

Protection of Prior Learning in Complex Consumer Learning Environments

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As a product category evolves, consumers have the opportunity to learn a series of feature-benefit associations. Initially, consumers learn that some features predict a critical benefit, whereas other features do not. Subsequently, consumers have the opportunity to assess if previously predictive features, or novel features, predict new product benefits. Surprisingly, later learning is characterized by attenuated learning about previously predictive features relative to novel features. This tendency to ignore previously predictive features is consistent with a desire to protect prior learning.

As consumers gain experience in a product category, they learn product features (e.g., attributes, brand names) that predict product performance (i.e., overall quality or specific benefits). To illustrate, consider a consumer who has been eating in restaurants over a number of years. The consumer has likely learned a number of cues (e.g., type of cuisine, reservation policy, location, price point) that predict outcomes (e.g., food quality, service, ambience). These cue-outcome relationships have evolved, starting with very simple relationships (e.g., French cuisine → high quality food) and ending with more complex ones (e.g., French cuisine, poor location → high quality food, poor ambience). The development of this predictive knowledge structure is called adaptive learning.

Adaptive learning is a dynamic process; hence, it should not be surprising that a considerable amount of research effort has focused on how predictive associations are learned and updated over time. For representative approaches, see Janiszewski and van Osselaer (2000), Kruschke (1996), Le Pelley (2004), and Pearce (1994). At the simplest level, it could be assumed that association strengths increase (de-

crease) with each reinforcing (nonreinforcing) outcome (Keller 1993, 1998). These direct association models best describe single cue–single outcome learning contexts (e.g., cuisine → quality). At a more complex level, it could be assumed that association strengths are updated in order to minimize the error between the summed predictive ability of the available cues and the outcome (Gluck and Bower 1988; Rescorla and Wagner 1972). These least mean square (henceforth, LMS) models best describe multiple cue–single outcome (henceforth, MC–SO) learning contexts (e.g., cuisine and location → quality). The LMS models are more effective in multiple cue environments because they allow for cue interaction (i.e., the learning of a cue → outcome association may be affected by presence of other cues).

Learning environment complexity does not solely depend on the availability of multiple cues. There can also be multiple outcomes (e.g., food quality, ambience) occurring in the same learning period or across a series of learning periods. Although single cue–multiple outcome learning contexts have been extensively studied (e.g., how a brand name comes to indicate multiple benefits), multiple cue–multiple outcome (henceforth, MC–MO) learning contexts have received considerably less attention (but see Hutchinson and Alba 1991; and Janiszewski and van Osselaer 2000). Of particular interest to consumer researchers is the influence of prior learning about one benefit (e.g., cuisine → quality) on predictive learning about a second benefit (e.g., cuisine → ambience) when additional predictive cues (e.g., location, price point) are available, as is the case in many product categories (e.g., restaurants, wine, hotels). First, one might imagine that initial learning about one benefit does not influence subsequent learning about a second benefit, as predicted by the LMS model. Second, one might imagine that

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consumers try to minimize effort across learning periods by using prior cue predictability to allocate attention to specific cues. At new learning, consumers attend to previously relevant cues, while ignoring previously irrelevant cues, because they want to learn efficiently. Third, one might imagine that consumers try to protect learning across learning periods. At new learning, consumers ignore previously relevant cues because they want to protect prior learning about the cue. The first strategy is based on the assumption that the learning history of a cue should not affect novel learning about this cue. The remaining two strategies, however, assume that the learning history of a cue should influence novel learning about this cue. We focus on understanding the impact of prior learning on novel learning.

We begin with a review of the MC-SO learning literature because it represents the bulk of consumer research on adaptive learning in complex information environments. We discuss the models that describe MC-SO learning and speculate about the learning goals people might bring to these environments. Next, we discuss whether the learning goals supporting MC-SO learning will generalize to the MC-MO environment and, if not, what other learning goals might become active. Our empirical work begins with a pilot study that shows that people attempt to protect prior learning by ignoring cues that were predictive of benefits during prior learning. Experiment 1 shows that a majority of participants behave in a manner that suggests that they are trying to protect prior learning but that a subset behave in a manner that suggests that they are trying to maximize efficiency. Experiment 2 shows that people protect prior learning even if previously relevant cues are the only cues available to predict a novel outcome. Experiment 3 shows that people protect prior learning even when they are aware that a cue can predict multiple outcomes. Experiment 4 tests our hypotheses in an applied information search context. Collectively, the results indicate that people attenuate learning about a cue and a novel outcome in an attempt to protect prior learning about this cue.

MULTIPLE CUE ADAPTIVE LEARNING

A consumer's expectation about the performance of a product often depends on the attribute levels of the product. Implicit in the generation of this expectation is the assumption that the consumer has learned the "value" of each attribute. Although some attributes (e.g., price) acquire value via an independent source, many other attributes acquire value owing to their prior association with product performance. These associations may be to a single outcome (e.g., product quality, a specific product benefit) or to multiple outcomes (e.g., a collection of valued product benefits). To date, consumer research has focused primarily on MC-SO learning, a likely consequence of the importance of a single diagnostic outcome for choice. We review this literature prior to discussing MC-MO learning.

Multiple Cue–Single Outcome Learning

MC-SO learning studies assess how consumers learn the relationships between predictive cues (e.g., product attributes) and an outcome (e.g., product quality). Although different researchers implicitly (explicitly) assume different models, the general consensus is that learning depends on a feedback system. The system (*a*) notes the availability of predictive cues, (*b*) uses the summed association strengths of the available cues to predict an outcome, (*c*) acts on this prediction, (*d*) receives feedback on the realized outcome, and (*e*) updates the association strengths. The cue additivity and error reduction properties together create a cue interdependence property—the associations between multiple cues and an outcome are learned interdependently.

In cases in which cues are redundant, cue competition (e.g., blocking) can occur. For example, van Osselaer and Alba (2000) show that if a cue (e.g., a brand name) has a strong association with an outcome (i.e., high quality), subsequent presentations of an accompanying cue (e.g., a feature) will not result in a learned association between the accompanying cue and the outcome. In cases in which cues are not redundant, cue integration occurs. For example, Meyer (1987) uses an unfamiliar product category (e.g., copper alloys) to show that consumers can learn diagnostic attribute levels and the relative importance of each attribute for predicting product quality. West (1996) shows that agents can use feedback to adjust their attribute weights to more closely approximate the weights of their client. Eisenstein and Hutchinson (2006) show that learning goals and task procedures can make people sensitive to different combinations of predictor variables. In each of these cases, no one cue perfectly predicts the outcome, so consumers use cue combinations to assess the relative impact of each cue on the outcome.

The studies on MC-SO learning not only provide insight into how people learn but also shed light on the goals people bring to the learning process. Clearly, one of these goals is accurate learning. The accuracy of learning has been a primary focus of MC-SO research (e.g., classical conditioning, multiple cue probability learning) throughout its history. Less obvious, but as important, is the goal of efficient learning. For example, Eisenstein and Hutchinson (2006) asked participants to learn how to predict the price of real estate. The task was either numerical (e.g., "What is the price?") or categorical (e.g., "Is the price above or below \$X?"), and the feedback was numerical or categorical and numerical, respectively. Eisenstein and Hutchinson (2006) found that participants assigned to the numerical (categorical) task quite accurately identified the predictors that aided numerical (categorical) accuracy, but they were fairly insensitive to predictors that aided categorical (numerical) accuracy. In other words, participants directed their attention and effort in order to be locally accurate (i.e., as defined by the task) but not generally accurate (i.e., as defined by the data). Thus, people exhibit the common accuracy-effort trade-off when engaging in MC-SO learning (see West [1996] for additional evidence).

Multiple Cue–Multiple Outcome Learning

Multiple cue–multiple outcome (MC–MO) learning is a natural extension of MC–SO learning with the caveat that the learning environment has become more complex. Relative to MC–SO learning, where cues compete to predict a single outcome, MC–MO learning also provides an opportunity for outcomes to “compete” within or across learning trials. For example, a recent study by Miller and Matute (1998) finds that passive learning about the association between a cue (e.g., click) and an outcome (e.g., white noise) at time 1 ($A \rightarrow O1$) can inhibit passive learning about the cue (e.g., click) and a second outcome (e.g., tone) at time 2 ($A \rightarrow O1, O2$). If this is so, it is also possible that outcomes may compete in active learning situations as well. More specifically, when human subjects have to learn about meaningful outcomes (e.g., product benefits), it is possible that learning that a cue predicts a benefit at time 1 ($A \rightarrow O1$) may inhibit learning that the cue predicts a second benefit at time 2 ($A \rightarrow O2$). Whether Miller and Matute’s (1998) outcome competition result will generalize to consumer learning contexts is an open question owing to different populations (e.g., rats vs. humans), learning goals (e.g., no goal vs. causal learning), and learning procedures (e.g., simultaneous vs. sequential presentation of competing outcomes).

Models that have traditionally been used to account for MC–SO learning (e.g., the LMS model) assume that learning about each outcome is independent; hence, these models are agnostic about multiple outcome learning. In contrast, there is a class of models that assume predictive cues compete for attentional capacity, a likely characteristic of MC–MO learning. These models (also called conditioned stimulus processing models) assume that the associability of a cue can vary across learning trials, where the associability of a cue is a stimulus-specific learning rate parameter (Mackintosh 1975). Although a number of attention allocation models have been proposed (e.g., Kruschke 1996; Mackintosh 1975; Pearce and Hall 1980), Mackintosh’s (1975) original model is sufficient to illustrate the basic principles of such a class of models. 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,

$$\Delta s_{ij} = \alpha_i \times \beta(q_j - s_{ij}), \quad (1)$$

where α_i is the associability of cue i , β is the learning rate parameter of the outcome, q_j is the experienced outcome level, and s_{ij} is the outcome level predicted by the cue. Notice that, unlike the LMS model, the Mackintosh model does not assume that the expected outcome is a sum of the predictive associations of the available cues. Learning and prediction are unique to each cue–outcome dyad.

One of the most interesting characteristics of the Mackintosh model is that it allows the associability of a cue (α_i) to vary as a function of (1) the salience of the cue and (2) the learning history of the cue. First, it has long been rec-

ognized that the salience of a cue influences the degree of learning about the cue (Pavlov 1927). Pavlov (1927) found that dogs pay more attention to, and are more likely to learn associations to, intense cues (i.e., overshadowing). Hutchinson and Alba (1991) found that people are better at learning predictive associations when classification cues are salient as opposed to nonsalient. Kruschke and colleagues (Kruschke and Blair 2000; Kruschke, Kappenman, and Hetrick 2005) found that people pay more attention to, and are more likely to learn, associations to novel cues. Kruschke et al. (2005) argue that novel cues are more distinctive and hence more likely to engage attention.

Second, cue associability is a function of the learning history of a cue. Mackintosh proposed that the associability of a cue can change as a function of the discrepancy between the predicted and experienced outcomes for a cue relative to the summed discrepancies of the accompanying cues.

$$\Delta \alpha_i^n > 0 \text{ when } |q_j^n - s_{ij}^{n-1}| < |q_j^n - s_x^{n-1}|, \quad (2)$$

$$\Delta \alpha_i^n < 0 \text{ when } |q_j^n - s_{ij}^{n-1}| \geq |q_j^n - s_x^{n-1}|, \quad (3)$$

where α_i is the associability of the cue, 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 (i.e., the summed discrepancies of the cues accompanying cue i), and n is the learning trial number. When cue i is a better predictor than the accompanying cues, the associability of cue i increases. When the accompanying cues are as effective as, or more effective than, cue i at predicting the outcome, the associability of cue i decreases. In effect, people strategically allocate attention to cues that exhibit predictability across learning trials (i.e., potentially relevant causal factors). This strategic allocation of attention allows for an acceleration of learning.

Learning Efficiency. The Mackintosh model proposes that people allocate attention toward cues that are predictive and away from cues that are nonpredictive. Yet, it is important to recognize that Mackintosh intended to apply this associability updating assumption to learning about a single outcome. When the associability updating assumption is extended to learning about multiple outcomes, there is uncertainty about whether the associability parameters will generalize from learning about outcome 1 to learning about outcome 2. First, it may be the case that people put an emphasis on efficient learning. If cues have been predictive in the past, then they are likely to be predictive in the future, even for novel outcomes. For example, if a consumer has learned that French restaurants serve good food, then the cuisine cue should be the first cue considered when predicting a novel outcome (e.g., service). To the extent that the cue is not a good predictor of the novel outcome, the associability of the cue will drop over time and other cues will be considered. These predictions are consistent with the results of the overtraining reversal effect (Reid 1953). In this learning phenomenon, rats that are overtrained (i.e.,

experience larger number of trials) in a discrimination task (e.g., A [−] and B [+]) more rapidly learn reversals of cue-outcome associations in a subsequent learning task (e.g., A [+] and B [−]). Mackintosh (1969) explains the increased efficiency in learning reversals as a function of the increased associability parameter (α 's) of the cues in the overtraining condition, which makes novel learning about these cues more efficient.

H1a: *Learning Efficiency:* Cues that are effective predictors of past outcomes will initially have high associability parameters (i.e., receive more attention) when people learn about novel outcomes.

Hypothesis 1a captures the predictions of equations 2 and 3. When a cue is a better predictor of the outcome than the accompanying cues, its associability parameter (α) increases. It follows that this cue will attract more attention when paired with a novel outcome and, as per equation 1, will acquire associative strength more rapidly than the accompanying cues with smaller associability parameters.

Learning Protection. An alternative to the goal of efficient learning is the goal to protect learning. A learning system that emphasizes a small set of predictive cues is more likely to experience retroactive interference and a degradation of learning. One way to avoid retroactive interference is to protect prior learning. The original Mackintosh model cannot accommodate learning protection, because it predicts that cues with large (small) α 's should always attract more (less) attention in a given learning trial. Thus, we propose an extension of this model by transforming extreme associability parameters (α) so that they are close to zero when new outcomes are being predicted. Alphas that are already close to zero, as a result of the prior irrelevance of the cue, remain the same in the initial trials of new learning. Alphas that are close to one, as a result of the prior relevance of the cue, however, are subtracted from one and are initially set near zero. After this transformation, updating of the cues should follow equations 2 and 3. To summarize, we assume that the starting value for a current α is a function of learning about a prior cue-outcome relationship. For a two-outcome learning environment, this can be formalized as

$$\alpha_{i2} = \alpha_{i1} \text{ for } \alpha_{i1} \leq 0.5, \quad (4)$$

$$\alpha_{i2} = 1 - \alpha_{i1} \text{ for } \alpha_{i1} > 0.5. \quad (5)$$

There is some evidence that, when learning about a new outcome, people allocate attention away from cues that have been relevant (Cunha and Laran 2007; Kruschke 1996; Kruschke and Blair 2000; Kruschke and Johansen 1999; Kruschke et al. 2005). For example, Kruschke and Johansen (1999) show results that suggest that people allocate attention away from cues that have already been learned to predict diseases. Kruschke et al. (2005) use a paired associate learning task to show that learning a cue-outcome association

reduces attention to that cue when a new cue-outcome (i.e., paired association) relationship must be learned.

H1b: *Learning Protection:* Cues that are effective predictors of past outcomes will have low associability parameters (i.e., receive less attention) when people learn about novel outcomes.

Hypothesis 1b summarizes the predictions of equations 4 and 5. When the associability of a cue (α) is high, there is a decrease in the associability parameter when this same cue is present to predict a novel outcome. Thus, as per equation 1, this cue will acquire associative strength more slowly than novel cues with larger associability parameters.

Summary

There are two plausible hypotheses about the influence of prior learning about one outcome on learning about a novel outcome. First, consumers may attend to previously predictive cues when learning about new outcomes (hypothesis 1a). This strategy is likely a consequence of a learning efficiency goal. Second, consumers may ignore previously predictive cues when learning about new outcomes (hypothesis 1b). This strategy is a likely consequence of a learning protection goal. These two strategies are variations of the same basic learning process: strategic allocation of attention aimed at error reduction and learning acceleration; thus, they are both plausible strategies. Of course, it is also possible that people simply ignore prior learning about other outcomes, as assumed by the LMS model. We begin our empirical investigation with a pilot study designed to assess how prior learning influences the associability of a cue with a novel outcome.

PILOT STUDY

Consumers commonly learn about product attributes and product benefits over the course of time. Thus, there should be MC-MO learning environments where people behave as if they are emphasizing the goal of learning efficiency (hypothesis 1a) or learning protection (hypothesis 1b). The pilot study focused on the influence of previously relevant cues on subsequent learning since the learning efficiency and learning protection hypotheses make common predictions about previously irrelevant cues (i.e., nonpredictive cues should be ignored in the future). More specifically, the learning protection hypothesis predicts that the ability to learn about previously relevant cues will be attenuated in new learning environments, whereas the learning efficiency hypothesis does not. The pilot study was admittedly exploratory because it lacked the internal validity controls (e.g., cue/outcome counterbalancing) of a true experiment.

The procedure involved learning about attributes that predict the taste benefits of cheese. Cheese was selected as a stimulus class because it varies in attributes (e.g., color of rind, type of milk, country of production) and benefits (e.g., mild/strong, dry/creamy). Thus, it was possible to focus attention on one benefit dimension in learning stage 1 (mild/

strong) and a second benefit dimension in learning stage 2 (dry/creamy). To the extent that there was learning in stage 1 and an attribute from stage 1 was present during the learning of a novel benefit in stage 2, we could assess whether learning in stage 1 resulted in learning protection in stage 2.

Method

Learning Procedure and Stimuli. The learning procedure was designed to assess whether prior learning about one benefit (e.g., mild/strong) could influence subsequent learning about a second benefit (e.g., dry/creamy). As shown in table 1, the control condition represented baseline learning (participants tasted only learning stage 2 cheeses). In this condition, participants used a seven-point “dry” (1)/“creamy” (7) scale to rate the creaminess of a Port Salut cheese (a mild, creamy cheese) with an orange rind and a label of “goat milk cheese” and a Manchego cheese (a dry cheese) with a label of “product of Belgium” (no rind). A pretest had confirmed that the Port Salut cheese ($M = 6.00$) was creamier than the Manchego cheese ($M = 1.97$; $F(1, 29) = 605.0$, $p < .01$). We expected both the orange rind and “goat milk cheese” to establish some associability with creaminess.

In the treatment condition, participants initially used a seven-point “mild” (1)/“strong” (7) scale to rate the strength of the flavor of a Raclette cheese (a mild, creamy cheese) with an orange rind and a Drunken Goat cheese (a strong, semi-dry cheese) with a purple rind. Then, as in the control condition, they rated the Port Salut and the Manchego cheeses using the “dry”/“creamy” scale. If learning protection was occurring, then learning that the orange rind indicated a mild cheese in stage 1 should attenuate learning that the orange rind indicated creaminess in stage 2. To guard against alternative hypotheses, the orange rind cheese had to be creamier at stage 1, even though this benefit dimension was not rated. A pretest confirmed that the Raclette ($M = 6.60$) was creamier than the Drunken Goat ($M = 3.00$; $F(1, 18) = 110.0$, $p < .01$).

The critical test was whether learning about the orange rind and strength of flavor in learning stage 1 attenuated learning (i.e., learning protection) about the orange rind and creaminess in learning stage 2. At the test stage, all participants used a seven-point scale to indicate whether a “Belgian goat cheese”

(1) or a “Belgian orange rind cheese” (7) would be creamier. Note that this test was diagnostic because the stage 2 creamy cheese had an orange rind and was described as a “goat cheese.” Thus, a lower associability parameter for orange rind meant a higher associability parameter for “goat cheese” and vice versa.

Results

Fifty-one undergraduates at the University of Florida participated in the study for extra credit. A manipulation check of stage 1 learning showed that treatment participants rated the orange rind cheese ($M = 4.58$) milder than the purple rind cheese ($M = 5.50$; $t(23) = 2.58$, $p < .05$). A manipulation check of stage 2 learning showed that treatment group participants rated the orange rind cheese labeled “goat milk cheese” ($M = 6.29$) creamier than the no-rind cheese labeled “product of Belgium” ($M = 2.83$; $t(23) = 11.95$, $p < .05$). Control group participants also rated the orange rind cheese labeled “goat milk cheese” ($M = 6.04$) creamier than the no-rind cheese labeled “product of Belgium” ($M = 2.70$; $t(26) = 15.15$, $p < .05$). Consistent with the learning protection hypothesis, treatment group participants were less likely to expect that a Belgian orange rind cheese would be creamy ($M_{\text{treatment}} = 1.67$, $M_{\text{control}} = 3.00$; $F(1, 49) = 7.62$, $p < .01$). Learning that the orange rind predicted a difference in the strength of flavor in learning stage 1 attenuated the learning that the orange rind predicted creaminess in learning stage 2.

Discussion

Although the pilot study was designed with ecological, as opposed to internal, validity in mind, two conclusions can be drawn. First, the results are not consistent with the predictions of a LMS model. A LMS model predicts that stage 1 learning should have no influence on stage 2 learning (i.e., the treatment and control groups should be equivalent). Second, the results suggest that people are more likely to protect learning (hypothesis 1b) than to generalize an associability parameter in an effort to learn more efficiently (hypothesis 1a). Experiment 1 uses a more tightly controlled

TABLE 1
LEARNING PROCEDURE AND RESULTS OF PILOT STUDY

Learning stage	Cue	Stimulus	Control		Treatment	
			Attribute	Rating	Attribute	Rating
Learning stage 1:						
A → O1	A Orange rind	Raclette			Mild/strong	4.58
B → O2	B Purple rind	Drunken Goat			Mild/strong	5.50
Learning stage 2:						
AC → O3	A Orange rind; C Goat milk cheese	Port Salut	Dry/creamy	6.04	Dry/creamy	6.29
D → O4	D Product of Belgium	Manchego	Dry/creamy	2.70	Dry/creamy	2.83
Test stage:						
	Creamy?		CD/AD	3.00	CD/AD	1.67

procedure to test whether people protect prior learning in MC–MO learning environments.

EXPERIMENT 1

The idea that people will ignore previously relevant cues, in favor of novel cues when trying to learn about new benefits is puzzling, especially given the long history of research in single-cue, multi-outcome learning. Thus, it is important to replicate the pilot study results in a more controlled setting. A more controlled setting will allow us to rule out alternative hypotheses including (1) prior beliefs about the associability of a cue (e.g., the color of a rind should predict only a single outcome) and (2) inferences about attribute correlations (e.g., mild cheeses cannot be creamy). This more controlled setting involved learning about restaurant features and benefits.

Method

Procedure and Stimuli. The computer-based learning procedure is shown in table 2. In learning stage 1, participants saw two $A \rightarrow O1$ and two $B \rightarrow O2$ trials (stimulus screens listed the restaurant feature(s) in the middle of the screen and the outcome at the bottom of the screen). After reviewing the learning trials, participants were asked to predict outcomes using only the feature information. A restaurant feature appeared in the middle of the screen and the four possible outcomes ($O1$ to $O4$) appeared on the bottom of the screen. The words “correct” or “wrong” (followed by the correct response) appeared on a new screen after participants made a prediction. This procedure was repeated until learning was perfect for a two block trial consisting of A and B.

In learning stage 2, features A and C predicted outcome 3 ($AC \rightarrow O3$), features A and D predicted outcome 3 ($AD \rightarrow O3$), and features E and F predicted outcome 4 ($EF \rightarrow O4$). The procedure in stage 2 also reminded participants that $A \rightarrow O1$ and $B \rightarrow O2$. After two learning trials for each

cue-outcome pairing, participants predicted outcomes using only the feature information. This procedure was repeated until learning was perfect for all five cues (A, B, AC, AD, and EF). In the test phase, participants chose whether AE, AF, CE, CF, DE, and DF predicted $O3$ or $O4$. The procedure included a counterbalance factor for outcomes and a counterbalance factor for presentation of the compound stimulus cues (e.g., A or C listed first).

The stimuli consisted of six features (i.e., cues) and four benefits (i.e., outcomes). The six restaurant features were “specializes in seafood”; “price rating: expensive”; “award winning wine list”; “reservation recommended”; “located in trendy neighborhood”; and “offers a tasting menu (fixed price multi-course meal).” The features were randomly assigned to the cues for each participant. The four restaurant outcomes were the positive and negative level of two factors. The *taste* factor had the levels of “bad food” and “great food,” and the *portion-size* factor had the levels of “really small portions” and “large portions.” The outcomes were blocked, so that the same cue could not predict opposing levels of the same factor.

Predictions. Recall that hypothesis 1a predicts learning efficiency. If cue A was a relevant predictor of a restaurant-related outcome in learning stage 1, then people should focus attention on this cue in learning stage 2. Thus, hypothesis 1a predicts that AE, AF (CE, CF, DE, and DF) elicit response $O3$ ($O4$). Alternatively, hypothesis 1b predicts learning protection. If cue A was a relevant predictor of a restaurant-related outcome in learning stage 1, then people should shift attention away from cue A in learning stage 2. Thus, hypothesis 1b predicts that AE, AF (CE, CF, DE, and DF) elicit response $O4$ ($O3$).

Results

Primary Analysis. One hundred and ninety-four participants from an undergraduate subject pool at both the

TABLE 2
LEARNING PROCEDURE AND RESULTS OF EXPERIMENT 1

	Sample cue-outcome set	
	Cue	Outcome
Learning stage 1:		
A \rightarrow O1	A Specializes in seafood	Great food
B \rightarrow O2	B Price rating: expensive	Bad food
Learning stage 2:		
A \rightarrow O1	A Specializes in seafood	Great food
B \rightarrow O2	B Price rating: expensive	Bad food
AC \rightarrow O3	A Specializes in seafood; C Award winning wine list	Small portions
AD \rightarrow O3	A Specializes in seafood; D Reservation recommended	Small portions
EF \rightarrow O4	E Trendy neighborhood; F Offers tasting menu	Big portions
		Share
Test stage:		
AE \rightarrow ? AF \rightarrow ?		$O3$: .34; $O4$: .66
CE \rightarrow ? CF \rightarrow ? DE \rightarrow ? DF \rightarrow ?		$O3$: .58; $O4$: .42

NOTE.—Cues and outcomes were randomly assigned.

University of Florida and the University of Washington received extra credit to participate in the experiment. The results are shown in table 2. Within-subject tests showed that there were no differences in the response rates to the AE and AF test compounds ($F(1, 186) = 3.50, p > .05$) or the CE, CF, DE, and DF test compounds ($F(3, 558) = 2.14, p > .05$); thus, we collapsed the choice shares. As predicted by the learning protection hypothesis (hypothesis 1b), participants expected restaurants having the AE and AF features to have benefit O4 ($\hat{\pi}_{O3} = .34, \hat{\pi}_{O4} = .66; z = 6.42, p < .05$) and the CE, CF, DE, and DF features to have benefit O3 ($\hat{\pi}_{O3} = .58, \hat{\pi}_{O4} = .42; z = 4.23, p < .05$).

Supplemental Analyses of Counterbalance Factors. Three supplemental analyses were performed. First, the counterbalance factor representing the assignment of outcomes did not interact with different response rates between AE/AF and CE/CF ($F(2, 188) = 1.99, p > .05$) or AE/AF and DE/DF ($F(2, 188) = 1.49, p > .05$). This implies that the participants were not letting preexisting beliefs about the causal relationships between outcomes (e.g., great food comes in small portions) guide their learning. Second, the counterbalance factor did not exhibit a main effect in either analysis, respectively (both $F(2, 188) < 1$). This implies that the learning process was not sensitive to the relationship between O3 and O4 (e.g., similarly valenced outcomes did not encourage more learning than differently valenced outcomes). Third, the two-level counterbalance factor representing the order of attribute presentation on the compound stimulus screens in learning phase 2 did not interact with the difference between response rates to AE/AF and CE/CF ($F(1, 188) < 1$) or AE/AF and DE/DF ($F(1, 188) < 1$) or exhibit a main effect in either analysis (both $F(1, 188) < 1$). This implies that the associability parameter (i.e., α) is not simply a function of perceptual salience (i.e., participants do not pay more attention to the first cue listed on a training trial).

Classification of Learning Strategies. We analyzed the responses to the six compound stimuli to identify each participant's learning strategy. A coding system classified participants as having used an efficient learning strategy if they responded O3 to AE and AF ($n = 22$), responded O4 to CE, CF, DE, and DF ($n = 2$), or both ($n = 1$). Participants were classified as having used a learning protection strategy if they responded O4 to AE and AF ($n = 71$), responded O3 to CE, CF, DE, and DF ($n = 7$), or both ($n = 12$). A paired-preference test based on a binomial distribution confirmed that the learning protection strategy ($\hat{\pi} = .46$) was used significantly more often than the efficient learning strategy ($\hat{\pi} = .13; t = 5.98, p < .01$). We note that 35 participants exhibited a response pattern that suggested that the associability parameters for C and D were more or less dispersed than the associability parameters for E and F (i.e., cue salience was not uniform for these participants). These response patterns could not uniquely support either strategy. The remaining 44 participants did not respond in a strategic manner.

Discussion

The results of experiment 1 indicate that a larger proportion of consumers behave according to the learning protection hypothesis than behave according to the learning efficiency hypothesis. Once people learned that a cue predicted an outcome, they became less likely to learn about this very same cue with respect to a different outcome. For example, when people learned that feature A predicted O1 in learning stage 1, they became less likely to learn that feature A predicted O3 in learning stage 2, provided that feature A was also paired with feature C or D. The extended Mackintosh model represents learning protection as a change in the associability parameter (see eq. 5), as exemplified by reduced attention to previously relevant features. This strategy allows learners to protect previous learning and accelerate new learning.

The results of the pilot study and experiment 1 are inconsistent with the hypothesis of learning efficiency. Yet, this conclusion depends on acceptance of our claim that efficiency is defined by the generalization of the associability parameter from learning stage 1 to learning stage 2. If we were to redefine learning efficiency as "paying more attention to novel cues in novel learning environments," then the evidence from the initial experiment would not be as compelling. In light of this concern, we identified a second difference between learning efficiency and learning protection. Learning efficiency is more likely to involve the "here-and-now" allocation of attention, whereas learning protection should involve "a prior learning influence" on the allocation of current attention.

To illustrate the difference between learning efficiency and learning protection, consider a situation in which a previously relevant cue and a previously irrelevant cue are jointly available to predict a novel outcome. If people are engaging in learning efficiency, it seems reasonable that people will allocate more attention to the previously relevant cue than to the previously irrelevant cue. As per equations 2 and 3, the associability parameter (α) should be large for the relevant cue and small for the irrelevant cue. Thus, the relevant cue should attract more attention and acquire associative strength more rapidly. If people are engaging in learning protection, both the irrelevant cue and the relevant cue should start new learning with small associability parameters. The extended Mackintosh model predicts that an irrelevant cue will have low associability owing to prior learned irrelevance (as per eq. 4) and a relevant cue will have low associability owing to prior learned relevance (as per eq. 5). Thus, relative to situations in which cues have no prior history of learning, previously irrelevant and previously relevant cues should acquire associative strength more slowly. Therefore, we hypothesize:

- H2a:** *Learning Efficiency:* A previously relevant cue will have a higher associability parameter than a previously irrelevant cue when these cues are jointly available to predict a novel outcome.

H2b: *Learning Protection:* A previously relevant cue and a previously irrelevant cue will both have low associability parameters when these cues are jointly available to predict a novel outcome.

These hypotheses can be tested by comparing learning about a previously relevant/irrelevant compound cue and a novel outcome to learning about a novel compound cue and a second novel outcome.

EXPERIMENT 2

Experiment 2 was designed to provide further insight into how prior learning about a cue influences the associability of the cue in a subsequent learning task. We started by establishing the prior relevance and the prior irrelevance of two unique cues. In a subsequent learning task, these cues were used to simultaneously predict a novel outcome, while two other (novel) cues were used to simultaneously predict a second novel outcome. The critical test was the strength of association between these prior cues and the first novel outcome relative to the strength of association between the novel cues and the second novel outcome.

Method

Procedure and Stimuli. The computer-based learning procedure is shown in table 3. In learning stage 1, participants learned that feature A predicted outcome 1 (A → O1) and that feature C predicted outcome 2 (C → O2). In learning stage 2, in addition to learning A → O1 and C → O2, participants learned that features B and C predicted outcome 2 (BC → O2) and that features D and E predicted outcome 5 (C → O5). The two learning stages were expected to result

in learned relevance for feature A and learned irrelevance (blocking) for feature B. This assumption was tested for half of the participants using the compounds AD, AE, BD, and BE. It was expected that AD and AE would be more associated with O1 than O5 (i.e., learned relevance for feature A) and that BD and BE would be more associated with O5 than O2 (i.e., learned irrelevance for feature B). In learning stage 3, participants learned that features A and B predicted outcome 3 (AB → O3) and that features F and G predicted outcome 4 (FG → O4). After learning these relationships to asymptote, participants were asked if AF, AG, BF, BG predicted O3 or O4.

The design required seven features and five outcomes. The seven restaurant features were “specializes in seafood”; “price rating: expensive”; “award winning wine list”; “reservation recommended”; “located in trendy neighborhood”; “offers a tasting menu (fixed price multi-course meal)”; and “extensive dessert menu.” The five outcomes were “great food,” “large portions,” “wonderful ambience,” “popular hot spot,” and “excellent service.” Features and outcomes were randomly assigned for each participant. Except for the changes described above, the procedure, stimulus presentation format, and test stimulus formats were identical to those used in experiment 1.

Predictions. First, consider the hypothesis that learning is efficient across outcomes (hypothesis 2a). At the start of learning stage 3, feature A has prior relevance and feature B has prior irrelevance. Although the literature is silent on the consequences of putting cues of this type in competition, the learning efficiency hypothesis predicts that feature A will have a larger associability parameter (see eqq. 2 and 3) than feature B. Thus, feature A should acquire associative

TABLE 3
LEARNING PROCEDURE AND RESULTS OF EXPERIMENT 2

	Sample cue-outcome set	
	Cue	Outcome
Learning stage 1: A → O1 C → O2	A Specializes in seafood C Award winning wine list	Great food Large portions
Learning stage 2: A → O1 C → O2 BC → O2 DE → O5	A Specializes in seafood C Award winning wine list B Price rating: expensive; C Award winning wine list D Reservation recommended; E Trendy neighborhood	Great food Large portions Large portions Excellent service Share
Test stage 1: AD → ? AE → ? BD → ? BE → ?		O1: .65; O5: .35 O2: .36; O5: .64
Learning stage 3: AB → O3 FG → O4	A Specializes in seafood; B Price rating: expensive F Offers tasting menu; G Extensive dessert menu	Nice ambience Popular hot spot Share
Test stage 2: AF → ? AG → ? BF → ? BG → ?		O3: .42; O4: .58 O3: .38; O4: .62

NOTE.—Cues and outcomes were randomly assigned.

strength more rapidly than feature B (eq. 1). At test stage, feature A (B) should have a strong (weak) association to O3; hence, AF and AG should predict O3 and BF and BG should predict O4.

Second, consider the hypothesis that learning is protected across outcomes (hypothesis 2b). If this is so, the absolute associability of a feature in a prior learning task should determine its associability in a subsequent learning task. In learning stages 1 and 2, participants learned that feature A is an effective predictor of O1. This learned relevance should reduce the associability of feature A in learning stage 3 (eq. 5). In learning stage 2, participants also learn that feature B is a redundant predictor of O2. This learned irrelevance should reduce the associability of feature B in learning stage 3 (eq. 4). If this is so, then the associability parameters of features A and B should be lower than the associability of features F and G in learning stage 3. As a consequence, the association of features A and B with O3 should be weaker than the association of F and G with O4. When participants are asked to predict the outcome of AF, AG, BF, or BG, features F and G should have more associative strength to their outcome and O4 should be predicted.

Results

One hundred and one participants from an undergraduate subject pool at both the University of Florida and the University of Washington received extra credit to participate in the experiment.

Manipulation Check. One-half of the participants indicated the outcome they most associated with AD, AE, BD, and BE (test stage 1). AD and AE were more associated with O1 than O5 ($\hat{\pi}_{O1} = .65$, $\hat{\pi}_{O5} = .35$; $z = 3.09$, $p < .05$). This result confirms the learned relevance of feature A: BD and BE were more associated with O5 than O2 ($\hat{\pi}_{O2} = .36$, $\hat{\pi}_{O5} = .64$; $z = 2.89$, $p < .05$). This result confirms the learned irrelevance of feature B.

Primary Analysis. The results are shown in table 3. Within-subject tests showed that there were no differences in the response rates to the AF and AG stimuli ($F(1, 99) = 1.86$, $p > .05$) or the BF and BG stimuli ($F(1, 99) = 1.00$, $p > .05$). Thus, we collapsed the choice shares. Consistent with the learning protection hypothesis, participants expected restaurants having features AF and AG to have benefit O4 ($\hat{\pi}_{O3} = .42$, $\hat{\pi}_{O4} = .58$; $z = 2.42$, $p < .05$) and restaurants having BF and BG features to have benefit O4 ($\hat{\pi}_{O3} = .38$, $\hat{\pi}_{O4} = .62$; $z = 3.48$, $p < .05$). An additional analysis showed that the pattern of results for test stage 2 did not vary as a function of whether participants were exposed to test stage 1 (AF/AG analysis $F(1, 99) < 1$; BF/BG analysis $F(1, 99) < 1$).

Supplemental Analyses. The order of the compound stimuli on the screen in learning stage 3 did not generate different response rates for AF/AG ($F(1, 99) < 1$), BF/BG ($F(1, 99) = 1.06$, $p > .05$), or between AF/AG and BF/BG ($F(1, 99) < 1$). A response strategy analysis showed that

more participants had responses consistent with a learning protection strategy ($\hat{\pi} = .43$) than a learning efficiency strategy ($\hat{\pi} = .15$; $t = 3.67$, $p < .05$).

Discussion

The results of experiment 2 provide further evidence that people attempt to protect prior learning when learning about novel outcomes. Cues that had previously been shown to be irrelevant or relevant continued to exhibit low associability when a new outcome needed to be learned, even when those cues were the only cues available for predicting the new outcome. The implication is that the learning system is designed to discourage single cue–multiple outcome learning. Of course, this does not mean that single cue–multiple outcome learning cannot occur. Even though there were lower levels of associability for cues with prior relevance and prior irrelevance, people learned that these cues were associated with novel outcomes. Still, the strength of the associations between the cues and outcomes were attenuated by the lower associability parameters (i.e., α_A , α_B) as a consequence of prior learning. These results are consistent with the proposed extension of the Mackintosh model.

The first two experiments provide results that are inconsistent with the hypothesis of learning efficiency. Yet, it is important to remember that 13% of the participants in experiment 1 and 15% of the participants in experiment 2 exhibited a response pattern consistent with an efficient learning strategy. One possible explanation for the individual differences in the use of learning strategies is that participants have expectations regarding the learning environment. These expectations define the degree to which participants strive to preserve prior learning. We test this prediction in experiment 3.

EXPERIMENT 3

Experiments 1 and 2 show that the prior relevance of a cue reduces the future associability of this cue. One reason why participants might protect prior learning about a cue is that they assume a cue should predict a single outcome. Therefore, after learning an initial cue–outcome association (e.g., learning stage 1), participants may have assumed that the same cue should not predict other outcomes (i.e., learning should be protected). This may have led participants to focus on a different cue in learning stage 2. It is possible that, when the learning environment suggests a cue should predict multiple outcomes, participants will not strive to protect prior learning. In experiment 3, we manipulated participants' expectations about whether a cue should predict single or multiple outcomes. If the expectations regarding the number of outcomes a cue predicts influence the type of learning goals adopted, we should expect a larger proportion of participants engaging in learning efficiency (protection) when a cue is expected to predict multiple (single) outcomes in the environment.

Method

Procedure and Stimuli. The computer-based experiment used a learning procedure similar to that of experiment 1 (see table 2). The only procedural change was that we started the experimental procedure by priming participants to expect a feature to predict a single outcome or multiple outcomes. For example, the prime manipulation asked participants in both conditions to look at an Italian restaurant review. In the single outcome prime, a single outcome was listed (e.g., superior food quality). In the multiple outcome prime, three outcomes were listed (superior food quality, outstanding ambience, and excellent service). Below the review, participants saw the statement, "If you were to read a number of restaurant reviews, you might conclude that Italian restaurants have superior food [superior food quality, outstanding ambience, excellent waiters/waitresses]. Thus, you could use the type of restaurant to help predict food quality [characteristics of restaurants]." As a check of the efficacy of the priming manipulation, we asked participants, after presenting the information regarding Italian restaurants, which outcomes they would expect for a novel type of restaurant (e.g., French; open-ended question). Except for these changes, the procedure, stimulus presentation format, and test stimulus formats were identical to those used in experiment 1.

Results

One hundred and seven participants from an undergraduate subject pool at the University of Florida were given extra credit to participate in the experiment.

Manipulation Check. Two judges who were unaware of the study hypothesis coded the number of outcomes participants expected from a French restaurant. Agreement was 96%, and differences were resolved after discussion. As expected, a larger number of outcomes was listed in the multiple outcome than in the single outcome priming condition ($M_{\text{single}} = 1.28$, $M_{\text{multiple}} = 1.70$; $F(1, 105) = 4.00$, $p < .05$).

Primary Analysis. Within-subject tests showed that there were no differences in the response rates to the AE and AF test compounds ($F(1, 105) < 1$) or the CE, CF, DE, and DF test compounds ($F(3, 105) = 2.47$, $p > .05$); thus, we collapsed the choice shares. The interaction between the type of prime (single, multiple) and the type of test compound (AE and AF vs. CE, CF, DE, and DF) factors was not significant ($F(1, 105) = 1.94$, $p > .10$), indicating that the choices did not vary according to the expectations that a feature could be associated with single or multiple outcomes. Follow-up tests showed that the results of experiment 1 were replicated both in the single and the multiple outcome prime conditions. In the single outcome condition, participants expected restaurants having features AE and AF to have benefit O4 ($\hat{\pi}_{O3} = .31$, $\hat{\pi}_{O4} = .69$; $z = 4.14$, $p < .05$) and features CE, CF, DE, and DF to have benefit O3

($\hat{\pi}_{O3} = .61$, $\hat{\pi}_{O4} = .39$; $z = 2.29$, $p < .05$). In the multiple outcome prime condition, participants expected restaurants having the AE and AF features to have benefit O4 ($\hat{\pi}_{O3} = .41$, $\hat{\pi}_{O4} = .59$; $z = 1.87$, $p < .05$) and features CE, CF, DE, and DF to have benefit O3 ($\hat{\pi}_{O3} = .58$, $\hat{\pi}_{O4} = .42$; $z = 1.68$, $p < .05$).

Classification of Learning Strategies. Similar to experiment 1, we used responses to the six compound stimuli to identify each participant's learning strategy. Fifty-five percent of the participants in the single outcome prime condition behaved in a manner consistent with the predictions of the learning protection hypothesis, whereas only 16% behaved in a manner consistent with the predictions of the efficient learning hypothesis ($t = 3.40$, $p < .01$). Forty-six percent of the participants in the multiple outcome prime condition behaved in a manner consistent with the predictions of the learning protection hypothesis, whereas 21% behaved in a manner consistent with the predictions of the efficient learning hypothesis ($t = 2.24$, $p < .05$). A test comparing the use of the learning protection strategy across the two prime conditions was not significant ($\chi^2 = .69$, $p > .10$).

Discussion

Experiment 3 investigated whether an expectation about learning multiple outcomes would encourage a larger proportion of participants to abandon the learning protection strategy. Surprisingly, there was only a slight increase in the percent of participants who used an efficient learning strategy in the multiple outcome condition relative to the single outcome condition. Two subsequent attempts to encourage participants to form expectations about multiple outcome learning and use an efficient learning strategy were also unsuccessful.

Undeterred by our initial failure to encourage the use of an efficient learning strategy, we investigated another potential moderator: the extent to which a prior outcome was important or unimportant. The design replicated that of experiment 1 (see table 2). The outcomes were manipulated so that the outcome in learning stage 1 was important (unimportant) and the outcome in learning stage 2 was unimportant (important), with outcome importance being determined by participant rankings of the outcomes (collected at the beginning of the procedure). When the outcome in learning stage 1 (2) was important (unimportant), we expected participants to exhibit a response pattern consistent with a learning protection strategy (i.e., protect learning about important outcomes). When the stage 1 (2) outcome was unimportant (important), we expected participants to exhibit a response pattern consistent with efficient learning (i.e., use previously relevant cues to learn about important, novel outcomes). The procedure was also changed so that participants were not reminded of the A → O1 and B → O2 associations in stage 2 (to decrease the reinforcement of the history of learning). Despite these changes, we were unable to significantly shift the processing strategy. The choice shares for AE, AF, CE, CF, DE, and DF

were consistent with a learning protection strategy (all $p < .05$) and differed by 7.2% or less across the two importance conditions (all $F < 1$). There was no appreciable difference in the percentage of people that used each learning strategy across the two importance conditions.

EXPERIMENT 4

Experiment 4 was designed to test the application of learned relevance in an information search context. To be specific, we tested whether consumers protect prior learning when they sequentially learn about products with features that are common and unique to other products on a retailer's Web site. The learning protection hypothesis predicts that people should protect the learning of a feature that is common to two products.

Learning Procedure. Participants learned about the performance of two products with a feature that was common (C) to the products and a feature that was unique (U) to each product. For instance, participants learned about the feature-outcome configuration $C.U_1 \rightarrow O1$ (i.e., common feature and unique feature 1 predict outcome 1) followed by learning about $C.U_2 \rightarrow O2$ (i.e., common feature and unique feature 2 predict outcome 2), where O1 and O2 were low and high quality, respectively (counterbalanced). At test, participants were asked to rate whether a product possessing a common feature (i.e., C) or a product possessing two unique features ($U_1.U_2$) was more likely to provide O1 or O2.

Predictions. When participants learn that $C.U_1 \rightarrow O1$, there is no prior learning about either of the cues and thus no need to protect prior learning. In this situation, both the common (C) and the unique (U_1) features should acquire moderate associative strength with O1. When participants subsequently learn $C.U_2 \rightarrow O2$, they should try to protect learning about the common feature C (eq. 5). This learning protection should lead to a weak association between feature C and O2 and a strong association between feature U_2 and O2. Thus, participants should expect products presenting a common feature C only to be more likely to predict O1 and products presenting the pair of unique features U_1 and U_2 to be more likely to predict outcome O2.

Stimuli. We used two types of product replicates: office chairs and HDTV tuners. We also manipulated whether the common/unique features were a brand or an attribute. Thus, the experiment required two sets of three features per product replicate. For the office chair replicate, the features were "Brand: True Seating" (A); "Brand: AK Designs" (B); and "Final Assembly: USA" (C); "Lock: Tilt Lock" (1); "Wheels: Urethane" (2); and "Seat: Contoured" (3). For the HDTV tuner replicate, the features were "Brand: Sony" (A); "Brand: Samsung" (B); "Final Assembly: USA" (C); "Output: HDMI digital A/V" (1); "Controls: Parental Control" (2); and "Communication: Ethernet Port" (3). Each product replicate generated four products: two in which the common feature was a brand (or an assembly) and the unique features

were attributes (e.g., A.1 and A.2) and two in which the common feature was an attribute and the unique features were brands/assembly (e.g., 3.B and 3.C). The brand/attribute labels were randomly assigned to the cues within the sets A, B, C and 1, 2, 3. We blocked the random assignment of "Final Assembly: USA" so that it would always be randomly assigned to features B or C. This prevented one of the test stage products consisting of two unique features (B.C) from being a product with two brands (that was also the reason one of the features was country of assembly). Notice that our design allows us to test both the protection of learning about brands ($A.1 \rightarrow O1$, $A.2 \rightarrow O2$) and attributes ($3.B \rightarrow O1$, $3.C \rightarrow O2$).

Experimental Procedure. Participants were told that they would see descriptions of four products resulting from a search on a major retailer's Web site. After acknowledging the instructions, the program simulated a connection to a Web site emulating the Best Buy Web site (see the appendix for screen shots of the chair replicate for an illustration). On the main screen of the Web site, they saw pictures of four products. After clicking on one of the pictures they saw a new Web page containing the picture of the selected product, a product description (e.g., the features assigned to A and to 1) and a star rating based on 1,000+ reviews (1 star or 4.5 stars depending on the condition). Following a 5-second delay, a "back" button appeared on the screen and participants were taken back to the main portion of the Web site once they clicked on this button. Then, they proceeded to click on another picture (of their choice) to see information about another product (the hyperlink of a product became inactive once a respondent reviewed the information about that product). After reviewing all four products, participants received a message that they were leaving the Web site and were instructed that they would rate the expected performance of other products in the product category. The ratings at test were performed on a product-performance scale, with 0.5 star increments (ranging from 1, "Very Poor" [0 stars], to 11, "Outstanding" [5 stars]). The order of the four test items (A, 3, 1.2, and B.C) was randomized.

Results

One hundred and three participants from an undergraduate subject pool at the University of Washington received extra credit to participate in the experiment. The key prediction is that test items presenting the common feature only should be more strongly associated with O1, while test items that are combinations of unique cues should be more strongly associated with O2. This prediction implies an interaction between the type of test item factor and the value of the outcomes factor. Specifically, products with the common feature only should receive a lower performance rating than products that were a combination of unique features when $O1 = 1$ star and $O2 = 4.5$ stars. The exactly opposite pattern should be observed when $O1 = 4.5$ stars and $O2 = 1$ star.

The interaction of the type of test item (common cue

only or pair of unique cues) and value of the outcomes (1 or 4.5 stars) was significant ($F(1, 72) = 14.95, p < .05$). Simple effect tests showed that participants expected products presenting the common feature only to perform significantly worse than products presenting two unique features ($M_{\text{common}} = 6.29, M_{\text{unique}} = 7.08; (F(1, 72) = 5.17, p < .05)$ when $O1 = 1$ star and $O2 = 4.5$ stars. Alternatively, participants expected products presenting a common feature only to perform significantly better than products presenting two unique features ($M_{\text{common}} = 7.48, M_{\text{unique}} = 6.45; (F(1, 72) = 12.13, p < .05)$ when $O1 = 4.5$ stars and $O2 = 1$ star.

Discussion

Experiment 4 provides evidence supporting learning protection hypothesis in an ecologically valid experiment. Results show that consumers protect prior learning of both brands and attributes in situations in which the learning involved multiple cues in all phases of learning (unlike the previous experiments), in situations in which feedback about the outcomes was subtle, and when amount of exposure to the stimuli was minimal (once per stimulus).

GENERAL DISCUSSION

Our research focused on two ways in which prior learning about feature-benefit associations could influence a person's ability to learn that the feature predicts novel benefits. The efficient learning hypothesis predicts that prior learning helps identify features that are potentially more relevant and, hence, are worthy of increased attention during new learning. The protected learning hypothesis predicts that prior learning is protected so that new learning about previously relevant and irrelevant features is attenuated. In the process of formalizing these learning strategies, we extended an attention allocation model and provided empirical evidence for the model's predictions.

The pilot study showed support for the hypothesis of learning protection in a cheese-tasting task. Experiment 1 showed that the learning of associations between a previously relevant cue and a novel outcome was attenuated. Experiment 2 showed that people resisted novel learning about cues that were previously relevant (irrelevant) for predicting an outcome, even when these were the only cues available for predicting the new outcome. This result is a challenge to current associative learning models, including the original Mackintosh model, but is predicted by the proposed extended Mackintosh model. In experiment 3, we were unable to find evidence that expectations about the number of outcomes moderated consumers' learning strategies. Experiment 4 showed that the results can be replicated in an information search context that limited stimulus exposures to a single trial and lacked supervised feedback.

Despite the relevant theoretical and practical implications of attenuated learning, this topic is understudied in the human learning literature. To the best of our knowledge, Kruschke and Blair (2000) are the only researchers to provide evidence

of attenuated learning for human subjects. However, Kruschke and Blair (2000) relied on null effects in order to test whether the LMS processing model could account for learning about novel outcomes after cue relevance was established. Moreover, their evidence for the attenuation of learning is not irrefutable. Specifically, they found no differences for critical test items (Kruschke and Blair 2000; experiment 1), implying only partial support for allocated attention processing models. Our research provides a better basis for distinguishing between learning strategies in the context of new learning. In addition, our research is the first to provide evidence of the learning goals that contribute to attenuated learning (experiment 2).

Implications

Multiple Outcome Learning. We add to the growing interest in multiple outcome learning. Research in associative learning has traditionally focused on how cues compete to become associated with an outcome, implying that outcomes cannot compete for associative strength with a cue. Recently, Miller and Matute (1998) have shown that outcomes can compete for associative strength with a cue during passive learning. We show that outcomes can compete for strength with a cue during active (i.e., motivated) learning. Our procedure differs from Miller and Matute's in that the outcomes were meaningful, there was an incentive for the participant to learn cue-outcome associations, and these outcomes were learned in a sequential manner. This allowed us to make inferences about the processes that were responsible for learning protection. We anticipate that an investigation of the simultaneous versus sequential learning of outcomes may lead to further insight into outcome competition in motivated learning situations.

Blocking. The processes implied by our findings suggest another way of understanding the blocking phenomenon. Recall that blocking occurs when prior learning ($A \rightarrow O1$) inhibits future learning ($AB \rightarrow O1$) about a redundant cue (e.g., B). For example, LMS models assume that the lack of discrepancy between the predicted and the actual outcome in learning session two limits the updating of the association strength between the blocked cue and the outcome. If a previously predictive cue perfectly predicts an outcome, then there is no reason to update the strength of the cue-outcome association. In contrast, attention allocation models assume that the lack of discrepancy between the predicted and the actual outcome in learning session two forces the associability parameter of the blocked cue to zero. In effect, the blocked cue has lost its "ability" to be predictive in the future (as shown in experiment 2). The idea that blocking can render product features nonpredictive (i.e., valueless), even for novel benefits, is a hypothesis that has not been explored in the consumer behavior literature.

Brand Extensions. Our research also suggests opportunities for research on brand extensions (e.g., Meyvis and Janiszewski 2004). We pose that the prior learning in a host

category may impede learning in an extension category (i.e., it will be harder to associate the extended brand name with novel features). For instance, in 1992 Merck introduced the cholesterol-lowering drug Simvastatin under the brand name Zocor. In 2001, researchers found that Simvastatin was also effective at preventing the onset of Alzheimer's disease (Refolo et al. 2001). This opportunity created a branding dilemma for Merck. Merck could (1) continue to use the brand name Zocor when promoting Simvastatin to the Alzheimer's market, even though many consumers in this market knew of Zocor's cholesterol-lowering benefits or (2) introduce Simvastatin under a new brand name. Our findings suggest consumers may be slower to learn the Alzheimer's relief association to Simvastatin than to a new brand name. However, it remains an empirical question how the cost of overcoming learning protection for an existing brand compares to the cost of introducing a new brand. We note that the cost of overcoming learning protection may also depend on the degree to which a segment values a new outcome (e.g., Johar, Sengupta, and Aaker 2005) and the specificity of the representation (e.g., effective vs. effective at cholesterol reduction) of the original outcome (e.g., Pham and Muthukrishnan 2002).

Future Research

Future research should focus on identifying conditions that encourage learning protection and learning efficiency. One possibility is that the correlation among the outcomes influences the learning process. Perhaps the strategic allo-

cation of attention away from cues with learned relevance/irrelevance becomes less valuable as the positive correlation among the outcomes increases. Second, there might be individual differences influencing the learning goal one adopts. For example, people who are high in need for cognition (NFC) may be more resistant to learning protection because this learning goal conflicts with high-NFC individuals' goal of thoroughly processing information. Third, it may be that learning protection is a passive process that occurs as a natural part of associative learning but that this process is amended when it is useful to have a rich array of outcome associations. For example, humans associate more than one outcome (e.g., kind, funny, caring) with people they know well. It is efficient to use the "people cue" to predict multiple outcomes. Admittedly, this efficiency may occur only when there are contextual markers that help differentiate the expected outcomes.

Finally, it is important to note that attenuated learning of novel outcomes is a consequence of a rational attention allocation process. In evolutionary terms, it is important to protect and accelerate learning through shifts of attention. An organism that protects the learning of a previous negative episode will have a higher chance of survival. For example, the protection of the learning that a certain type of plant is associated with a deadly disease, that a specific sound indicates danger, or that a certain fruit color predicts nutrition is a crucial survival skill. Thus, the attention allocation strategy seems appropriate for complex learning environments consisting of multiple features and outcomes, as is the case for most consumer markets.

APPENDIX

EXPERIMENT 4 SCREEN SHOT SAMPLES

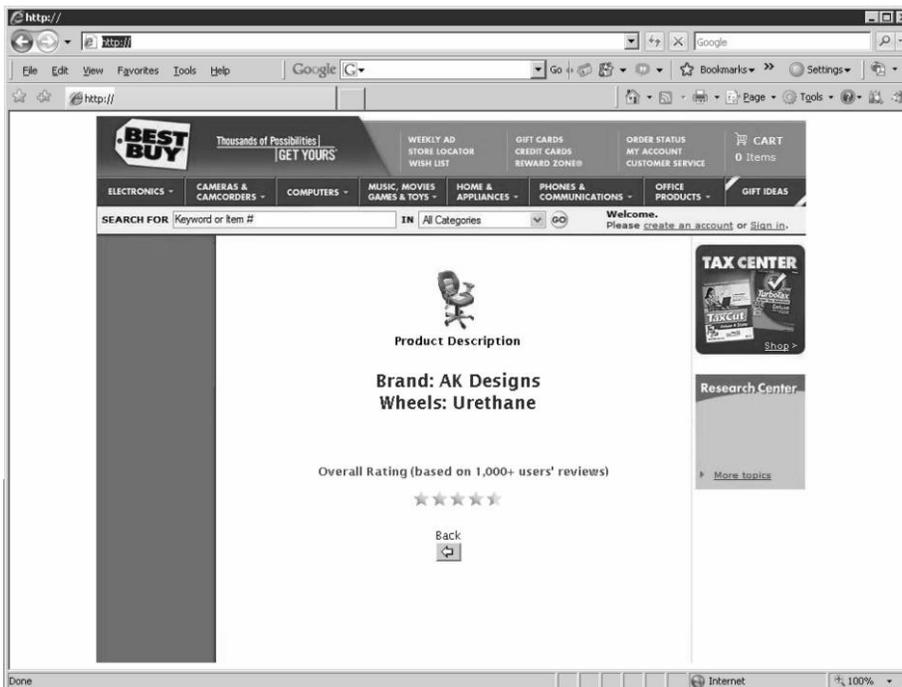
FIGURE A1

SCREEN SHOT SAMPLE 1



FIGURE A2

SCREEN SHOT SAMPLE 2



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