. Please explain how you decided whether a product is of Brand A or Brand B? (An open-ended question)

Q2. To what extent have you based your judgments on what you have learned from the learning process (scale 0-10)?
Scale = 0: I relied completely on information I already knew before the study.
Scale = 5: I relied equally on what I already knew and what I learned.
Scale = 10: I relied completely on information I learned in this study.
If the answer < 10, go to Q2 follow, otherwise go to Q3.

Q2 follow. Please explain what previous information you used when you made decisions? (An open-ended question)

Q3. Based on the information provided during the learning process, do you think there is ONE single product feature that ALWAYS predicts that a product is of Brand A or Brand B? Put in another way, whether a product is of Brand A or Brand B can be SOLELY based on this one feature, without the need to consider other features? (Yes, no, I don't know.)
If the answer is yes, go to Q4a, otherwise go to Q4b.

Q4a. Which is the product feature that always predicts whether a product is of Brand A or Brand B? (To choose among the five attributes)
Price Quality Advertising Target toward Stores

Q4a2. Did you totally base your judgments on XXX (attribute specified here according to the response to Q4) without considering other information? (Yes, no)
If the answer is no, go to Q4a2follow, otherwise go to Q5.

Q4a2follow. Please explain why you still considered other information while you know that one feature can always predicts? (An open-ended question)
Go to Q5.

Q4b. Based on the information provided during the learning process, do you think some product feature(s) are more important than others in predicting a product's brand? (Yes, I put more weight on some feature(s) than on others; No, they were all equally important; I don't know.)
If the answer is yes, go to Q4b2, otherwise go to Q5.

Q4b2 (if the response to Q4b is yes). Specify below which feature(s) were more important than others in predicting a product's brand. (An open-ended question)

Q5 (only for constrained participants). When you had to memorize the letter string during the learning process, did you feel that your learning had been interfered by the rehearsal? (Yes, no)

Q6. How difficult overall was it to judge about a product's brand (scale 0-10)?

Q7. The last question, what is your gender?

6. Statistics for Experiment 2.

(1) MANOVA analysis for the likelihood ratings of the five attributes.

Descriptive Statistics

	Mean	Std. Deviation	N
ad	5.1500	2.87045	20
quality	6.9000	2.82657	20
place	4.4000	2.72223	20
target	5.2500	2.86310	20
price	7.2000	2.64774	20

Mauchly's Test of Sphericity[b]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[a]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
att	.474	12.990	9	.165	.743	.896	.250

Tests the null hypothesis that the error covariance matrix of the orthonormalized transform variables is proportional to an identity matrix.

a. May be used to adjust the degrees of freedom for the averaged tests of significance. tests are displayed in the Tests of Within-Subjects Effects table.

b.

Design: Intercept
Within Subjects Design: att

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
att	Sphericity Assumed	117.060	4	29.265	6.273	.000
	Greenhouse-Geisser	117.060	2.973	39.369	6.273	.001
	Huynh-Feldt	117.060	3.586	32.645	6.273	.000
	Lower-bound	117.060	1.000	117.060	6.273	.022
Error(att)	Sphericity Assumed	354.540	76	4.665		
	Greenhouse-Geisser	354.540	56.495	6.276		
	Huynh-Feldt	354.540	68.130	5.204		
	Lower-bound	354.540	19.000	18.660		

(2) T-test for the likelihood ratings between price and targeted consumers

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	Upper			
Pair 1	price - target	1.95000	2.23548	.49987	.90376	2.99624	3.901	19	.001

(3) T-test for the likelihood ratings between quality and targeted consumers

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	Upper			
Pair 1	quality - target	1.65000	3.18343	.71184	.16011	3.13989	2.318	19	.032

(4) T-test for the likelihood ratings between price and quality

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	Upper			
Pair 1	price - quality	.30000	3.02794	.67707	-1.11712	1.71712	.443	19	.663

(5) Chi-square test for the percentage of analytic categorization usage when both behavior results and self-reports are considered.

UsedRule * Task * Rule Crosstabulation

Count

Rule			Task: no constraints	Task: constraints	Total
pseudo rule	UsedRule	not used rules	18	23	41
		used rules	7	2	9
	Total		25	25	50
perfect rule	UsedRule	not used rules	18	8	26
		used rules	10	16	26
	Total		28	24	52

Chi-Square Tests

Rule		Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
pseudo rule	Pearson Chi-Squa	3.388[b]	1	.066		
	Continuity Correcti	2.168	1	.141		
	Likelihood Ratio	3.553	1	.059		
	Fisher's Exact Tes				.138	.069
	Linear-by-Linear Association	3.320	1	.068		
	N of Valid Cases	50				
perfect rule	Pearson Chi-Squa	4.952[c]	1	.026		
	Continuity Correcti	3.792	1	.052		
	Likelihood Ratio	5.036	1	.025		
	Fisher's Exact Tes				.050	.025
	Linear-by-Linear Association	4.857	1	.028		
	N of Valid Cases	52				

a. Computed only for a 2x2 table

b. 2 cells (50.0%) have expected count less than 5. The minimum expected count is 4.5

c. 0 cells (.0%) have expected count less than 5. The minimum expected count is 12.00.

(6) Chi-square test for the percentage of analytic categorization usage when only behavior results are considered.

UsedRule_beha * Task * Rule Crosstabulation

Count

Rule			Task: no constraints	Task: constraints	Total
pseudo rule	UsedRule_beha	0	16	21	37
		1	9	4	13
	Total		25	25	50
perfect rule	UsedRule_beha	0	12	7	19
		1	16	17	33
	Total		28	24	52

Chi-Square Tests

Rule		Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
pseudo rule	Pearson Chi-Squar	2.599[b]	1	.107		
	Continuity Correctio[a]	1.663	1	.197		
	Likelihood Ratio	2.651	1	.103		
	Fisher's Exact Test				.196	.098
	Linear-by-Linear Association	2.547	1	.111		
	N of Valid Cases	50				
perfect rule	Pearson Chi-Squar	1.045[c]	1	.307		
	Continuity Correctio[a]	.538	1	.463		
	Likelihood Ratio	1.054	1	.305		
	Fisher's Exact Test				.391	.232
	Linear-by-Linear Association	1.024	1	.311		
	N of Valid Cases	52				

a. Computed only for a 2x2 table

b. 0 cells (.0%) have expected count less than 5. The minimum expected count is 6.50.

c. 0 cells (.0%) have expected count less than 5. The minimum expected count is 8.77.

(7) Chi-square test for the percentage of analytic categorization usage when only self-reports are considered.

UsedRule_self * Task * Rule Crosstabulation

Count

Rule			Task: no constraints	Task: constraints	Total
pseudo rule	UsedRule_self	0	17	23	40
		1	8	2	10
	Total		25	25	50
perfect rule	UsedRule_self	0	18	8	26
		1	10	16	26
	Total		28	24	52

Chi-Square Tests

Rule		Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
pseudo rule	Pearson Chi-Squar	4.500[b]	1	.034		
	Continuity Correctio[a]	3.125	1	.077		
	Likelihood Ratio	4.758	1	.029		
	Fisher's Exact Test				.074	.037
	Linear-by-Linear Association	4.410	1	.036		
	N of Valid Cases	50				
perfect rule	Pearson Chi-Squar	4.952[c]	1	.026		
	Continuity Correctio[a]	3.792	1	.052		
	Likelihood Ratio	5.036	1	.025		
	Fisher's Exact Test				.050	.025
	Linear-by-Linear Association	4.857	1	.028		
	N of Valid Cases	52				

a. Computed only for a 2x2 table

b. 0 cells (.0%) have expected count less than 5. The minimum expected count is 5.00.

c. 0 cells (.0%) have expected count less than 5. The minimum expected count is 12.00.

(8) Normality test of weight of quality

One-Sample Kolmogorov-Smirnov Test

		quality
N		102
Normal Parameters(a,b)	Mean	61.8186
	Std. Deviation	34.73338
Most Extreme Differences	Absolute	.136
	Positive	.136
	Negative	-.115
Kolmogorov-Smirnov Z		1.372
Asymp. Sig. (2-tailed)		.046

a Test distribution is Normal.

b Calculated from data.

(9) Levene's test of equality of error variances for weight of quality

Levene's Test of Equality of Error Variances(a)

Dependent Variable: quality

F	df1	df2	Sig.
.718	3	98	.543

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.
a Design: Intercept+Rule+Task+Rule * Task

(10) ANOVA test of weight of quality

Descriptive Statistics

Dependent Variable: quality

Rule	Task	Mean	Std. Deviation	N
pseudorule	no constraints	58.1400	29.81402	25
	constraints	35.6950	33.83070	25
	Total	46.9175	33.53300	50
perfect rule	no constraints	73.1719	30.22855	28
	constraints	79.6172	29.31294	24
	Total	76.1466	29.69493	52
Total	no constraints	66.0814	30.69359	53
	constraints	57.2079	38.42022	49
	Total	61.8186	34.73338	102

Tests of Between-Subjects Effects

Dependent Variable: quality

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	28611.429[a]	3	9537.143	10.024	.000
Intercept	386472.615	1	386472.615	406.221	.000
Rule	22083.876	1	22083.876	23.212	.000
Task	1626.563	1	1626.563	1.710	.194
Rule * Task	5303.375	1	5303.375	5.574	.020
Error	93235.770	98	951.385		
Total	511644.555	102			
Corrected Total	121847.199	101			

a. R Squared = .235 (Adjusted R Squared = .211)

(11) T test of the effect of rule type on weight of quality under the unconstrained condition.

Independent Samples Test[a]

		Levene's Test for Equality of Variances		t-test for Equality of Means				
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
quality	Equal variances assumed	.038	.846	-1.819	51	.075	-15.03188	8.26428
	Equal variances not assumed			-1.820	50.477	.075	-15.03188	8.25769

a. Task = no constraints

(12) T test of the effect of rule type on weight of quality under the constrained condition.

Independent Samples Test[a]

		Levene's Test for Equality of Variances		t-test for Equality of Means				
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
quality	Equal variances assumed	1.593	.213	-4.848	47	.000	-43.92219	9.05915
	Equal variances not assumed			-4.863	46.525	.000	-43.92219	9.03231

a. Task = constraints

(13) T test of the effect of constraints on weight of quality when quality is the rule.

Independent Samples Test[a]

		Levene's Test for Equality of Variances		t-test for Equality of Means				
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
quality	Equal variances assumed	.002	.963	-.777	50	.441	-6.44531	8.29262
	Equal variances not assumed			-.779	49.210	.440	-6.44531	8.27263

a. Rule = perfect rule

(14) T test of the effect of constraints on weight of quality when quality comprised the pseudorule.

Independent Samples Test[a]

		Levene's Test for Equality of Variances		t-test for Equality of Means				
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
quality	Equal variances assumed	1.260	.267	2.489	48	.016	22.44500	9.01863
	Equal variances not assumed			2.489	47.253	.016	22.44500	9.01863

a. Rule = pseudo rule

(15) Normality test of percentage correct

One-Sample Kolmogorov-Smirnov Test

		percencorr
N		102
Normal Parameters(a,b)	Mean	.8554
	Std. Deviation	.18216
Most Extreme Differences	Absolute	.237
	Positive	.214
	Negative	-.237
Kolmogorov-Smirnov Z		2.397
Asymp. Sig. (2-tailed)		.000

a Test distribution is Normal.
b Calculated from data.

(16) Levene's test of equality of error variances for percentage correct

Levene's Test of Equality of Error Variances(a)

Dependent Variable: percencorr

F	df1	df2	Sig.
2.632	3	98	.054

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.
a Design: Intercept+Rule+Task+Rule * Task

(17) ANOVA test of percentage correct

Descriptive Statistics

Dependent Variable: percencorr

Rule	Task	Mean	Std. Deviation	N
pseudorule	No constraints	.8525	.16817	25
	Constraints	.7400	.20546	25
	Total	.7963	.19431	50
perfect rule	No constraints	.9040	.16091	28
	Constraints	.9219	.14066	24
	Total	.9123	.15070	52
Total	No constraints	.8797	.16484	53
	Constraints	.8291	.19755	49
	Total	.8554	.18216	102

Tests of Between-Subjects Effects

Dependent Variable: percencorr

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.505(a)	3	.168	5.801	.001
Intercept	74.249	1	74.249	2556.690	.000
Rule	.346	1	.346	11.918	.001
Task	.057	1	.057	1.960	.165
Rule * Task	.108	1	.108	3.718	.057
Error	2.846	98	.029		
Total	77.984	102			
Corrected Total	3.351	101			

a R Squared = .151 (Adjusted R Squared = .125)

(18) T-tests of percentage correct between constrained and unconstrained groups for the rule condition.

Independent Samples Test[a]

		Levene's Test for Equality of Variances		t-test for Equality of Means				
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
percencorr	Equal variances assumed	.103	.750	-.423	50	.674	-.01786	.04226
	Equal variances not assumed			-.427	49.97	.671	-.01786	.04182

a. Rule = perfect rule

(19) T-tests of percentage correct between constrained and unconstrained groups for the condition with a pseudorule.

Independent Samples Test[a]

		Levene's Test for Equality of Variances		t-test for Equality of Means				
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
percencorr	Equal variances assumed	3.175	.081	2.119	48	.039	.11250	.05310
	Equal variances not assumed			2.119	46.196	.040	.11250	.05310

a. Rule = pseudo rule

Appendix C: Materials for Experiment 3

1. Task instructions for Experiment 3.

Screen1:
In today's study, you are going to learn about sailboats.
Imagine that there are only two types of sailboats on the world: Type A and Type B. You will learn how to distinguish between them.
You don't need to know what exactly Type A or Type B refers to. Your task is to learn what kinds of boats are Type A and what kinds of boats are Type B.
The study has two phases. The first phase is a learning phase, where we will show you some sailboats, and for each sailboat, we will tell you whether it is Type A or Type B.
The second phase is a test phase, where you will see some new sailboats. But this time you need to make judgments about the sailboat type by yourself.

Screen2:
All the sailboats will be described by the following five attributes and each attribute has two possible values. Read the following information carefully. Figure 1 shows a sailboat with triangular sails and fin keel.
1. Bottom of hull: round bottom or deep-V-hull (Figure 2);
2. Hull coating: polyurethane or neoprene. Hull coating is the substance spread over hull surface to protect the hull;
3. Keel type: full keel or fin keel (Figure 3);
4. Shape of sail: square or triangular (Figure 4);
5. Material of sail: Tyvek or Dacron. These are two common materials that make a sail.

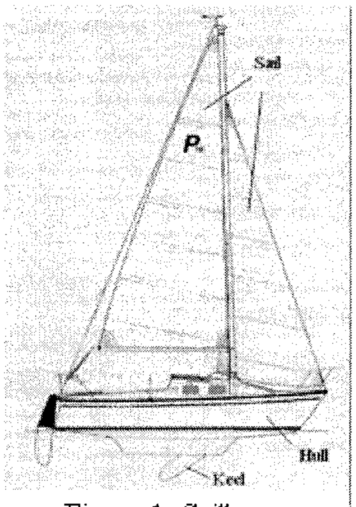


Figure 1. Sailboat

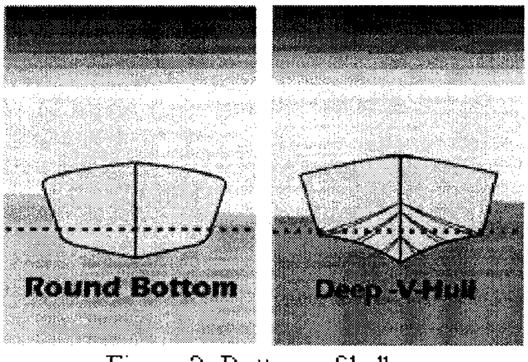


Figure 2. Bottom of hull

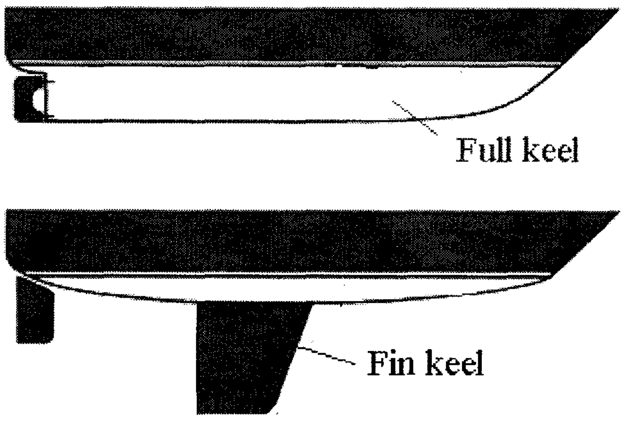


Figure 3. Keel type

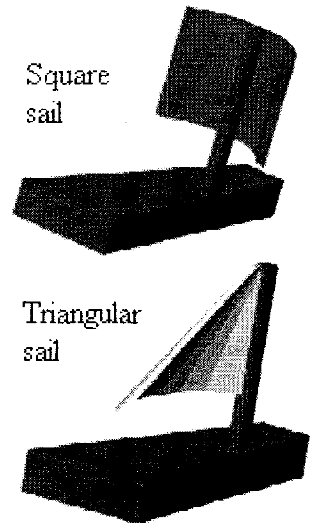
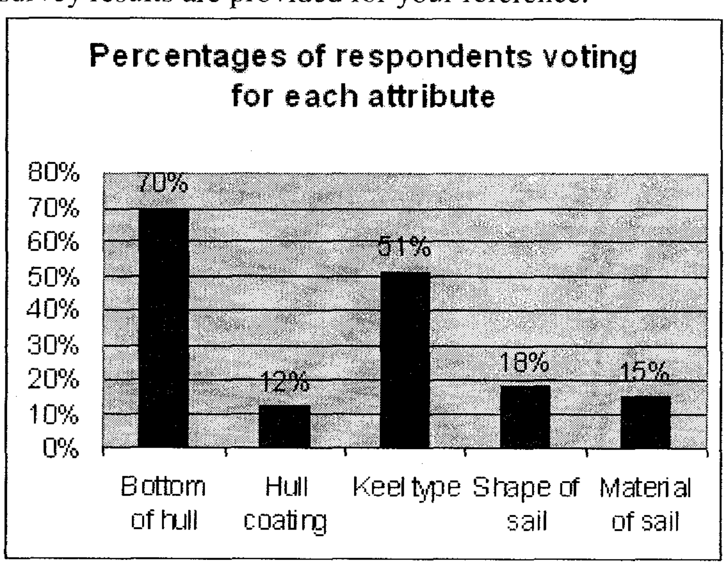


Figure 4. Sail

Screen 3:
A sports magazine has conducted a survey among its subscribers about a sailboat's type. For the question "how important is it to know the value of XXX (an attribute specified here) to predict a sailboat's type", the answers are summarized below.
The figures indicate the percentages of respondents who think the attributes are important. For instance, 70% for "bottom of hull" means 70% respondents think that knowing whether a boat's bottom of hull is round or deep-V-shaped is important to predicting its type.
Note that these respondents are not necessarily experts of sailboats, and these survey results are provided for your reference.



Screen 4:

Based on the information provided, please rate the importance of each attribute in predicting the type of a sailboat. (You can return to previous pages if needed.)

1. How important is it to know what kind of bottom of hull that a sailboat has in order to predict its type (scale 0-10)?
2. How important is it to know what kind of hull coating that a sailboat has in order to predict its type (scale 0-10)?
3. How important is it to know what kind of keel type that a sailboat has in order to predict its type (scale 0-10)?
4. How important is it to know what kind of shape of sail that a sailboat has in order to predict its type (scale 0-10)?
5. How important is it to know what kind of material of sail that a sailboat has in order to predict its type (scale 0-10)?

Screen 5:
During the learning phase, you will see one boat on each screen. There will be five buttons on a screen (shown below) representing the five attributes. You need to click on the buttons to see the values of the attributes, and the attribute values will disappear when you release the mouse OR move the mouse out of the button. You may try these buttons now.
(Five buttons are shown here)
There are 18 boats in the learning phase. Some of them are Type A and others are Type B. After learning about the 18 boats, you will enter the test phase and judge boat types for some new boats.

Screen 6 (for unconstrained participants):
In addition to $10, you will win a prize if you get points that meet our criterion! When your points are calculated, two factors are taken into account:
1. the more sailboats that you make correct judgments about during the test phase, the higher your points will be;
2. the less buttons that you click on during the learning phase, that is, the less attribute information that you look at, the higher your points will be.
However, you should click on those buttons that you think are necessary or helpful to your learning, in order to increase your accuracy in making judgments later.
In order to familiarize yourself with the procedure of this study, you can take three practice trials. In these practice trials, the type of a sail boat is not specified. Points are not calculated for practice trials.
Click here to start the practice trials.

Three learning practice trials are shown. They are the same as actual learning trials except that the category label (i.e., boat type) of a boat is not specified in a practice trial.

Screen 7 (for unconstrained participants):

This is the end of practice trials for the learning phase. In the real study, you are going to see 18 sailboats.
Click here to see what the test phase would look like.

A test trial is shown for practice. It is the same as an actual test trial except that participants were not asked to provide the probability judgment. They were only asked to judgment the boat type.

Screen 8 (for unconstrained participants):
The practice trials ended. The learning phase will start with the next screen.
Note that your judgments should be entirely based on what you've learned from the learning phase.
Again, your points are based on two factors:
1. the more sailboats that you make correct judgments about, the higher your points will be;
2. the less buttons that you click on in the learning phase, the higher your points will be.
If you have any questions about the instructions, ask the research assistant now. You are not allowed to take any notes.
Now, get ready and win your prize!
(Instructions for unconstrained participants end here.)

Screen 6 (for constrained participants):
While you are learning, you also need to memorize a 6-digit number. The number will be on the screen for 10 seconds, then you see a boat. After you choose to continue, you will be asked to recall the number. Then you will see more boats.
Every time before a boat is presented, you need to memorize a 6-digit number. So the procedure is like this : memorize a number --> see a boat --> recall the number --> memorize a new number --> see a boat --> recall the number --> memorize a new number--> see a boat ...

Screen 7 (for constrained participants)
In addition to $10, you will win a small prize if you get points that meet our criterion! When your points are calculated, three factors are taken into account:
1. the more sailboats that you make correct judgments about during the test phase, the higher your points will be;
2. the more numbers that you recall correctly during the test phase, the higher your points will be;
3. the less buttons that you click on during the learning phase, that is, the less attribute information that you look at, the higher your points will be.
However, you should click on those buttons that you think are necessary or helpful to your learning, in order to increase your accuracy in making judgments later.

In order to familiarize yourself with the procedure of this study, you can take three practice trials. In these practice trials, the type of a sail boat is not specified.
Click here to start the practice trials.

Three learning practice trials are shown. They are the same as actual learning trials except that the category label (i.e., boat type) of a boat is not specified in a practice trial.

Screen 8 (for constrained participants)
This is the end of practice trials for the learning phase. In the real study, you are going to see 18 sailboats.
Click here to see what the test phase would look like.

A test trial is shown for practice. It is the same as an actual test trial except that participants were not asked to provide the probability judgment. They were only asked to judgment the boat type.

Screen 9 (for constrained participants)
The practice trials ended. The learning phase will start with the next screen.
Note that your judgments should be entirely based on what you've learned from the learning phase.
Again, your points are based on two factors:
1. the more sailboats that you make correct judgments about, the higher your points will be;
2. the more numbers that you recall correctly, the higher your points will be;
3. the less buttons that you click on in the learning phase, the higher your points will be.
If you have any questions about the instructions, ask the research assistant now. You are not allowed to take any notes.
Now, get ready and win your prize!
(Instructions for constrained participants end here.)

At the end of the learning phase, the instructions are shown for the test phase:

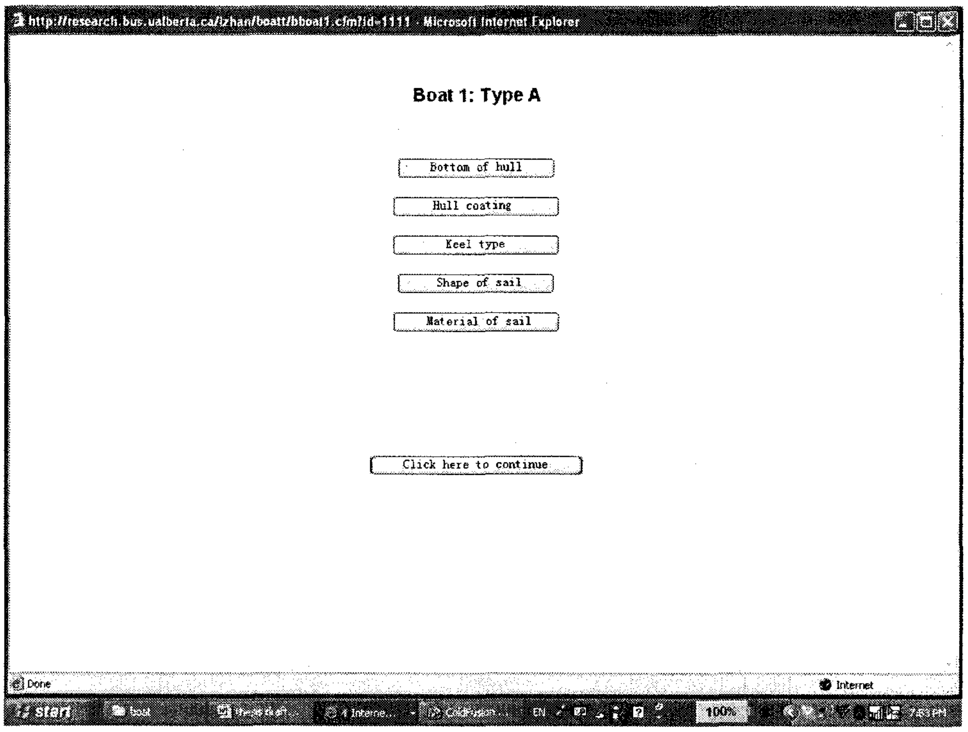
This is the end of the learning phase.
Beginning with the next screen, you are going to see 16 new boats and make judgments about each boat's type.
Again, your judgments should be entirely based on what you have learned in the learning phase.

After judgments about boat types are made for 16 test boats, instructions are provided asking participants to indicate the probability of each boat being its type:

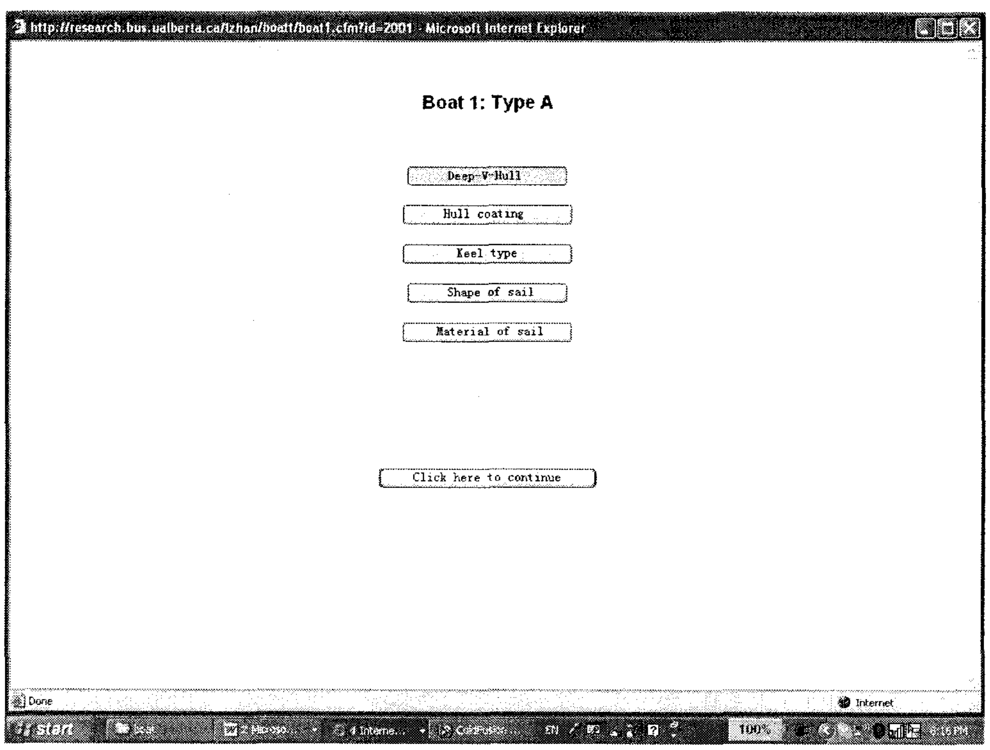
You have made judgments about 16 new boats.

Beginning with the next screen, we are going to show you the same 16 boats as what you've just seen, as well as the judgment you've made about each of them. Please rate the likelihood of each boat being the type that you judged it to be.

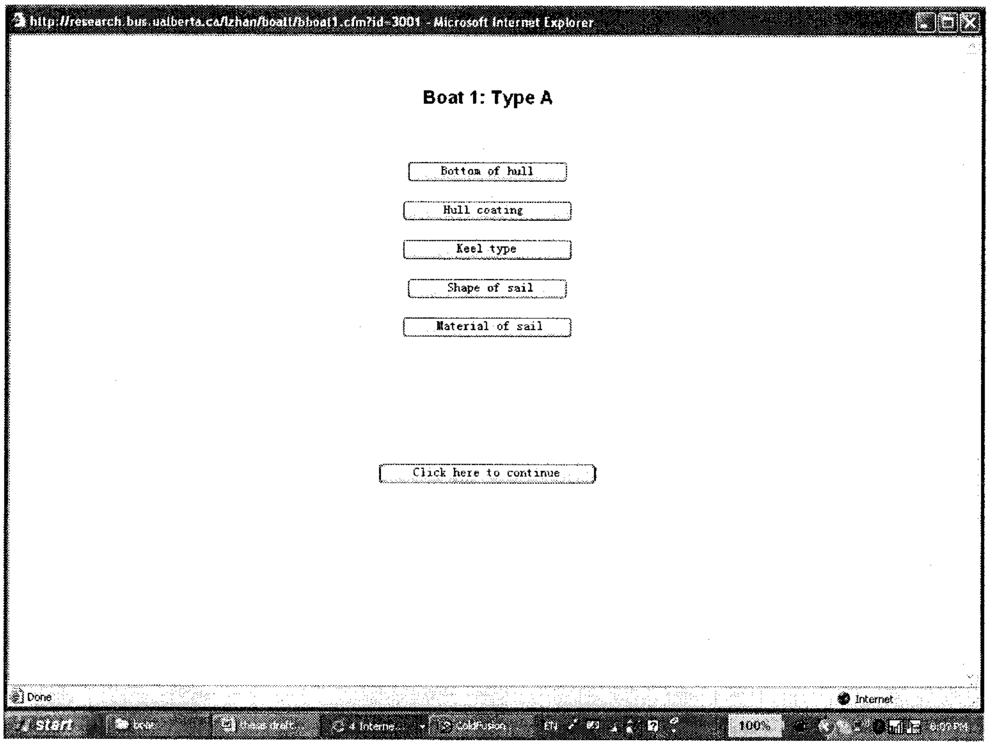
2. Screen shots for a learning trial under the unconstrained condition in Experiment 3.



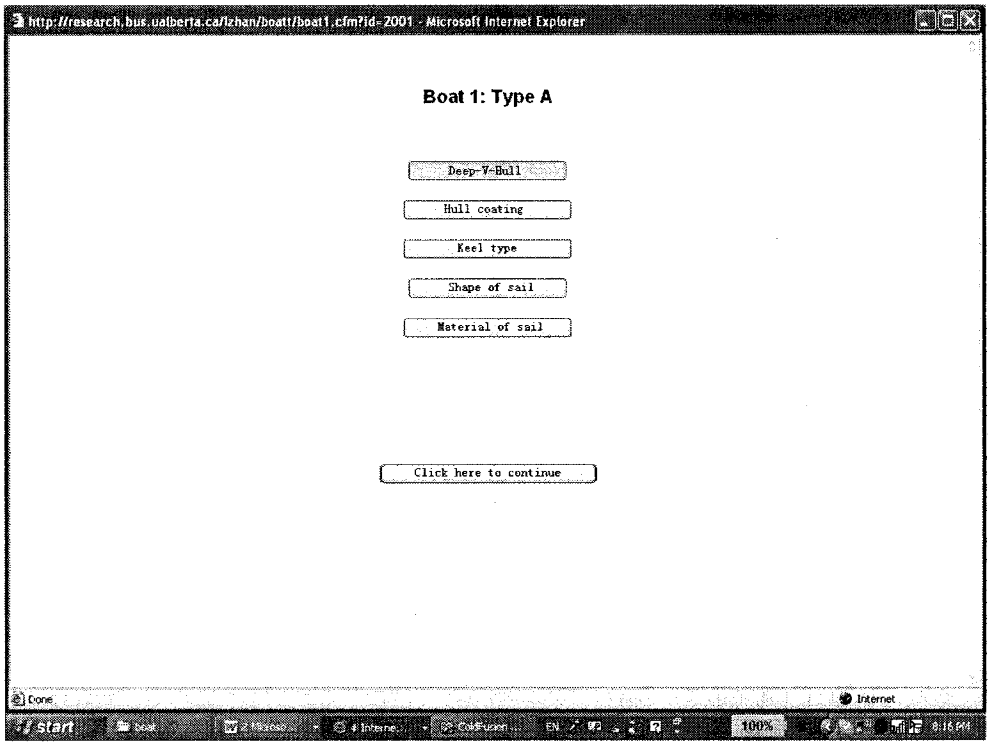
If the button of "bottom of hull" is clicked, its attribute value will be shown.

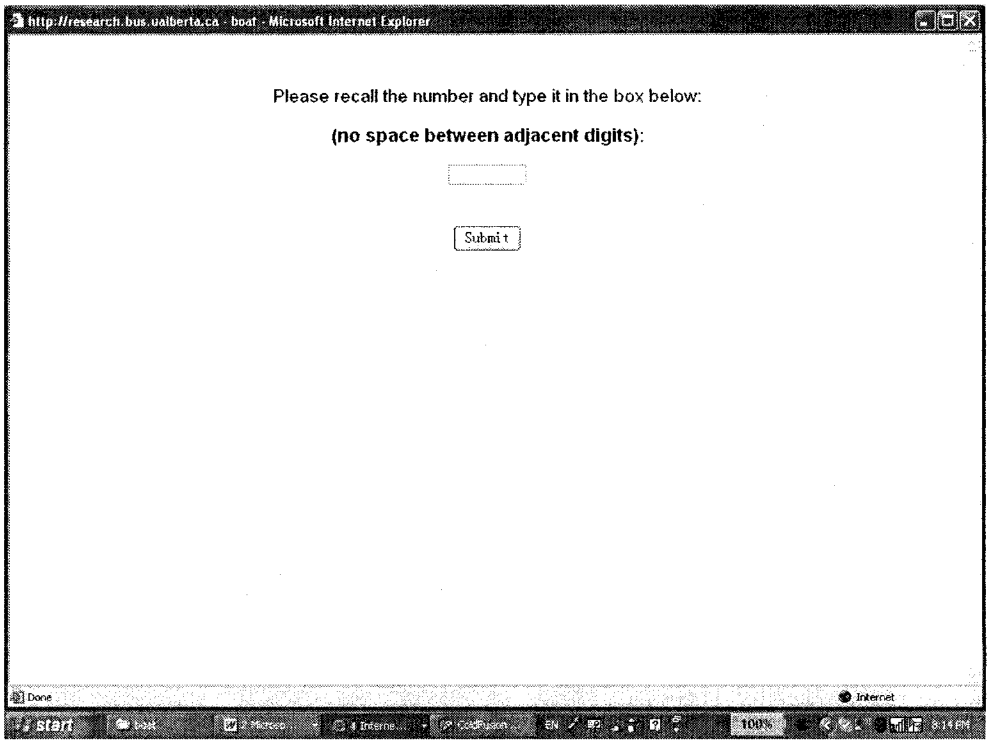


3. Screen shots for a learning trial under the constrained condition in Experiment 3.

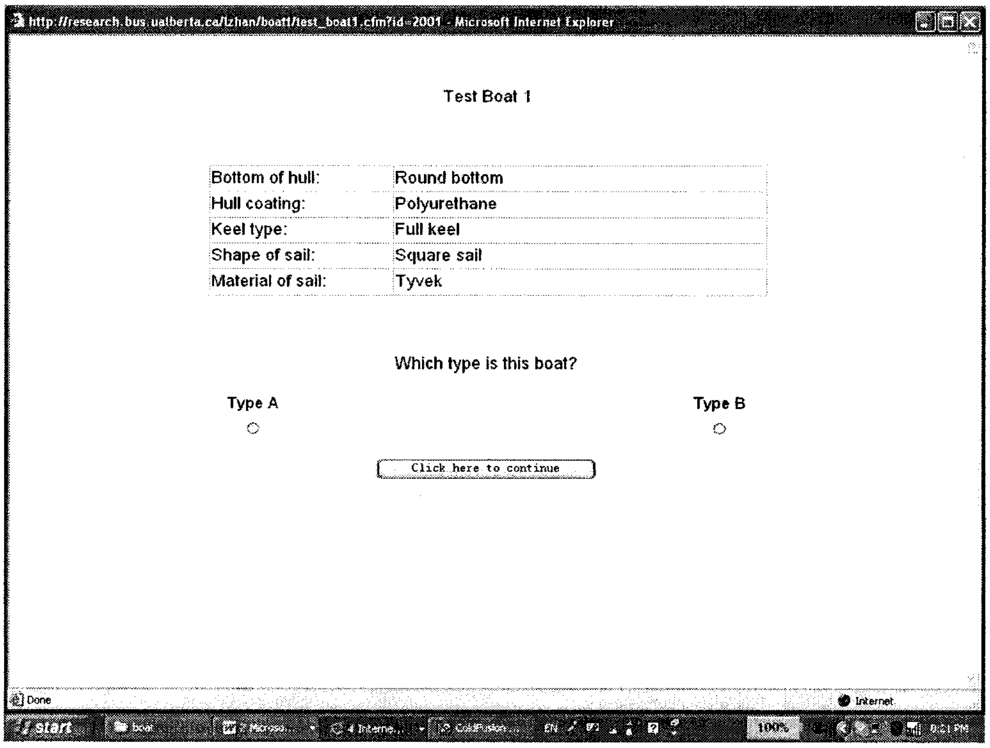


If the button of "bottom of hull" is clicked, its attribute value will be shown.

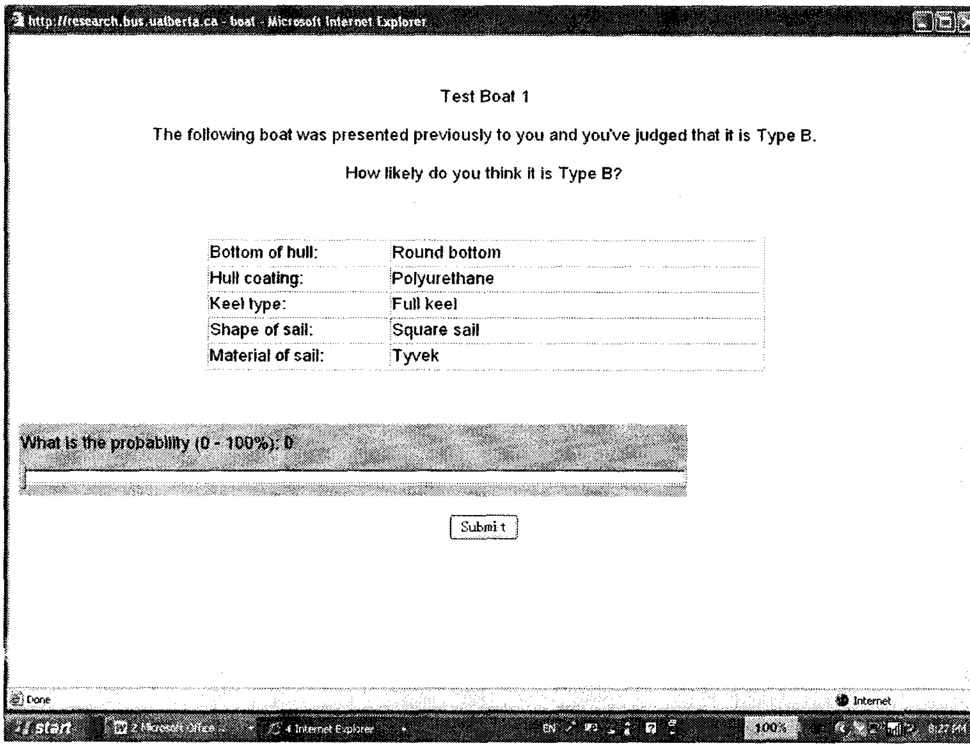




4. Screen shots for a test trial in Experiment 3.



After 16 judgments, test boats are shown again for the probability responses.



5. Post-decision questions for Experiment 3.
(The responses were collected on computer.)

Q1. Please explain how you've decided whether a boat is Type A or Type B? (An open-ended question)

Q2. Do you think there are some attribute(s) that ALWAYS predict a boat's type?
In other words, do you think you can predict a boat's type entirely based on these attribute(s), without the need to consider other attributes? (Yes, no, I don't know)
If the answer is yes, go to Q3a, otherwise go to Q3b.

Q3a. Which attribute(s) that ALWAYS predict a boat's type? (You can choose one or multiple attributes.)
Bottom of hull Hull coating Keel type Shape of sail Material of sail

Q3a2. Did you totally base your judgments on those attributes that you've checked, without considering other information? (Yes, no)
If the answer is no, go to Q3a2follow, otherwise go to Q4.

Q3a2follow: Please explain why you've still considered other information while you know those attributes can always predict a boat's type? (An open-ended question)
Go to Q10.

Q3b. Do you think some attribute(s) were more important than others in predicting a boat's type? (Yes, I think so; no, they were all equally important; I don't know.)
If the answer is yes, go to Q3b2, otherwise go to Q4.

Q3b2. Specify below which attribute(s) were more important than others in predicting a boat's type. You may rank the five attributes in terms of their importance if you like.
The five attributes are (in the order that they were presented): bottom of hull, hull coating, keel type, shape of sail and material of sail.

Q4. How seriously did you take this study (scale 0-10)?

Q5. How difficult was it to learn how to predict a boat's type (scale 0-10)?

Q6. How familiar are you with sailboats (scale 0-10)?

Q7. How knowledgeable are you with sailboats (scale 0-10)?

Q8. Is English your first or second language? (First language, second language)

Q9. Please indicate your gender below. (Male, female)

Q10. Please indicate your nationality below. (An open-ended question)

Q11. Did you participate in a learning study about Brand A vs. Brand B last term? (Yes, no)

6. Statistics for Experiment 3.

(1) MANOVA analysis of mean importance ratings among the five attributes.

Descriptive Statistics

	Mean	Std. Deviation	N
bottom_of_hull	8.0654	1.48115	107
hull_coating	3.7477	2.35962	107
keel_type	7.1215	1.82597	107
shape_of_sail	5.7757	2.50776	107
material_of_sail	3.8879	2.19058	107

Mauchly's Test of Sphericity[b]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[a]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
attribute	.434	87.238	9	.000	.726	.749	.250

Tests the null hypothesis that the error covariance matrix of the orthonormalized transform variables is proportional to an identity matrix.

a. May be used to adjust the degrees of freedom for the averaged tests of significance. (are displayed in the Tests of Within-Subjects Effects table.

b.

Design: Intercept
Within Subjects Design: attribute

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
attribute	Sphericity Assume	1574.523	4	393.631	126.336	.000
	Greenhouse-Geiss	1574.523	2.903	542.290	126.336	.000
	Huynh-Feldt	1574.523	2.994	525.892	126.336	.000
	Lower-bound	1574.523	1.000	1574.523	126.336	.000
Error(attribut	Sphericity Assume	1321.077	424	3.116		
	Greenhouse-Geiss	1321.077	307.768	4.292		
	Huynh-Feldt	1321.077	317.364	4.163		
	Lower-bound	1321.077	106.000	12.463		

(2) T test of mean importance ratings between the bottom of hull and the shape of sail

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	Upper			
Pair 1	bottom_of_hull - shape_of_sai	.28972	2.68823	.25988	1.77448	2.80496	8.811	106	.000

(3) T test of mean importance rating between the keel type and the shape of sail

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	Upper			
Pair 1	keel_type - shape_of_sail	.34579	2.12844	.20576	.93785	1.75374	6.540	106	.000

(4) T test of mean importance rating between the bottom of hull and the keel type

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	Upper			
Pair 1	bottom_of_hu - keel_type	94393	1.70920	.16523	.61633	1.27152	5.713	106	.000

(5) Chi-square test for the number of participants using analytic categorization between constrained group and unconstrained group.

ruleusers * constraints * rule Crosstabulation

Count

rule			constraints: no constraints	constraints: constraints	Total
single	ruleusers	-1	8	7	15
		rule users	20	19	39
	Total		28	26	54
conjunctive	ruleusers	-1	25	21	46
		rule users	4	3	7
	Total		29	24	53

Chi-Square Tests

rule		Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
single	Pearson Chi-Squar	.018[b]	1	.893		
	Continuity Correctio	.000	1	1.000		
	Likelihood Ratio	.018	1	.892		
	Fisher's Exact Test				1.000	.567
	Linear-by-Linear Association	.018	1	.894		
	N of Valid Cases	54				
conjunctive	Pearson Chi-Squar	.019[c]	1	.890		
	Continuity Correctio	.000	1	1.000		
	Likelihood Ratio	.019	1	.890		
	Fisher's Exact Test				1.000	.609
	Linear-by-Linear Association	.019	1	.891		
	N of Valid Cases	53				

a. Computed only for a 2x2 table

b. 0 cells (.0%) have expected count less than 5. The minimum expected count is 7.22.

c. 2 cells (50.0%) have expected count less than 5. The minimum expected count is 3.1

(6) Chi-square test for the main effect of rule type on the number of participants using analytic categorization

usedrule * rule Crosstabulation

Count

		rule: single-attribute-based rule	rule: conjunctive rule	Total
usedrule	not used rules	22	46	68
	used rules	32	7	39
Total		54	53	107

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	24.489[b]	1	.000		
Continuity Correction[a]	22.541	1	.000		
Likelihood Ratio	26.004	1	.000		
Fisher's Exact Test				.000	.000
Linear-by-Linear Association	24.260	1	.000		
N of Valid Cases	107				

a. Computed only for a 2x2 table

b. 0 cells (.0%) have expected count less than 5. The minimum expected count is 19. 32.

(7) Chi-square test for the effects of rule type on the number of participants using analytic categorization under constrained and unconstrained conditions.

Chi-Square Tests

task		Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
no constraints	Pearson Chi-Square	11.754(b)	1	.001		
	Continuity Correction(a)	9.927	1	.002		
	Likelihood Ratio	12.359	1	.000		
	Fisher's Exact Test				.001	.001
	Linear-by-Linear Association	11.547	1	.001		
	N of Valid Cases	57				
constraints	Pearson Chi-Square	12.738(c)	1	.000		
	Continuity Correction(a)	10.742	1	.001		
	Likelihood Ratio	13.675	1	.000		
	Fisher's Exact Test				.000	.000
	Linear-by-Linear Association	12.484	1	.000		
	N of Valid Cases	50				

a Computed only for a 2x2 table
b 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.82.
c 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.12.

(8) Normality tests for weight of hull and weight of keel

One-Sample Kolmogorov-Smirnov Test

		Hull	Keel
N		106	106
Normal Parameters[a,b]	Mean	48.8520	-9.7919
	Std. Deviation	42.09200	24.03294
Most Extreme Differences	Absolute	.132	.185
	Positive	.112	.158
	Negative	-.132	-.185
Kolmogorov-Smirnov Z		1.359	1.907
Asymp. Sig. (2-tailed)		.050	.001

a. Test distribution is Normal.

b. Calculated from data.

(9) Levene's test of equality of error variances for hull

Levene's Test of Equality of Error Variances(a)

Dependent Variable: Hull

F	df1	df2	Sig.
1.275	3	102	.287

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.
a Design: Intercept+Rule+Task+Rule * Task

(10) Levene's test of equality of error variances for keel

Levene's Test of Equality of Error Variances(a)

Dependent Variable: Keel

F	df1	df2	Sig.
13.476	3	102	.000

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.
a Design: Intercept+Rule+Task+Rule * Task

(11) Mann-Whitney test of the effect of rule type on weight of hull

Test Statistics(a)

	Hull
Mann-Whitney U	463.000
Wilcoxon W	1841.000
Z	-5.948
Asymp. Sig. (2-tailed)	.000

a Grouping Variable: Rule

(12) Mann-Whitney test of the effect of rule type on the weight of keel

Test Statistics(a)

	Keel
Mann-Whitney U	732.000
Wilcoxon W	2110.000
Z	-4.253
Asymp. Sig. (2-tailed)	.000

a Grouping Variable: Rule

(13) Mann-Whitney test of the effect of constraints on weight of hull for the single-attribute-based rule condition

Test Statistics(a,b)

	Hull
Mann-Whitney U	346.000
Wilcoxon W	752.000
Z	-.312
Asymp. Sig. (2-tailed)	.755

a Grouping Variable: Task
b Rule = -1.00

(14) Mann-Whitney test of the effect of constraints on weight of hull for the conjunctive rule condition

Test Statistics(a,b)

	Hull
Mann-Whitney U	308.500
Wilcoxon W	743.500
Z	-.461
Asymp. Sig. (2-tailed)	.645

a Grouping Variable: Task
b Rule = 1.00

(15) Mann-Whitney test of the effect of constraints on weight of keel for the single-attribute-based rule condition

Test Statistics(a,b)

	Keel
Mann-Whitney U	354.500
Wilcoxon W	705.500
Z	-.166
Asymp. Sig. (2-tailed)	.868

a Grouping Variable: Task
b Rule = -1.00

(16) Mann-Whitney test of the effect of constraints on weight of keel for the conjunctive rule condition

Test Statistics(a,b)

	Keel
Mann-Whitney U	219.000
Wilcoxon W	654.000
Z	-2.110
Asymp. Sig. (2-tailed)	.035

a Grouping Variable: Task
b Rule = 1.00

(17) Mann-Whitney test between weight of hull and weight of keel under the nconstrained-conjunctive-rule condition

Test Statistics(a)

	Weight
Mann-Whitney U	407.000
Wilcoxon W	842.000
Z	-.210
Asymp. Sig. (2-tailed)	.834

a Grouping Variable: Attribute

(18) Mann-Whitney test between weight of hull and weight of keel under the constrained-conjunctive-rule condition

Test Statistics[a]

	Weight
Mann-Whitney U	166.500
Wilcoxon W	442.500
Z	-2.153
Asymp. Sig. (2-tailed)	.031

a. Grouping Variable: Attribute

(19) Normality test for weight of hullxkeel

One-Sample Kolmogorov-Smirnov Test

		HullKeel
N		106
Normal Parameters(a,b)	Mean	-4.1409
	Std. Deviation	19.16649
Most Extreme Differences	Absolute	.205
	Positive	.138
	Negative	-.205
Kolmogorov-Smirnov Z		2.107
Asymp. Sig. (2-tailed)		.000

a Test distribution is Normal.
b Calculated from data.

(20) Levene's test of equality of error variances for hullxkeel

Levene's Test of Equality of Error Variances(a)

Dependent Variable: HullKeel

F	df1	df2	Sig.
13.053	3	102	.000

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.
a Design: Intercept+Rule+Task+Rule * Task

(21) Mann-Whitney test of the main effect of rule type on weight of hullxkeel

Test Statistics(a)

	HullKeel
Mann-Whitney U	1052.500
Wilcoxon W	2430.500
Z	-2.225
Asymp. Sig. (2-tailed)	.026

a Grouping Variable: Rule

(22) Normality test for total number of clicks in the first three learning trials

One-Sample Kolmogorov-Smirnov Test

		T123total
N		107
Normal Parameters(a,b)	Mean	10.4299
	Std. Deviation	4.22283
Most Extreme Differences	Absolute	.216
	Positive	.140
	Negative	-.216
Kolmogorov-Smirnov Z		2.230
Asymp. Sig. (2-tailed)		.000

a Test distribution is Normal.
b Calculated from data.

(23) Levene's test of equality of error variances for total number of clicks in the first three learning trials

Levene's Test of Equality of Error Variances(a)

Dependent Variable: T123total

F	df1	df2	Sig.
1.139	3	103	.337

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.
a Design: Intercept+rule+task+rule * task

(24) Mann-Whitney test of the main effect of constraints on total number of clicks in the first three learning trials

Test Statistics(a)

	T123total
Mann-Whitney U	1058.500
Wilcoxon W	2333.500
Z	-2.345
Asymp. Sig. (2-tailed)	.019

a Grouping Variable: -1=notask,1=task

(25) Normality test for number of clicks on hull in the first three learning trials

One-Sample Kolmogorov-Smirnov Test

		hullclick123
N		107
Normal Parameters[a,b]	Mean	2.7757
	Std. Deviation	.63407
Most Extreme Differences	Absolute	.498
	Positive	.362
	Negative	-.498
Kolmogorov-Smirnov Z		5.152
Asymp. Sig. (2-tailed)		.000

a. Test distribution is Normal.

b. Calculated from data.

(26) Levene's test of equality of error variances for number of clicks on hull in the first three learning trials

Levene's Test of Equality of Error Variances[a]

Dependent Variable: hullclick123

F	df1	df2	Sig.
9.568	3	103	.000

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept+rule+constraints+rule * constraints

(27) Mann-Whitney test of the main effect of constraints on number of clicks on hull in the first three learning trials

Test Statistics[a]

	hullclick123
Mann-Whitney U	1208.500
Wilcoxon W	2483.500
Z	-2.241
Asymp. Sig. (2-tailed)	.025

a. Grouping Variable: constraints

(28) Normality test for number of clicks on keel in the first three learning trials

One-Sample Kolmogorov-Smirnov Test

		keelclick123
N		107
Normal Parameters[a,b]	Mean	2.4112
	Std. Deviation	.97083
Most Extreme Differences	Absolute	.410
	Positive	.272
	Negative	-.410
Kolmogorov-Smirnov Z		4.243
Asymp. Sig. (2-tailed)		.000

a. Test distribution is Normal.

b. Calculated from data.

(29) Levene's test of equality of error variances for number of clicks on keel in the first three learning trials

Levene's Test of Equality of Error Variances[a]

Dependent Variable: keelclick123

F	df1	df2	Sig.
3.760	3	103	.013

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept+rule+constraints+rule * constraints

(30) Mann-Whitney test of the main effect of constraints on number of clicks on keel in the first three learning trials

Test Statistics[a]

	keelclick123
Mann-Whitney U	1064.500
Wilcoxon W	2339.500
Z	-2.733
Asymp. Sig. (2-tailed)	.006

a. Grouping Variable: constraints

(31) Normality test for number of clicks on irrelevant attributes in the first three learning trials

One-Sample Kolmogorov-Smirnov Test

		irreclick123
N		107
Normal Parameters(a,b)	Mean	5.2430
	Std. Deviation	3.37818
Most Extreme Differences	Absolute	.222
	Positive	.149
	Negative	-.222
Kolmogorov-Smirnov Z		2.297
Asymp. Sig. (2-tailed)		.000

a Test distribution is Normal.
b Calculated from data.

(32) Levene's test of equality of error variances for irrelevant attributes in the first three learning trials

Levene's Test of Equality of Error Variances(a)

Dependent Variable: irreclick123

F	df1	df2	Sig.
.750	3	103	.525

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.
a Design: Intercept+rule+task+rule * task

(33) Mann-Whitney test of the main effect of constraints on irrelevant attributes in the first three learning trials

Test Statistics(a)

	irreclick123
Mann-Whitney U	1124.000
Wilcoxon W	2399.000
Z	-1.929
Asymp. Sig. (2-tailed)	.054

a Grouping Variable: -1=notask,1=task

(34) Mann-Whitney test of the main effect of constraints on the ratio of the number of clicks on irrelevant attributes over the total clicks in the first three learning trials

Test Statistics[a]

	irreintotal123
Mann-Whitney U	1265.500
Wilcoxon W	2490.500
Z	-.853
Asymp. Sig. (2-tailed)	.394

a. Grouping Variable: constraints

(35) Normality test for total number of clicks, number of clicks on relevant attributes, and number of clicks on irrelevant attributes during the 18 learning trials

One-Sample Kolmogorov-Smirnov Test

		totalclick	totalirreclick	totalreleclick
N		107	107	107
Normal Parameters[a,b]	Mean	47.2804	22.9720	24.3084
	Std. Deviation	24.51368	17.27877	9.73363
Most Extreme Differences	Absolute	.095	.145	.132
	Positive	.095	.145	.115
	Negative	-.076	-.092	-.132
Kolmogorov-Smirnov Z		.986	1.500	1.364
Asymp. Sig. (2-tailed)		.286	.022	.048

a. Test distribution is Normal.

b. Calculated from data.

(36) Mann-Whitney test of the main effect of constraints on total number of clicks during the 18 learning trials

Test Statistics[a]

	totalclick
Mann-Whitney U	1210.500
Wilcoxon W	2485.500
Z	-1.341
Asymp. Sig. (2-tailed)	.180

a. Grouping Variable: -1=no task, 1=task

(37) Mann-Whitney test of the main effect of constraints on number of relevant clicks during the 18 learning trials

Test Statistics[a]

	totalreleclick
Mann-Whitney U	1245.000
Wilcoxon W	2520.000
Z	-1.129
Asymp. Sig. (2-tailed)	.259

a. Grouping Variable: -1=no task, 1=task

(38) Mann-Whitney test of the main effect of constraints on number of irrelevant clicks during the 18 learning trials

Test Statistics[a]

	totalirreclick
Mann-Whitney U	1263.000
Wilcoxon W	2538.000
Z	-1.013
Asymp. Sig. (2-tailed)	.311

a. Grouping Variable: -1=no task, 1=task

(39) Mann-Whitney test of the main effect of rule types on total number of clicks during the 18 learning trials

Test Statistics[a]

	totalclick
Mann-Whitney U	872.500
Wilcoxon W	2357.500
Z	-3.483
Asymp. Sig. (2-tailed)	.000

a. Grouping Variable: -1=single,1=conjun

(40) Mann-Whitney test of the main effect of rule types on number of relevant clicks during the 18 learning trials

Test Statistics[a]

	totalreleclick
Mann-Whitney U	821.500
Wilcoxon W	2306.500
Z	-3.813
Asymp. Sig. (2-tailed)	.000

a. Grouping Variable: -1=single,1=conjun

(41) Mann-Whitney test of the main effect of rule types on number of irrelevant clicks during the 18 learning trials

Test Statistics(a)

	totalirreclick
Mann-Whitney U	954.000
Wilcoxon W	2439.000
Z	-2.976
Asymp. Sig. (2-tailed)	.003

a Grouping Variable: -1=single,1=conjun

(42) Mann-Whitney test between the number of clicks on the bottom of hull and the number of clicks on the keel type for unconstrained participants during the 18 learning trials

Test Statistics[a,b]

	clicks
Mann-Whitney U	365.500
Wilcoxon W	800.500
Z	-.898
Asymp. Sig. (2-tailed)	.369

a. Grouping Variable: attributes

b. constraints = no task

(43) Mann-Whitney test between the number of clicks on the bottom of hull and the number of clicks on the keel type for unconstrained participants during the 18 learning trials

Test Statistics[a,b]

	clicks
Mann-Whitney U	269.000
Wilcoxon W	569.000
Z	-.403
Asymp. Sig. (2-tailed)	.687

a. Grouping Variable: attributes

b. constraints = task

(44) Normality test for number of trials that were ever clicked

One-Sample Kolmogorov-Smirnov Test

		everclicktrials
N		107
Normal Parameters(a,b)	Mean	15.5234
	Std. Deviation	3.88841
Most Extreme Differences	Absolute	.345
	Positive	.262
	Negative	-.345
Kolmogorov-Smirnov Z		3.573
Asymp. Sig. (2-tailed)		.000

a Test distribution is Normal.
b Calculated from data.

(45) Levene's test of equality of error variances for number of trials that were ever clicked

Levene's Test of Equality of Error Variances(a)

Dependent Variable: everclicktrials

F	df1	df2	Sig.
4.986	3	103	.003

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.
a Design: Intercept+rule+task+rule * task

(46) Mann-Whitney test of the main effect of constraints on number of trials that were ever clicked

Test Statistics(a)

	everclicktrials
Mann-Whitney U	1092.500
Wilcoxon W	2367.500
Z	-2.358
Asymp. Sig. (2-tailed)	.018

a Grouping Variable: -1=notask,1=task

(47) Box's test of equality of covariance matrices for learning time

Box's Test of Equality of Covariance Matrices(a)

Box's M	1458.944
F	1.922
df1	513
df2	21496.703
Sig.	.000

Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.
a Design: Intercept+rule+task+rule * task
Within Subjects Design: trials

(48) MANOVA analysis of learning time

Mauchly's Test of Sphericity

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[a] Greenhouse-Geisser	Huynh-Feldt	Lower-bound
trials	.000	787.155	152	.000	.454	.508	.059

Tests the null hypothesis that the error covariance matrix of the orthonormalized transforr dependent variables is proportional to an identity matrix.

a. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

b.

Design: Intercept+rule+task+rule * task
Within Subjects Design: trials

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
trials	Sphericity Assumed	23372148200.112	17	1374832247.065	46.562	.000
	Greenhouse-Geisser	23372148200.112	7.715	3029601948.132	46.562	.000
	Huynh-Feldt	23372148200.112	8.642	2704467127.165	46.562	.000
	Lower-bound	23372148200.112	1.000	23372148200.112	46.562	.000
trials * rule	Sphericity Assumed	769359801.102	17	45256458.888	1.533	.075
	Greenhouse-Geisser	769359801.102	7.715	99727844.111	1.533	.145
	Huynh-Feldt	769359801.102	8.642	89025119.695	1.533	.135
	Lower-bound	769359801.102	1.000	769359801.102	1.533	.219
trials * constraints	Sphericity Assumed	1053473314.291	17	61969018.488	2.099	.005
	Greenhouse-Geisser	1053473314.291	7.715	136555903.118	2.099	.036
	Huynh-Feldt	1053473314.291	8.642	121900816.453	2.099	.029
	Lower-bound	1053473314.291	1.000	1053473314.291	2.099	.150
trials * rule * constraints	Sphericity Assumed	508070731.300	17	29886513.606	1.012	.441
	Greenhouse-Geisser	508070731.300	7.715	65858391.114	1.012	.424
	Huynh-Feldt	508070731.300	8.642	58790513.363	1.012	.427
	Lower-bound	508070731.300	1.000	508070731.300	1.012	.317
Error(trials)	Sphericity Assumed	51701651219.100	1751	29526928.166		
	Greenhouse-Geisser	51701651219.100	794.603	65066002.987		
	Huynh-Feldt	51701651219.100	890.131	58083163.791		
	Lower-bound	51701651219.100	103.000	501957778.826		

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	1.506E+011	1	1.506E+011	422.458	.000
rule	3849661997	1	3849661997	10.799	.001
constraints	746052365	1	746052364.6	2.093	.151
rule * constraints	454828683	1	454828683.4	1.276	.261
Error	3.672E+010	103	356490192.5		

(49) Mann-Whitney test of the main effect of constraints on learning time

Test Statistics[a]

	totalms
Mann-Whitney U	1263.000
Wilcoxon W	2916.000
Z	-1.012
Asymp. Sig. (2-tailed)	.312

a. Grouping Variable: -1=no task, 1=task

(50) Normality test for percentage correct

One-Sample Kolmogorov-Smirnov Test

		percorrect
N		107
Normal Parameters[a,b]	Mean	.7839
	Std. Deviation	.24392
Most Extreme Differences	Absolute	.223
	Positive	.188
	Negative	-.223
Kolmogorov-Smirnov Z		2.311
Asymp. Sig. (2-tailed)		.000

a. Test distribution is Normal.

b. Calculated from data.

(51) Levene's test of equality of error variances for percentage correct

Levene's Test of Equality of Error Variances[a]

Dependent Variable: percorrect

F	df1	df2	Sig.
.911	3	103	.438

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept+rule+constraints+rule * constraints

(52) ANOVA analysis of percentage correct

Descriptive Statistics

Dependent Variable: percorrect

rule	constraints	Mean	Std. Deviation	N
single-attribute-based rule	no constraints	.9040	.21211	28
	constraints	.8678	.25880	26
	Total	.8866	.23419	54
conjunctive rule	no constraints	.7112	.19294	29
	constraints	.6406	.22288	24
	Total	.6792	.20803	53
Total	no constraints	.8059	.22307	57
	constraints	.7588	.26577	50
	Total	.7839	.24392	107

Tests of Between-Subjects Effects

Dependent Variable: percorrect

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1.233[a]	3	.411	8.342	.000
Intercept	64.907	1	64.907	1317.576	.000
rule	1.173	1	1.173	23.818	.000
constraints	.076	1	.076	1.541	.217
rule * constraints	.008	1	.008	.159	.691
Error	5.074	103	.049		
Total	72.055	107			
Corrected Total	6.307	106			

a. R Squared = .195 (Adjusted R Squared = .172)