RAN KIVETZ, OLEG URMINSKY, and YUHUANG ZHENG*

The goal-gradient hypothesis denotes the classic finding from behaviorism that animals expend more effort as they approach a reward. Building on this hypothesis, the authors generate new propositions for the human psychology of rewards. They test these propositions using field experiments, secondary customer data, paper-and-pencil problems, and Tobit and logit models. The key findings indicate that (1) participants in a real café reward program purchase coffee more frequently the closer they are to earning a free coffee; (2) Internet users who rate songs in return for reward certificates visit the rating Web site more often, rate more songs per visit, and persist longer in the rating effort as they approach the reward goal; (3) the illusion of progress toward the goal induces purchase acceleration (e.g., customers who receive a 12-stamp coffee card with 2 preexisting "bonus" stamps complete the 10 required purchases faster than customers who receive a "regular" 10-stamp card); and (4) a stronger tendency to accelerate toward the goal predicts greater retention and faster reengagement in the program. The conceptualization and empirical findings are captured by a parsimonious goal-distance model, in which effort investment is a function of the proportion of original distance remaining to the goal. In addition, using statistical and experimental controls, the authors rule out alternative explanations for the observed goal gradients. They discuss the theoretical significance of their findings and the managerial implications for incentive systems, promotions, and customer retention.

The Goal-Gradient Hypothesis Resurrected: Purchase Acceleration, Illusionary Goal Progress, and Customer Retention

> [R]ats in a maze … run faster as they near the food box than at the beginning of the path.
>
> —Hull (1934)

*Ran Kivetz is Sidney Taurel Associate Professor of Business (e-mail: rk566@columbia.edu), and Oleg Urminsky is a doctoral candidate (e-mail: opu1@columbia.edu), Graduate School of Business, Columbia University. Yuhuang Zheng is Assistant Professor of Marketing, Graduate School of Business Administration, Fordham University (e-mail: ayuzheng@fordham.edu). The authors are indebted to David Katz, the manager of Columbia University Café Cappuccino, and to MoodLogic Inc. for their cooperation. The authors are also grateful for helpful comments and suggestions from Pradeep Chintagunta; Sunil Gupta; Raghu Iyengar; Gita Johar; Yifat Kivetz; Rajeev Kohli; Donald Lehmann; Oded Netzer; P.B. Seetharaman; Itamar Simonson; Andrea Vag; participants in seminars at Columbia University, Stanford University, the University of Florida, the University of Pennsylvania, and the Society for Judgment and Decision Making; and the anonymous *JMR* reviewers. The research reported in this article was supported by the Lang Faculty Research Fellowship in Entrepreneurship.

The goal-gradient hypothesis, originally proposed by the behaviorist Clark Hull in 1932, states that the tendency to approach a goal increases with proximity to the goal. In a classic experiment that tests this hypothesis, Hull (1934) found that rats in a straight alley ran progressively faster as they proceeded from the starting box to the food. Although the goal-gradient hypothesis has been investigated extensively with animals (e.g., Anderson 1933; Brown 1948; for a review, see Heilizer 1977), its implications for human behavior and decision making are understudied. Furthermore, this issue has important theoretical and practical implications for intertemporal consumer behavior in reward programs (hereinafter RPs) and other types of motivational systems (e.g., Deighton 2000; Hsee, Yu, and Zhang 2003; Kivetz 2003; Lal and Bell 2003).

In this article, we build on the behaviorist goal-gradient hypothesis and generate new propositions in the context of two real RPs. In the interdisciplinary spirit of bridging the

ISSN: 0022-2437 (print), 1547-7193 (electronic)

consumer behavior and marketing science fields (Winer 1999; Wittink 2004), we investigate these propositions using various methods, data, and modeling approaches (e.g., field experiments, paper-and-pencil problems, and secondary customer data; hazard rate, Tobit, and logit models). Consistent with the goal-gradient hypothesis, its corollaries, and their adaptation to the human psychology of rewards, some key findings indicate the following:

- Members of a café RP (e.g., "buy ten coffees, get one free") purchase coffee more frequently the closer they are to earning a free coffee (on average, interpurchase times decrease by 20% or .7 days throughout the program).
- The findings generalize beyond coffee purchases to effort involving repeatedly rating music over the Internet and goal gradients operationalized by acceleration in intervisit times, lift in rating quantities, and enhanced persistence closer to the reward threshold.
- The illusion of progress toward the goal induces purchase acceleration. For example, customers who receive a 12-stamp coffee card with two preexisting "bonus" stamps complete the ten required purchases faster than customers who receive a "regular" 10-stamp card. Process experiments show that the illusionary goal progress effect cannot be explained by rival accounts, such as sunk cost.
- Consistent with the notion that a steeper goal gradient indicates a stronger motivation to earn rewards, people's tendency to accelerate toward their first reward predicts a greater probability of retention and faster reengagement in the program.
- We capture all of the findings with a parsimonious goal-distance model (GDM), in which effort investment is a function of the proportion of original distance remaining to the goal (i.e., psychological distance).
- The observed purchase and effort acceleration cannot be explained by habituation, expiration concerns, other time-trend effects, or heterogeneity bias. For example, we observe goal-motivated acceleration after accounting for weekly sales and other time-varying covariates, and we find a majority of accelerators after accounting for unobserved heterogeneity in both the hazard rate and the tendency to accelerate. Notably, purchase and effort rates reset (to a lower level) after the first reward is earned and then reaccelerate toward the second reward goal.

We organize this article as follows: We begin with a brief review of the behaviorist goal-gradient hypothesis and consider its relevance for the context of incentive systems. Then, we propose a theoretical GDM that incorporates the goal-gradient hypothesis. In subsequent sections, we use this model to generate and test new propositions that highlight the intriguing consequences of the goal-gradient hypothesis for the human psychology of rewards: We discuss a real café RP and a discrete-time proportional hazard rate model used to test for purchase acceleration; we report field and questionnaire experiments that test the effect of illusionary goal progress; we report data from a second real incentive system, which generalizes the findings to acceleration and persistence in effort involving repeatedly rating music; and we explore the implications of the goal gradient for customer retention. Finally, we discuss the theoretical and managerial implications of this research.

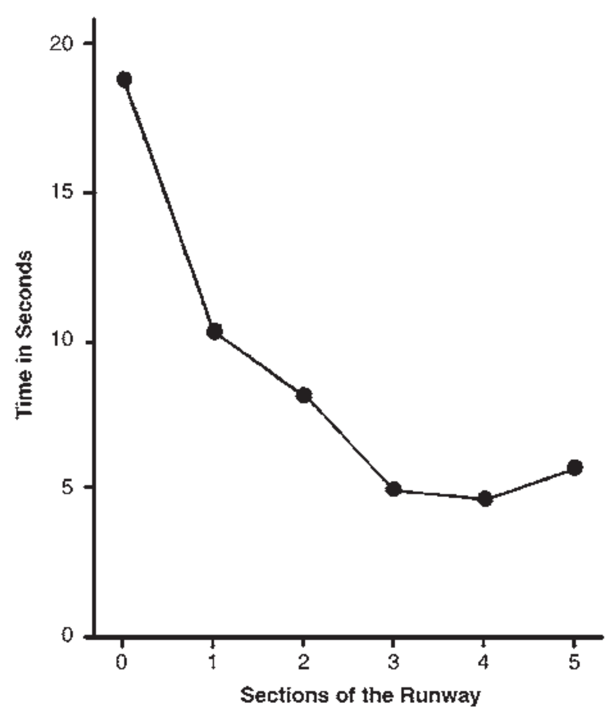
THE GOAL-GRADIENT HYPOTHESIS IN BEHAVIORISM

Originally formulated by Hull (1932) and refined by Miller (1944), the goal-gradient hypothesis states that the tendency to approach a goal increases with proximity to the goal. The strongest evidence for this hypothesis has been obtained in the context of animal learning, consistent with Hull's (1932, p. 42) prediction "[t]hat animals in traversing a maze will move at a progressively more rapid pace as the goal is approached." Hull (1934) constructed a straight runway with electrical contacts placed so that he could precisely measure the time it took rats to cross each of several six-foot sections. The key finding, which was replicated in several variations of the procedures and the apparatus, indicated that the animals ran faster the closer they were to the food reward. Figure 1 displays a typical set of results from Hull (1934) that reveals this pattern. In another widely quoted study, Brown (1948) attached rats to an apparatus that recorded the force in grams with which the rats pulled (toward the region of reinforcement) when stopped either close to or far from the food. Consistent with the goal-gradient hypothesis, rats that were stopped closer to the food pulled more strongly than those stopped farther away (see also Anderson 1933).

A review of the literature (Heilizer 1977) reveals that most goal gradients were obtained with rats and physical responses (e.g., speed of locomotion). A considerable portion of goal-gradient studies examined issues that are not directly related to the current investigation, such as con-

Figure 1

TYPICAL FINDINGS FROM HULL'S (1934) EXPERIMENTS WITH RATS



Notes: This is a composite graph from 11 blind rats, showing the length of time it took to traverse the several sections of a straight runway that extended from the starting box beginning at Segment 0, continued to the food, and finished some 21 inches beyond Segment 5. The several points on the curve represent means from approximately 160 measurements.

trasting approach versus avoidance gradients (e.g., Förster, Higgins, and Idson 1998). The limited research conducted with humans used mostly physiological measurements (e.g., galvanic skin response, heart rate, arm pressure) that were noninstrumental for goal achievement. As Heilizer (1977) details, it is difficult to interpret noninstrumental behaviors and physiological measurements as evidence supporting (or refuting) the goal-gradient hypothesis. To the best of our knowledge, there is no published study that provides unequivocal evidence of a systematic, behavioral goal gradient in humans. Thus, a primary goal of this article is to test for behavioral (approach) goal gradients and their various operationalizations (timing, quantity, and persistence of effort).

In this research, we use real RPs as an empirical context for an investigation of the goal-gradient hypothesis. Such programs share a common underlying structure, whereby people need to invest a stream of efforts to earn future rewards. This general effort–reward structure applies to many decision contexts and life domains, including consumer loyalty programs, employee incentive systems, sales force bonus plans, patient compliance programs, and even academic tenure tracks. Nevertheless, it is noteworthy that the empirical impact of RPs on actual customer behavior is still largely undetermined (cf. Dowling and Uncles 1997; Lewis 2004; Sharp and Sharp 1997).

THEORY AND MODEL

The notion that progress and distance to the goal affect consumer motivation is supported by theories of social cognition and human decision making. Dynamic models of motivation (e.g., Atkinson 1957; Lewin 1951; Miller 1944) propose that people possess a strong achievement drive, which is heavily influenced by goals. Carver and Scheier's (1990) cybernetic control model suggests that comparisons of the rate of progress toward the goal with a relevant criterion generate affect; when progress exceeds (falls short of) the criterion, positive (negative) affect arises (see also Fishbach and Dhar 2005; Soman and Shi 2003). Researchers have also highlighted the impact of people's psychological distance from their outcomes and goals on decision making and behavior (Lewin 1951; Trope and Liberman 2003). In addition, Heath, Larrick, and Wu (1999) propose that as a result of the diminishing sensitivity of prospect theory's value function, people should exert more effort as they near their (self-imposed) goals. In summary, prior theorization about human motivation, affect, and cognition supports the relevance of the goal-gradient hypothesis for the human psychology of rewards.

What are the implications, then, of the goal-gradient hypothesis for RPs? As Kivetz (2000) originally proposed, the notion that achievement motivation increases with smaller goal distance suggests that customers accelerate and persist in their efforts as they near the program's incentive threshold (i.e., the reward requirement or goal). The operationalization of "effort acceleration" depends on the specifics of the particular RP. When the program requirements involve discrete purchases or incidents (e.g., "stay ten nights, and earn a reward"), the acceleration will manifest in more frequent activity (shorter interpurchase or intervisit times). When the RP is structured so that more intense activity (e.g., a larger purchase or more units of effort) in any single visit earns more credits toward the reward (e.g., "earn one point for each dollar spent"), acceleration may be detected through both shorter interpurchase times and increased purchase (or effort) quantities. In the current research, we investigate both temporal and quantity operationalizations of goal-motivated acceleration. We also examine various forms of RP effort, including real purchases (of coffee) and actual work (rating music online). Finally, we generalize the goal-gradient hypothesis by examining whether people persist longer in their effort as a function of smaller goal distance. Next, building on prior research, we develop a parsimonious GDM that incorporates the aforementioned and other predictions.

The GDM

A great deal of research in psychophysics and judgment and decision making has shown that perception and preference are sensitive to relative rather than absolute dimensions. For example, Stevens (1957) and his predecessors demonstrate that sensory experiences reflect ratio (proportionality) judgments rather than absolute magnitude differences. Preference and choice have also been shown to be relative rather than absolute, depending on such factors as the salient reference point (Kahneman and Tversky 1979), the relative positions of other alternatives in the choice set (Huber, Payne, and Puto 1982; Simonson and Tversky 1992), the relative accuracy and effort of decision strategies (Payne, Bettman, and Johnson 1992), the preferences of other people (Kivetz and Simonson 2003), and the relative (proportional) value of the choice options (Herrnstein and Prelec 1991).

The sensitivity to relative and reference values suggests that consumers spontaneously consider their distance to a goal, incorporating the total distance as a reference point, which leads to an evaluation of relative goal distance. Accordingly, we conceptualize and model the psychological (or perceived) goal distance as the proportion of the total (original) distance remaining to the goal. We define this distance as $d_t = (r - n_t)/r$, where r is the perceived total effort requirement of the reward (i.e., the starting distance to the goal) and n_t is the amount of the requirements already fulfilled by a person at time t. The observed measure d_t has a possible range from 1 to 0, such that 1 occurs when no progress toward the goal has yet been made and 0 occurs when the goal is achieved. The goal-gradient hypothesis implies that the latent (unobserved) motivation at time t to achieve the goal (m_t*) is a decreasing function of d_t; that is, $\partial m_t^*/\partial d_t < 0$.[1]

Because the underlying motivation to achieve the reward is unobserved, we model the customer's observed behavior (or effort investment). Because the observed effort should increase with stronger goal motivation, we expect there to be greater effort with smaller proportional goal distance

[1]Consumers can still be sensitive to absolute magnitude, and the conceptualization of psychological goal distance in proportional terms is likely to apply only within a reasonable empirical range. Note that Hull (1934) reports that the goal gradient of a 20-foot runway resembles a foreshortened (proportionally contracted) gradient from a 40-foot runway. This finding can be captured by modeling the rats' behaviors as a function of proportional but not absolute goal distance.

(d_t). We use different operationalizations of the GDM that capture observed effort behavior as a function of d_t. Thus:

H_1: Consumers accelerate their efforts to earn a reward as the psychological distance (d_t) to the reward goal decreases.

Next, we test H_1 using a real café RP. We subsequently extend the goal-gradient hypothesis to the particularities of consumer behavior by exploring its implications for customer retention and by investigating the effects of illusionary goal progress. The latter allows for a direct test of the effect of proportional versus absolute goal distance and for ruling out rational accounts of the goal-gradient effect, such as time discounting.

THE CAFÉ RP

To facilitate a strong and realistic test of intertemporal behavior, we conducted a field study in which customers made real coffee purchases in the context of an actual café RP. By tracking purchases, we were able to test for purchase acceleration toward the reward goal (i.e., H_1). The study included two control groups: (1) members from whom we "bought back" incomplete cards and (2) customers participating in an experimental control program that was identical to the actual RP, except that purchasing coffee did not earn rewards. The inclusion of these control groups enabled us to compare the intertemporal purchase behavior of redeemers and nonredeemers (i.e., "loyals" and "defectors") and to examine differences between reinforced and nonreinforced behavior. We also investigate alternative explanations using various methodologies, including testing a key corollary termed "postreward resetting," exploring the behavior of the two aforementioned control groups, and incorporating unobserved heterogeneity in the tendency to accelerate.

Method

The participants in the field study were customers of a café located within the campus of a large East Coast university. At the time of data collection, the café had several on-campus locations. Customers were offered free enrollment in a café RP, in which they needed to make ten coffee purchases to earn a reward. To enable the tracking of their purchases, members were required to carry a frequent-coffee-buyer card (see Figure 2, Panel A). They received one stamp on the card for each coffee purchase they made (only one stamp per visit was permitted). Stamps were printed with six-wheel automatic numbering machines that, unbeknownst to customers, sequentially numbered each stamp issued (these numbers did not resemble dates). After members accumulated ten stamps from any combination of the café locations, they were eligible for a free coffee redeemable on their next visit to one of the café locations.[2] Members were asked to indicate their name and e-mail address on the back of the card, which enabled us to match cards redeemed by the same member. Overall, we obtained 949 completed (i.e., redeemed) ten-stamp cards, recording approximately 10,000 coffee purchases.

Buyback of incomplete cards. The design of the café RP enabled us to collect only those cards that were completed and redeemed for a reward. Therefore, to sample from the broader member population (i.e., including the members that would otherwise fail to complete or redeem their card), we instituted a card buyback offer. Research assistants posing as café employees approached individual card-holding members and offered them the opportunity to return their cards to the café (regardless of the number of stamps on them) for a cash award of $4 per card and a 1% chance to win $100. Members were told that the cards were needed for the café's customer research. Overall, we acquired 73 buyback cards.

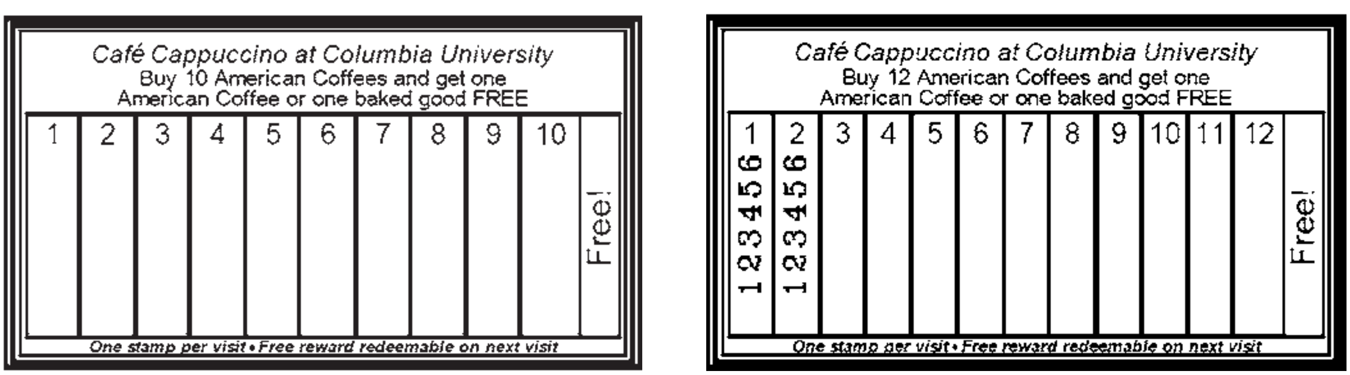
Recruitment of experimental control group with transparent cards. We recruited 42 customers for an experimental control condition in which they carried "transparent cards." These cards were similar to the regular ten-stamp card but

[2]Members could also earn a free baked good of equal monetary value (biscotti, croissant, or muffin). However, the majority (85%) of reward redemptions were for coffee, and the results did not differ on the basis of the redeemed reward.

Figure 2

THE CAFÉ RP CARDS

A: 10-Stamp Card | *B: 12-Stamp Card with Two "Bonus" Stamps*



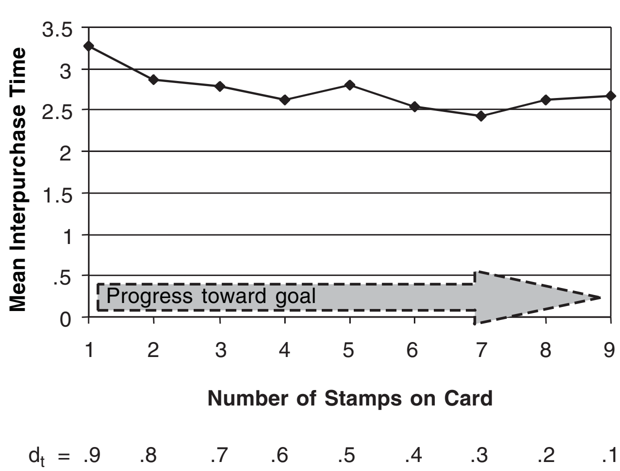
were marked on the back so that they could not be redeemed for a reward. The control customers were randomly sampled from the population of program members. Research assistants (posing as café employees) intercepted customers who requested a regular program card and offered instead to enroll them in a "purchase-habit" study designed to help the café management better understand its customers. Participants were asked to carry a "transparent" card and have it stamped every time they made a qualifying purchase at the café. They received \$5 when they agreed to participate in the study, and they were told that they would receive \$15 more when they surrendered their cards six weeks later, regardless of how many coffee purchases they made during that time. We verified that control participants did not use the regular RP cards during the study.

Results

A plot of the raw mean interpurchase times, aggregated across all redeemed cards (excluding transparent and buy-back cards), demonstrates purchase acceleration as a function of smaller goal distance (see Figure 3).[3] Consistent with H_1, as members accumulated more stamps on their cards, the average length of time before their next coffee purchase decreased. The mean difference between the first and the last observed interpurchase times was .7 days ($t = 2.6$, $p < .05$), representing an average acceleration of 20% from the first to the last interpurchase time. As an estimate of the overall effect of acceleration on the average card, it is possible to compare the mean observed time to complete a card, which was 24.6 days, with the number of days it would have taken to complete a card at the rate of the first observed interpurchase time, which was 29.4 days. This yields a difference of nearly 5 days (16%) in card completion time.

[3]We excluded from the analysis days on which the café was closed.

Figure 3
PURCHASE ACCELERATION AS A FUNCTION OF SMALLER GOAL DISTANCE



Although the analysis of raw data provides preliminary support for purchase acceleration (H_1), it does not account for various important factors. Accordingly, we used more sophisticated data analysis, namely, a discrete-time proportional hazard rate model. This modeling approach incorporates time-varying covariates and controls (e.g., weekly number of issued stamps) intended to rule out alternative explanations, such as time-trend effects. Our modeling approach also enables us to account for unobserved heterogeneity (i.e., individual differences in base purchase rates and acceleration tendencies).

Hazard rate modeling methodology. In the main data set, each row represented one day per customer on a card on which the customer could have made a purchase; we included the days after the first stamp was received up to the day of the last stamp. There are variables in the data set at the customer level, day level, and card level. Overall, from 949 completed (i.e., redeemed) ten-stamp cards that captured nearly 10,000 coffee purchases, this data set yielded 29,076 rows of data.

Hazard rate models (Cox 1972) are an important method to model interpurchase times. In these models, the instantaneous probability of purchase (called the hazard function, h[t]) is estimated, conditional on the amount of time since the prior purchase. In the discrete-time model (Gupta 1991; Helsen and Schmittlein 1993), the hazard model likelihood is decomposed into probabilities of purchase within given time intervals.

In a hazard rate model, the baseline continuous survival function S(t) represents the probability that no purchase will occur after time t has elapsed since the previous purchase:

$$(1) \qquad S(t) = \exp\left[-\int_0^t h(u)du\right].$$

We used a discrete-time proportional hazard model parameterized as the discretized survival function. In line with Seetharaman and Chintagunta's (2003) derivation, the full discretized survival function can be expressed as a function of the baseline hazard function h(t), time-varying covariates $\mathbf{X}_t$ (including the proportional distance to the goal), and estimated covariate coefficients $\boldsymbol{\beta}$ (including a constant term):

$$(2) \qquad S(t, \mathbf{X}_t) = \exp\left[-\sum_{u=1}^{t} e^{\mathbf{X}_u\beta} \int_{u-1}^{u} h(w)dw\right].$$

In our application, we decompose the survival function into day-specific components, and our dependent variable is the probability of purchase on a given day, conditional on no purchase having yet occurred:

$$(3) \quad \Pr(t, \mathbf{X}_t) = 1 - \frac{S(t, \mathbf{X}_t)}{S(t-1, \mathbf{X}_{t-1})} = 1 - \exp\left[-e^{\mathbf{X}_t\beta}\int_{t_l}^{t_u} h(u)du\right]$$

$$= 1 - \left[\frac{S(t_u)}{S(t_l)}\right]^{e^{\mathbf{X}_t\beta}}.$$

In conducting our analysis at the day level, we assume that each day is a potential purchase occasion, except for days on which the café is closed. Because we estimate each day's probability as the difference in survival probability from the start of the day to the end of the day, it was necessary to code each day t as a range of continuous times between the lower bound t_l and the upper bound t_u when applying Equation 3. Purchases made on the same day were coded as occurring between time $t_l = 0$ and time $t_u = .5$, purchases on the subsequent day were coded as occurring between $t_l = .5$ and $t_u = 1.5$, and so forth. In the following likelihood function for an observed purchase, we denote the observed number of days elapsed at time of purchase by T, and we code an indicator function δ_v, which represents whether a purchase occurred on day v ($\delta_v = 1$) or did not occur on day v ($\delta_v = 0$):

$$(4) \qquad L = \prod_{v=0}^{T} \Pr(v, \mathbf{X}_v)^{\delta_v}[1 - \Pr(v, \mathbf{X}_v)]^{1-\delta_v}.$$

The full likelihood is the product of all the purchase-specific likelihoods across cards and customers (Seetharaman and Chintagunta 2003).

We determined the best-fitting base hazard function with Schwarz's Bayesian information criterion (BIC) measure. The BIC measure trades off improvements in the log-likelihood for increases in the number of parameters. We used latent classes to account for unobserved heterogeneity in the hazard rate parameters (Kamakura and Russell 1989), which is important to rule out heterogeneity bias. Because the unit of analysis in the latent-class model is the customer, we took into account the common error variance when multiple cards belonged to a single individual, and we specifically accounted for cross-customer unobserved heterogeneity.[4] The latent-class modeling can be considered a nonparametric multivariate distribution on the hazard rate parameters across participants; each latent class represents a support point in the distribution. Although we found significant unobserved heterogeneity in the hazard rate parameters, when we ran the models without latent-class segmentation, all of the results still held. In all models, we used GAUSS software to implement Newton–Raphson maximum likelihood estimation, and we determined the number of latent classes using the BIC criterion.

Analyses of acceleration with common parameters across consumers. In this subsection, the primary focus of our modeling is the effect of goal distance on interpurchase times. Recall that the distance to the reward goal is captured with the measure $d_t = (r - n_t)/r$. In the café RP, n_t is the number of stamps accumulated on the card at time t, and r is the total number of required stamps. Given that in the main data set we model probability of purchase when there are between 1 and 9 stamps accumulated on the card (and r = 10), the measure d_t ranges between .9 and .1.

To test the goal-gradient hypothesis (H_1) in this and the subsequent empirical applications, we constructed the GDM, which includes linear and quadratic parameters that capture the effect of goal distance on observed behavior.[5] Here, we added the GDM as a covariate in the proportional hazard model. We parameterized the model by defining the probability of purchase for customer i on a given day t as follows:

$$(5) \qquad \Pr_i(t, \mathbf{X}_{it}) = 1 - \left[\frac{S(t_u)}{S(t_l)}\right]^g,$$

where

$g = \exp[\beta_0 + \beta_1 d_{it} + \beta_2(d_{it} - \bar{d}_i)^2 + \boldsymbol{\gamma}\mathbf{X}_{it}]$;
$S(t)$ = the baseline survival function;
d_{it} = the proportion of total distance remaining to the goal for individual i at time t;
$d_{it} - \bar{d}_i$ = the mean-centered proportion of total distance remaining to the goal;
β_1 and β_2 = the linear and quadratic goal-distance parameters, respectively;
$\mathbf{X}_{it}$ = the vector of covariates (i.e., control variables); and
$\boldsymbol{\gamma}$ = the corresponding vector of coefficients.

The parameters for estimation in the GDM are the intercept β_0, the goal-distance parameters β_1 and β_2, and the vector of coefficients $\boldsymbol{\gamma}$. Consistent with H_1, we expect the parameter β_1 to be less than zero, capturing the predicted increase in the probability of purchase (hazard rate) as a function of smaller goal distance (d_{it}). Note that if β_1 is greater than zero, we observe "effort deceleration" (i.e., lower probability of purchase as a function of smaller goal distance). Among the time-varying covariates, we included both the weekly number of issued stamps and a code for whether a given day was after the end of the spring classes to control for alternative explanations based on time trend.[6]

We accounted for unobserved heterogeneity in the base hazard rate parameters (but not in the goal-distance or the covariate parameters) using the methodology we described previously. Table 1 displays the estimated parameters for the log-logistic hazard rate function and the GDM in Equation 5.[7] The linear goal-distance parameter $\hat{\beta}_1$ was less than zero ($p < .01$). This result supports H_1 and demonstrates that members accelerated their coffee purchases as they got closer to earning a free coffee. Consistent with the goal-gradient curve in Figure 3, the negative quadratic parameter $\hat{\beta}_2$ ($p < .01$) implies a diminishing rate of acceleration. A nested likelihood ratio test indicated that the GDM provided an improvement in fit over a "naive" model in which β_1 and β_2 were restricted to zero ($\chi^2 = 18.8$, d.f. = 2, $p < .01$).

[4]All the results are replicated when we exclude from the analyses the subsequent cards of members who redeemed more than one card.

[5]In this and subsequent empirical applications, we examined higher-order parameters using orthogonal contrast codes (Fisher and Yates 1957), but we found that these were not significant.

[6]The control variables also included card type (indicating whether the member purchased American or Italian coffees) and additional time-varying covariates, such as midterm break (a code for whether the day was during the midterm break), day of week (linear trend from Monday through Thursday), and dummy codes for Friday and Saturday–Sunday. None of the covariates were allowed to vary across the latent classes.

[7]All covariates were normalized before model-fitting in this and the subsequent model estimations.

Table 1

THE GDM WITH UNOBSERVED HETEROGENEITY IN BASE HAZARD RATES (CAFÉ RP)

	A: Latent Class-Level Parameters				
	Class 1	*Class 2*	*Class 3*	*Class 4*	*Class 5*
Segment size (%)	30	28	7	32	3
γ (hazard rate)	.5**	.7**	1.5**	.06**	1.8*
α (hazard rate)	1.4**	2.3**	3.7**	1.15**	1.9**
β_0	.4*	–.3*	–.7**	1.5**	–.02

B: Parameters Not Varying by Latent Class	
Goal-Distance Parameters	*Estimate*
Linear effect of goal distance, $\hat{\beta}_1$	–.03**
Quadratic effect of goal distance, $\hat{\beta}_2$	–.04**
Covariate Parameters (i.e., Control Variables)	
Weekly number of stamps	–.005
End of semester	.04**
Midterm break	–.17**
Card type (American versus Italian)	–.10**
Day of week (Monday–Thursday)	–.02
Friday	–.18**
Saturday–Sunday	–.39**

*$p < .05$ (based on Wald test; two-tailed).
**$p < .01$ (based on Wald test; two-tailed).

Alternative Explanations

Although the observed and estimated purchase acceleration is consistent with H_1 and the existence of a goal gradient in RPs, several alternative explanations for this finding must be examined. One such rival account is that an unidentified time-trend effect led to a decrease in interpurchase times. For example, members could have developed a card-usage routine or an addiction to coffee (i.e., habituation). Relatedly, although café customers had no reason to expect the RP to expire, such concerns may have motivated members to accelerate their purchases.

Postreward resetting. As we previously discussed, we included in our models two time-varying covariates that are intended to control statistically for time-trend effects, namely, the weekly number of issued stamps (essentially a control for sales trend) and whether the day was after the end of spring classes (when some students graduate). Nevertheless, to examine the time-trend and habituation accounts directly, we analyzed the postredemption purchase behavior of 110 members who completed a first card and then reengaged in the program to complete a second card. These members demonstrated strong goal gradients (i.e., faster interpurchase times as a function of lower d_{it}) on both of their cards ($\hat{\beta}_1$ = –.06 and –.09 for the first and second card, respectively; both *p*s < .05).

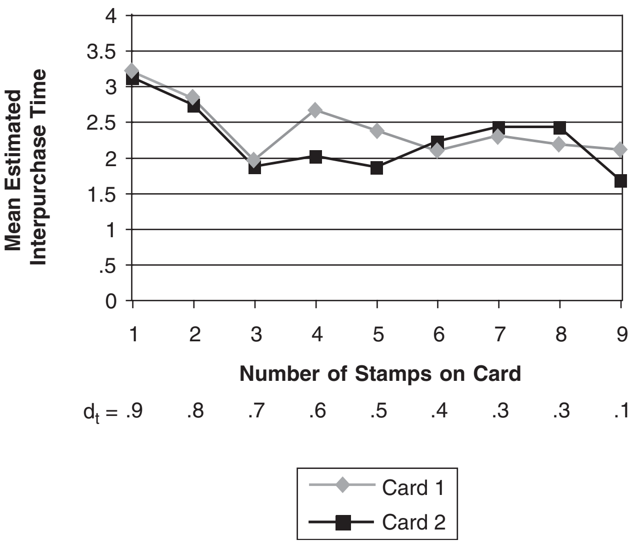
According to the goal-gradient hypothesis, the motivation to invest effort increases with progress toward the reward threshold. Therefore, a corollary of this hypothesis is that after customers earn their first reward, they should exhibit a postreward resetting (i.e., a slowdown) in their purchase rates when they begin working toward their second reward, followed by a second pattern of purchase acceleration. In contrast, time-trend and habituation accounts predict monotonic acceleration in coffee purchases across the two cards, at least until some plateau or ceiling effect is reached. Therefore, according to these rival accounts, the interpurchase times on the second card should be a direct continuation of the trend on the first card.

To contrast the resetting corollary with the time-trend and habituation accounts, we calibrated a nonparametric model with individual dummy codes that represented each different interpurchase time across the two cards. The advantage of using this nonparametric model is that we can separately estimate the 18 interpurchase times for the two sequential cards, while controlling for the covariates $\mathbf{X}_{it}$ and for the unobserved heterogeneity in the base hazard rates. Figure 4 reveals a clear overlap between the plots of the interpurchase times estimated for the two cards. The figure also shows that the first two interpurchase times on the second card ($\overline{X}$ = 3.1 and 2.7 days, respectively) are substantially slower than the last two interpurchase times on the first card ($\overline{X}$ = 2.2 and 2.1 days, respectively) and are similar to the first two interpurchase times on the first card ($\overline{X}$s = 3.2 and 2.8 days, respectively).

To test for postreward resetting statistically while controlling for time-varying covariates and heterogeneity in the base hazard rates, we modeled only the last two interpurchase times on the first card and the first two interpurchase times on the second card. Instead of linear and quadratic goal-distance parameters, we included a contrast code for first versus second card. The first two interpurchase times on the second card were slower than the last two interpurchase times on the first card ($p < .01$). The test was in the same direction and significant when we compared only the first interpurchase time on the second card with the last interpurchase time on the first card ($p < .05$).

In summary, consistent with the goal-gradient hypothesis, purchase rates revealed a clear postreward resetting. Members accelerated their coffee purchases toward their first reward (a free coffee) and then slowed down when they

Figure 4
AVERAGE INTERPURCHASE TIMES ON FIRST AND SECOND CARDS



began working toward a second similar reward; the same members subsequently reaccelerated their purchases as they approached the second reward. These findings rule out the habituation account and other forms of time trend (e.g., graduation or expiration concerns). Next, we examine the purchase behavior of two control groups, which enables us to compare reinforced and nonreinforced behavior and further rule out alternative explanations.

Analysis of nonreinforced behavior (*transparent cards*). According to the goal-gradient hypothesis (H_1), cardholding customers accelerate their purchases because they experience enhanced motivation as they get closer to the goal (i.e., the reward threshold). A corollary of this hypothesis is that customers will fail to exhibit acceleration when carrying a transparent card (similar to the regular ten-stamp card but unredeemable for a reward), that is, when their purchase behavior is not reinforced with any purchase-contingent reward. In contrast, if purchase acceleration reflects other factors, such as a time trend in sales, we would expect to observe similar acceleration among customers enrolled in the transparent card control group. The intertemporal purchase behavior of customers carrying transparent cards can serve as a benchmark or control for the assessment of the acceleration we detected in the main data set.

Unlike the main data set, which included only complete (redeemed) ten-stamp cards, some of the transparent cards were incomplete. Therefore, we first analyzed all transparent cards that included at least three stamps. We estimated the GDM (shown in Equation 5) using the same log-logistic hazard function, accounting for unobserved heterogeneity in the base hazard rates. All the significant coefficients for the control variables have the same sign and the same interpretation as in the model of redeemed cards. However, to account for observed differences in base hazard rates between cards collected with fewer or more stamps, we added a coefficient that captures the effect of the final number of stamps on the card.

In the GDM for transparent cards, we found deceleration ($\hat{\beta}_1 = .3$, $p < .01$) and no curvature ($\hat{\beta}_2 = .006$, $p > .1$). The interpurchase times on the transparent cards steadily increased as customers neared the nonreinforced (unrewarded) completion of the card. Note that this model was fit with data (i.e., days) only up to the last purchase on the transparent card. We found an even stronger deceleration effect ($\hat{\beta}_1 = .4$, $p < .01$; $\hat{\beta}_2 = -.1$, $p > .1$) when we included all observed days up to the collection of the transparent card (i.e., including days after the last purchase on incomplete transparent cards). Finally, we calibrated the GDM on the subsample of completed transparent cards, and again, we found deceleration ($\hat{\beta}_1 = .15$, $p < .05$; $\hat{\beta}_2 = .05$, $p > .1$).

Overall, the analysis of the transparent cards supports the notion that the purchase acceleration we found in the main data set was driven by goal motivation rather than by time-trend effects or habituation. Although participants in the transparent card program were sampled from the population of RP members, because their reward ($20) was not contingent on their purchase behavior, tendency to accelerate toward the ten-stamp threshold was reversed.

Analysis of incomplete (*buyback*) *cards*. We believe that the sample of buyback cards differs from the sample of redeemed cards (used in the main analyses) in that members from whom we bought back cards exhibited a lack of goal motivation. Buyback cards were in circulation for a period of time that was longer than that of redeemed cards ($\bar{X} = 65$ days versus $\bar{X} = 25$ days; $t = 7.6$, $p < .01$), which suggests that without our intervention, such buyback cards would have resulted in "breakage" (i.e., nonredeemed stamps or cards). This allows for a comparison of the intertemporal purchase behavior of nonredeemers (defectors) and redeemers (loyals).

We calibrated the GDM on the sample of buyback cards using the log-logistic hazard function, accounting for unobserved heterogeneity in the base hazard rates. We included buyback cards with at least three stamps and added the final number of stamps on the card as a covariate to account for observed differences in the base hazard rates of cards with fewer or more stamps. Again, all the significant coefficients for the control variables had the same sign and the same interpretation as the model of redeemed cards.

In the GDM for incomplete buyback cards, we found no linear effect of goal distance ($\hat{\beta}_1 = .02$, $p > .1$), but there was a quadratic effect ($\hat{\beta}_2 = -.1$, $p < .05$). This pattern suggests that, unlike redeemers, buyback customers do not accelerate their purchases as a function of progress toward the reward. Moreover, when we modeled all observed days up to the buyback of the incomplete card (i.e., including days after the last purchase on the card), we found an increasing deceleration effect ($\hat{\beta}_1 = .3$ and $\hat{\beta}_2 = -.1$, respectively; $ps < .01$). Overall, customers from whom we bought back incomplete cards (defectors) differed from redeemers (loyals) in that the former did not accelerate and even decelerated their purchases as a function of accumulated stamps.

Analysis of unobserved heterogeneity in goal-motivated acceleration. A final alternative explanation that we must consider is heterogeneity bias. Specifically, although we accounted for unobserved heterogeneity in the base hazard rates, it is possible that the estimation of homogeneous goal-distance parameters gave rise to an apparent goal gradient that did not exist among a majority of individual members. Therefore, we calibrated the GDM on the main data set by simultaneously (i.e., jointly) estimating unobserved heterogeneity in both the hazard rate and the goal-distance parameters. Table 2 displays the estimated segment (class) sizes and segment-level parameters. Segment 1, the largest segment (58%), has significant linear and quadratic goal-distance parameters; this pattern of acceleration is similar to that which we obtained previously with the homogeneous goal-distance parameters. Segment 2 (29%) has the same linear goal-distance parameter as the largest segment, but the coefficient does not reach statistical significance (p = .13) because of the smaller segment size. Segments 3 and 4 (7% and 6%, respectively) both have a linear goal-distance parameter near zero. Overall, the segmentation analysis is inconsistent with the heterogeneity bias rival account; we found a majority of significant accelerators after accounting for unobserved heterogeneity in the tendency to accelerate.

Evidence for the Goal-Gradient Hypothesis in the Café RP: Discussion

Consistent with the goal-gradient hypothesis (H_1), the findings from the café RP indicate that customers accelerated their purchases as a function of smaller goal distance. We observed the decrease in interpurchase times in the raw data and estimated it using a discrete-time proportional hazard rate model. The 20% (.7 day) decrease in average interpurchase times from the first to the last stamp on the card implies that in a typical month, on average, members purchased two more coffees than they would have without an RP in order to earn one free coffee.[8]

We ruled out several alternative explanations for the observed purchase acceleration using an experimental control (i.e., the transparent cards) and statistical controls. We also found that members exhibited a markedly similar acceleration pattern on two sequential cards; that is, we observed a slowdown in purchase rates after participants earned the first reward and began to work toward the second. Such postreward resetting is inconsistent with the rival accounts based on time trend or habituation, whereas it is consistent with the notion that the motivation to expend effort depends on goal distance.

The analysis of the incomplete (buyback) cards revealed that defectors were less likely to exhibit a goal gradient than were members who redeemed at least one card. This finding suggests that insufficient motivation to earn rewards underlies both defection (churn) and deceleration in purchase rates. In a subsequent section, we use individual-level acceleration estimates to examine more systematically the relationship between goal motivation and customer retention. Next, we extend the goal-gradient hypothesis to the particularities of the human psychology of rewards by exploring the effect of illusionary progress toward the goal.

THE ILLUSION OF PROGRESS TOWARD THE GOAL

Building on the behaviorist goal-gradient hypothesis, we predicted and found that customers accelerate their purchases as they get closer to the reward threshold. Although this result is consistent with our conceptualization that goal proximity increases motivation, it could also be explained on rational, cost–benefit grounds. In particular, as the distance to the reward diminishes, any additional unit of effort reduces a greater percentage of the remaining discrepancy to reward attainment. In addition, time-discounting theories imply that (temporal) proximity enhances the value of rewards. Thus, the perceived benefit from an incremental unit of effort may increase closer to the reward threshold.

The rational explanations for purchase acceleration rely on the absolute distance to the reward. In contrast, our conceptualization suggests that the key determinant of goal motivation is the proportion of original distance remaining to the goal. The GDM captures this psychological quantity through the measure d_t, which is influenced not only by the absolute distance remaining to the reward, $r – n_t$, but also by the perception of the original goal distance, r (i.e., the total a priori effort requirement for the reward). Thus, we posit that, all else being equal, goal motivation is influenced by the perceived rather than by the real progress toward the

[8]The first interpurchase time was 3.3 days, whereas the total card time yielded an average rate of 2.7 days per purchase. This is equivalent to 9 purchases per month based on the first interpurchase time, compared with 11 purchases per month based on the observed rate that includes purchase acceleration.

Table 2

PARAMETER ESTIMATES WITH UNOBSERVED HETEROGENEITY IN GOAL-DISTANCE AND HAZARD RATE PARAMETERS (CAFÉ RP)

Latent Class-Level Parameters	*Class 1*	*Class 2*	*Class 3*	*Class 4*
Segment size (%)	58	29	7	6
γ (hazard rate)	.6***	.07***	1.5***	.9
α (hazard rate)	1.7***	1.2***	3.5***	1.3***
β_0	.09	1.4***	–.7***	.5***
Goal-Distance Parameters				
Linear effect of goal distance, $\hat{\beta}_1$	–.04**	–.04	–.003	.007
Quadratic effect of goal distance, $\hat{\beta}_2$	–.06***	.005	–.10*	–.009

*p < .1 (based on Wald test; two-tailed).
**p < .05 (based on Wald test; two-tailed).
***p < .01 (based on Wald test; two-tailed).
Notes: The model includes the same control variables as those we report in Table 1. The covariate estimates were nearly identical, and we do not report them here.

goal. Perceived and real progress are distinct when the perception of the original goal distance can be systematically manipulated without affecting the real, absolute distance remaining to the goal.

Marketers (or researchers) can create "illusionary goal progress" by increasing the total original distance to the reward (i.e., increasing r), while increasing the perception of the distance (requirements) already completed (i.e., increasing n_t by the same quantity). Such a manipulation reduces the psychological (or proportional) distance to the reward, d_t, while holding constant the real, absolute remaining distance (i.e., the actual remaining requirements, $r - n_t$).[9] Accordingly, in the subsequent tests, we create illusionary progress by increasing the total requirements of a baseline RP, while awarding consumers with an equivalent, yet bogus, "head start" (i.e., bonus credit or points in the amount of the incremental requirements).

A manipulation of illusionary progress distinguishes between our goal-gradient conceptualization and the rational accounts of purchase acceleration. If the psychological distance to the reward influences motivation, as defined by the proportion of original distance remaining to the goal (d_t), illusionary progress should enhance goal motivation and consequently lead to increased efforts to earn the reward. In contrast, because illusionary goal progress does not affect the absolute (real) distance to the reward, cost–benefit calculations and time discounting cannot account for the predicted effort acceleration. Thus:

> H_2: Illusionary progress toward the reward goal motivates consumers to accelerate their efforts to earn the reward.

In H_2, we predict that illusionary goal progress leads to faster completion of the reward requirements. We begin with a strong and realistic (field) test of H_2, in which we examine actual purchase behavior. We then report the results of process tests that are intended to rule out alternative explanations based on the idiosyncratic fit heuristic (Kivetz and Simonson 2003) and sunk cost (Thaler 1980).

A Field Experiment of Illusionary Goal Progress

Method. The participants were 108 customers of the café we described previously. They were randomly assigned to either a control condition or an experimental (illusionary goal progress) condition. Specifically, research assistants posing as café employees randomly offered customers either a 10-stamp or a 12-stamp coffee card (see Figure 2, Panel A and Panel B, respectively). The 10-stamp and the 12-stamp cards indicated that members were required to accumulate 10 and 12 coffee purchases, respectively, to earn one free coffee. However, customers assigned to the 12-stamp experimental condition received two preexisting bonus stamps, described as an offer to anyone who opted to join the program. Thus, although the two groups faced identical effort requirements when joining the program (i.e., $r - n_t$ = accumulating 10 coffee purchases), the experimental group started with a lower proportion of original distance remaining to the goal than did the control group (i.e., $d_t^{+2} = .83$ and $d_t = 1.0$, respectively). All other aspects of the program were held constant across the two conditions and were identical to those we described previously for the café RP.

Results. Consistent with H_2, the results indicate that illusionary goal progress led to faster completion of the reward requirement. On average, customers in the control condition completed the ten required purchases (for the 10-stamp card) in 15.6 days. In contrast, customers in the experimental (illusionary goal progress) condition completed the ten required purchases (for the corresponding 12-stamp card) in only 12.7 days, nearly three days or 20% faster ($t = 2.0$, $p < .05$; medians = 15 versus 10 days; $Z = 2.1$, $p < .05$ [Mann–Whitney U test]).

Process Tests of Illusionary Goal Progress

In these questionnaire-based experiments, we tested H_2 and the alternative explanations using travelers who were waiting for trains at sitting areas in a major train station. We randomly assigned 65 travelers to either a control or an experimental condition of a hypothetical frequent-diner program offered by their favorite pizza chain. In the control condition, respondents were told that they would need to carry an eight-stamp card (shown in a picture), on which they would receive one stamp for each pizza meal they bought at the chain. After they accumulated eight stamps, they would earn a free medium-sized pizza of their choice. In the experimental condition, we asked respondents to evaluate a similar frequent-diner program, except that they needed to carry a ten-stamp card (i.e., the program supposedly required purchasing ten pizza meals). In this condition, respondents were exposed to an illusionary goal progress. In particular, they were told that as a special offer for joining the program, they would receive two free bonus stamps (they were shown a ten-stamp card with the first two stamp slots already checked). Thus, whereas the control and the experimental groups faced identical effort requirements (i.e., $r - n_t$ = eight pizza meals), the proportion of original distance remaining to the goal was lower for the experimental group than for the control group (i.e., $d_t^{+2} = .8$ and $d_t = 1.0$, respectively).

We first asked respondents in both conditions to rate the likelihood that they would join the program on an 11-point scale, ranging from 0 ("definitely would not join") to 10 ("definitely would join"). Then, we told respondents to assume that they actually joined, and we asked them to estimate how many weeks it would take them to complete the program. Consistent with H_2 and the results of the field experiment, respondents in the experimental versus control condition estimated completing the eight required purchases in fewer weeks ($\bar{X} = 11$ versus $\bar{X} = 16$ weeks; $t = 1.6$, $p < .1$; medians = 8 versus 12 weeks; $\chi^2 = 6.5$, $p < .05$ [nonparametric median test]).

We elicited respondents' likelihood of joining to rule out an alternative explanation (based on the idiosyncratic fit heuristic; Kivetz and Simonson 2003) for the predicted illusionary goal progress effect. In particular, according to the idiosyncratic fit heuristic, consumers decide whether to join RPs and other promotional programs on the basis of their individual fit (relative to typical other consumers) with the program. Therefore, in both the aforementioned field experiment and in the current test, we deliberately used a

[9]This is easy to verify algebraically by investigating the change in the function $d_t = (r - n_t)/r$ after an addition of Δ to both r and n_t. Specifically, $d_t^{+\Delta} = ([r + \Delta] - [n_t + \Delta])/(r + \Delta) = (r - n_t)/(r + \Delta) < (r - n_t)/r = d_t$. That is, unlike absolute goal distances, proportional distances are affected by a common addition, such that $d_t^{+\Delta} < d_t$.

manipulation of illusionary goal progress that we did not expect to affect respondents' idiosyncratic fit with the RP. Specifically, we described the two free bonus stamps in the experimental conditions as an offer to anyone who opted to join the program. Indeed, consistent with the notion that idiosyncratic fit was not affected by the manipulation of illusionary goal progress, we found no effect on the likelihood of joining the frequent-diner program ($\overline{X}$ = 5.9 and $\overline{X}$ = 5.8 in the experimental and control condition, respectively; t = .1, not significant [n.s.]).

An alternative explanation for the observed illusionary goal progress effect is that the two bonus stamps were considered a (virtual) sunk cost (e.g., Thaler 1980). Relatedly, the bonus stamps may have enhanced the perceived value of the card, thus leading to estimations of faster completion time. To examine this rival account, we randomly assigned 118 new respondents (sampled from the same population of travelers) to one of three conditions: (1) the previous illusionary goal progress experimental condition (i.e., a ten-stamp card with two preexisting bonus stamps), (2) the previous control condition (i.e., an eight-stamp card with no stamps yet), and (3) a sunk-cost condition. The experimental and control conditions were identical to the corresponding conditions we described previously, except that we asked respondents to imagine that they had recently joined the program. In the sunk-cost condition, we asked respondents to imagine that they had recently joined a ten-stamp frequent-diner program, had made two pizza meal purchases, and therefore had two stamps on their card. Thus, the sunk-cost condition was identical in all aspects to the experimental condition (including the picture of a ten-stamp card with two stamps already on it), except that the two stamps were due to the respondent's own purchase effort. Note that all three conditions entailed the same absolute remaining distance to the reward goal (eight additional pizza purchases).

In all three conditions, we asked respondents to imagine that they lost their current frequent-diner card. We then asked them to rate on four scales how sad, mad at themselves, upset, and disappointed they would feel as a result of the loss of the card. Participants rated these items on four seven-point scales, ranging from 1 (e.g., "not at all sad") to 7 (e.g., "very sad"). We averaged the scales into a single measure of feeling valence (α = .88).

Respondents' ratings indicated that they felt worse about losing their card in the sunk-cost condition ($\overline{X}$ = 2.1) than in either the experimental (illusionary goal progress) condition ($\overline{X}$ = 1.7; t = 1.9, p < .05) or the control condition ($\overline{X}$ = 1.7; t = 1.9, p < .05). Importantly, there was no difference in feeling valence between experimental and control respondents (t = .2, n.s.). These results are inconsistent with the sunk-cost alternative explanation. In particular, if illusionary goal progress gives rise to a faster purchase rate because bonus credits are construed as sunk cost, we would expect respondents to feel a greater sense of loss after losing the experimental rather than the control card. Because the sunk-cost respondents felt worse about losing their card, we can rule out the possibility that a measurement problem gave rise to the similarity in (good) feelings between the experimental and the control respondents.

The Illusion of Progress Toward the Goal: Discussion

The effect of illusionary goal progress provides direct support for our proposition that psychological goal distance (d_t) is a key determinant of achievement motivation and willingness to invest effort. Whereas this effect is consistent with the GDM and the conceptualization of proportional goal distance, it is inconsistent with the rational accounts of purchase acceleration. That is, illusionary goal progress does not reduce the absolute distance to or the delay of the reward and therefore should have no effect according to the cost–benefit and time-discounting explanations.

THE JABOOM MUSIC-RATING INCENTIVE PROGRAM

Thus far, we have operationalized our test of the goal gradient (H_1) using acceleration in interpurchase times. In this section, we generalize the findings to effort involved in repeatedly rating music and to goal gradients operationalized through acceleration in both intervisit times and rating quantities and through increased persistence closer to the goal. We analyze secondary data we obtained from a real incentive system, in which participants earned rewards for rating songs over the Internet. Next, we describe the music-rating program in detail.

The Methodology of the Music-Rating Incentive Program

The music-rating program was launched by MoodLogic Inc., a technology company that develops and sells music organization software. The company initiated the program to build a database of music perceptions and tastes (required for its music organizers and preference engines). The program, labeled "Jaboom," was operated on a dedicated Web site (members were addressed on the site as "Jaboomers"). Internet users, recruited through an e-mail marketing campaign, were offered free enrollment in the RP, in which they needed to rate 51 songs on the Jaboom Web site to earn a $25 Amazon.com certificate. The RP, which was presented to participants as an ongoing program, continued for a period of 24 months after our observation period. Thus, expiration concerns should not have affected the behavior of program members.

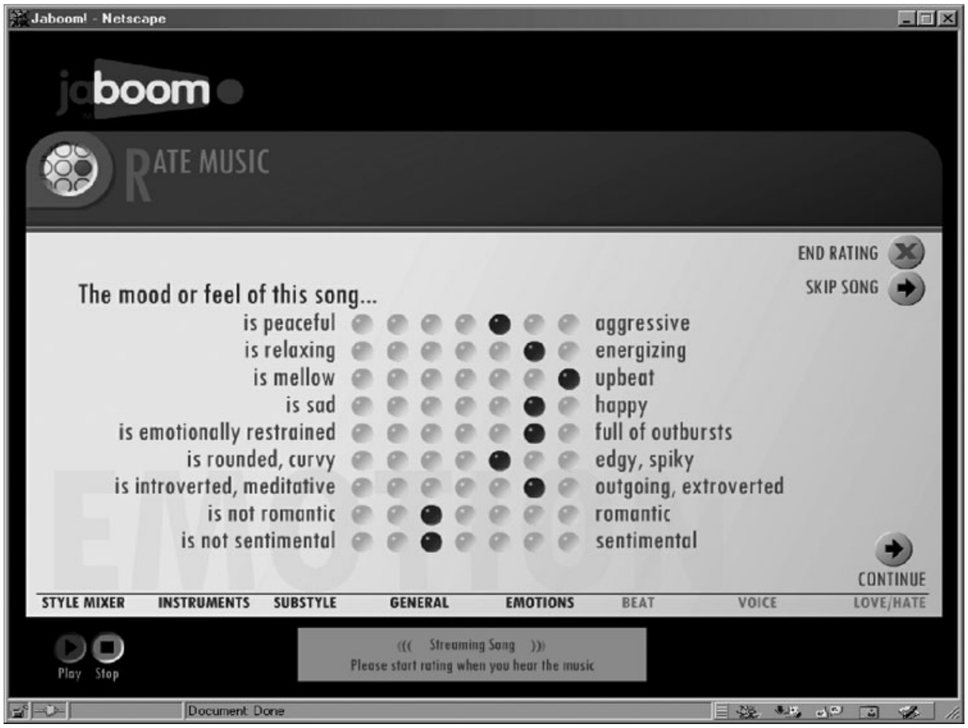
On joining, members were asked to provide a valid e-mail address and select a unique login name and password. This information was used to determine the dates of each member's site visits and the number of songs the individual member rated on each visit. There were no constraints on the number of songs that could be rated in a single visit or on the number of certificates that could be earned by a single member.

Members could rate songs from one of six genres of their choice (e.g., rock, country, jazz) and could skip a given song or terminate their rating session at any point. Each song was rated on approximately 50 scales, while the member repeatedly heard the same 30-second song snippet. The scales elicited subjective perceptions and tastes (e.g., mood and likeability of the song) and more objective judgments (e.g., predominating instruments). On average, it took about four minutes to rate a typical song. A screen shot of the Jaboom music-rating interface appears in Figure 5.

Results

The data set includes the rating behavior of 148 members, who rated a total of 14,866 songs in 472 separate Web

Figure 5
THE JABOOM MUSIC-RATING WEB INTERFACE



site visits. Given that during most (i.e., 96%) of the Web site visits members rated multiple songs, we examined both the quantity of ratings in each visit and the intervisit times. We modeled intervisit times using the discrete-time proportional hazard rate model we described previously. The findings were similar to those of the café RP. We briefly describe them here and then report the analyses and results of the quantity and persistence operationalizations of the goal-gradient hypothesis.

Tests of the Goal-Gradient Hypothesis with Intervisit Times

In our data set, there were 371 attempted reward certificates (i.e., with at least 1 song rated toward the certificate) and 262 earned certificates (i.e., with 51 songs rated). Of the 262 earned certificates, 114 were completed in a single visit. Although such single-visit certificates arguably signify strong goal motivation, they must be excluded from the analyses of intervisit times because they do not permit testing for acceleration (or deceleration). Therefore, we calibrated the hazard rate version of the GDM on the data from the remaining 148 certificates, which were earned in two or more visits. The data set was constructed such that each row represented a unique day on which a particular member could have visited the Jaboom Web site; we included the days after the first visit had occurred up to the day of the last visit.[10]

[10]In this section and in the subsequent subsections, we obtained similar results when we excluded from the analyses the data from subsequent certificates of members who earned more than one certificate.

We parameterized the survival function with the GDM shown in Equation 5 and used the likelihood function shown in Equation 4. Recall that the variable capturing the hypothesized acceleration is $d_t = (r - n_t)/r$, that is, the proportion of total distance remaining before the goal. In this empirical application, r is equal to 51 songs (i.e., the original total distance to the goal), and n_t is the number of song ratings accumulated at time t toward earning the reward certificate. Given that we modeled the probability of visiting when there were between 0 and 50 song ratings accumulated, the measure d_t ranges between 1 (when no goal progress has yet been made) and .02 (when the goal is almost achieved), respectively.

Table 3 displays the parameters for the GDM that we estimated with Weibull hazard parameterization. The linear goal-distance parameter was less than zero ($p < .01$). This result supports H_1 and demonstrates that members visited the Jaboom Web site more frequently as they got closer to earning the reward (i.e., intervisit times decreased as a function of goal proximity). Consistent with Hull's (1934) findings with rats and our results of the café RP, the rate of acceleration diminished, as indicated by the negative quadratic goal-distance parameter ($p < .01$). Note that the model includes two variables as controls: (1) the total number of visits to the Jaboom Web site at the day level, which was intended to control for time-trend effects, and (2) the number of visits it took to complete each certificate, which was intended to rule out aggregation bias. We obtained similar results when we excluded either or both of these controls from the model. In addition, the linear and quadratic goal-distance parameters remained significant and did not vary

Table 3

THE HAZARD RATE GDM OF INTERVISIT TIMES (MUSIC-RATING PROGRAM)

A: Latent Class-Level Parameters		
	Class 1	*Class 2*
Segment size (%)	71	29
α (hazard rate)	.5**	2.1**
β_0	1.4*	–.9**

B: Parameters Not Varying by Latent Class	
Acceleration Parameters	*Estimate*
Linear effect of goal distance, $\hat{\beta}_1$	–.25**
Quadratic effect of goal distance, $\hat{\beta}_2$	–.22*
Covariate Parameters (i.e., Control Variables)	
Daily number of visits	.1
Total visits to earn certificate	–.01
Saturday–Sunday	.03

*p < .05 (based on Wald test; two-tailed).
**p < .01 (based on Wald test; two-tailed).

in magnitude across models with different numbers of latent classes in the base hazard rate.

We also calibrated the GDM by simultaneously estimating unobserved heterogeneity in the acceleration and hazard rate parameters. Although the BIC favors a one-class solution, we report the two-class solution to rule out heterogeneity bias. In the larger class (65%), we found linear acceleration ($\hat{\beta}_1 = -.6$, $p < .1$; $\hat{\beta}_2 = -.1$, $p > .1$), and in the smaller class (35%), we found nonsignificant linear acceleration ($\hat{\beta}_1 = -.1$, $p > .1$; $\hat{\beta}_2 = -.3$, $p < .1$). The finding that both segments demonstrate acceleration is inconsistent with the heterogeneity bias rival account.

Finally, we recalibrated the same GDM on the data obtained from "incomplete" certificates (i.e., those with less than 51 songs rated toward the unattained certificate). There were 36 incomplete certificates with at least two Web site visits (i.e., at least one intervisit time that could be modeled as a function of goal distance). Consistent with the analysis of the incomplete cards in the café RP, we found deceleration ($\hat{\beta}_1 = .7$, $p < .1$; $\hat{\beta}_2 = .01$, $p > .9$). Furthermore, we calibrated the GDM on a data set that combined both complete and incomplete certificates, and we added an interaction term, β_{INT}, between completion (yes versus no) and linear acceleration. We found significantly stronger linear acceleration for complete than for incomplete certificates ($\hat{\beta}_{INT} = -.5$; Wald $\chi^2 = 16.2$, $p < .01$). That is, whereas acceleration is related to retention and goal attainment, deceleration is associated with program defection and goal abandonment.

Tests of the Goal-Gradient Hypothesis with Rating Quantity

Thus far, we have examined how goal distance influences interpurchase and intervisit times. In many cases, however, customers can accelerate their efforts by increasing the quantity of credits earned in a given interaction with the RP. Accordingly, in this subsection, we test the goal-gradient hypothesis by examining whether the quantity of songs rated per visit increases with goal proximity. We report separate tests of pooled and segment-level quantity acceleration, behavior on incomplete certificates, and postreward resetting.

Figure 6 presents the raw data obtained from the 148 complete certificates (with at least two visits) that we observed. Consistent with the goal-gradient hypothesis, as members approached the 51-song goal, they rated more songs in later visits.

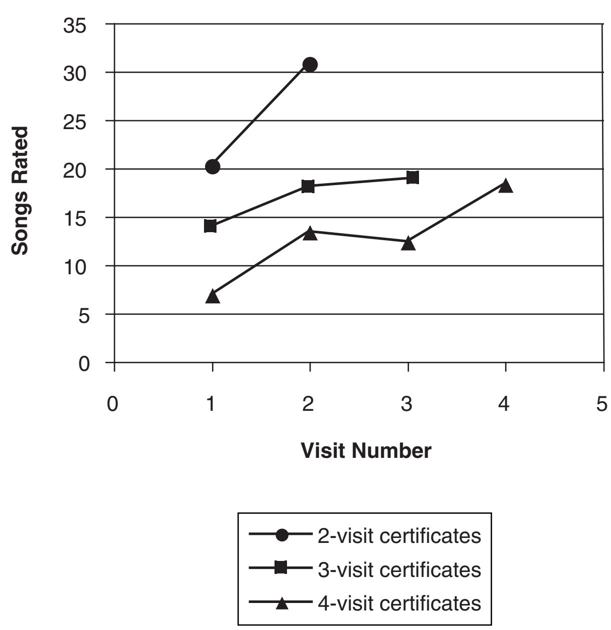
To model the quantity of songs rated in a visit, we used a Type I Tobit model (Tobin 1958). This approach enables us to capture the underlying motivation to rate songs, while taking into account the constraint of 51 songs per certificate. Specifically, in the final visit of each certificate, the number of song ratings is censored at $51 - n_t$, where n_t is the number of song ratings accumulated toward the certificate at the start of visit t. By definition, any additional songs rated in visit t beyond the $51 - n_t$ limit would be credited toward the next certificate rather than the goal of earning the present 51-song certificate. Relatedly, as $51 - n_t$ approaches zero, the inherent motivation to rate songs may increase (because $d_t \to 0$), but the 51-song constraint (i.e., the reward threshold) would suppress such an effect.

For uncensored data, the Tobit model is equivalent to maximum likelihood regression. However, because applying a regression to censored data leads to biased parameter estimates (Breen 1996), the Tobit models the censored data as the probability of rating $51 - n_t$ or more songs. Thus, we model the quantity Q_{it} rated in each visit t by participant i, incorporating the GDM into a Type I Tobit model:

$$Q_i(t, \mathbf{X}_{it}) = \begin{cases} g & \text{if } g < 51 - n_{it} \\ 51 - n_{it} & \text{if } g > 51 - n_{it} \end{cases}, \tag{6}$$

Figure 6

NUMBER OF SONGS RATED AS A FUNCTION OF GOAL PROGRESS



where $g = \beta_0 + \beta_1 d_{it} + \beta_2(d_{it} - \bar{d}_i)^2 + \boldsymbol{\gamma} \mathbf{X}_{it} + \varepsilon$, $\varepsilon \sim N(0, \sigma^2)$. Here, g can be considered a latent variable that represents the tendency to rate songs, which can be directly observed in the data Q_{it} only when sufficient songs remain on the certificate (i.e., when $g < 51 - n_{it}$). This model generalizes the GDM to the domain of effort quantity and uses the operationalization of goal distance (d_{it}) we used previously to test for temporal goal gradients. We expect the parameter β_1 to be negative, indicating that a smaller goal distance leads to a greater quantity of song ratings. We also included a visit-level control, which captures daily variations in the total number of songs rated on the Jaboom Web site, and a variable that represents certificates already earned in the visit by the participant.

Following Breen's (1996) exposition, we define the likelihood function as follows:

$$(7)\quad L_i = \sum\nolimits_1 (2\pi\sigma^2)^{-.5} \exp\left[\frac{Q_{it} - \beta_0 - \beta_1 d_{it} - \beta_2(d_{it} - \bar{d}_i)^2 - \boldsymbol{\gamma}\mathbf{X}_{it}}{2\sigma^2}\right] + \sum\nolimits_0 1 - \Phi\left[\frac{\beta_0 + \beta_1 d_{it} + \beta_2(d_{it} - \bar{d}_i)^2 + \boldsymbol{\gamma}\mathbf{X}_{it} - (51 - n_{it})}{\sigma}\right].$$

Here, the first sum Σ_1 is the likelihood function for the linear regression summed over all the noncensored cases (i.e., visits in which the certificate is not completed). The second sum Σ_0 is the probability of observing at least the censored amount $51 - n_{it}$, defined by the standard normal cumulative distribution function Φ and summed over the visits in which a certificate was completed (i.e., the censored cases). Note that in this model, the error variance σ^2 is a separate parameter to be estimated.

We calibrated this model on the data from the 148 certificates that were earned in two or more visits. Consistent with the goal-gradient hypothesis, we found a negative linear goal-distance parameter ($p < .01$; see Table 4) that indicated that members rated more songs per visit when they were closer to the goal. There was also a quadratic effect ($p < .01$) that indicated a diminishing rate of acceleration. In addition, we found a negative effect of the number of certificates already earned during the same visit ($p < .01$), consistent with satiation or fatigue. We obtained similar results when we forced the constant and error variance to vary across latent classes.

We also estimated the GDM using data from the 36 incomplete certificates (certificates with fewer than 51 song ratings but at least two visits). We found a weaker (though significant) effect of goal distance (d_{it}) in these data ($\hat{\beta}_1 = -2.5$, $p < .01$; $\hat{\beta}_1 = 2.9$, $p < .01$). Furthermore, we calibrated the GDM on a data set that combined both complete and incomplete certificates, and we added an interaction term, β_{INT}, between completion (yes versus no) and linear acceleration. Consistent with the findings from the analyses of intervisit times, we found that completed certificates exhibited a significantly stronger quantity goal gradient than did incomplete certificates ($\hat{\beta}_{INT} = -8.5$, $p < .01$).

Postreward resetting. An alternative explanation for the observed quantity acceleration is learning (or habituation). For example, it is possible that with repeated visits to the Jaboom Web site, members learned to rate songs faster, thus rating more songs in later visits. To examine the learning alternative explanation, we tested whether the 34 Jaboomers who earned two multivisit certificates exhibited postreward resetting. The resetting corollary predicts that members should rate more songs on the last visit of their first certificate (when $d_{it} < 1$) than on the first visit of their second certificate (when $d_{it} = 1$). These members demonstrated strong goal gradients (i.e., greater rating quantities as a function of lower d_t) on both of their earned certificates ($\hat{\beta}_1 = -11.6$ and -9.0 for the first and second certificate, respectively; *p*s < .01). Moreover, consistent with postreward resetting and inconsistent with the learning explanation, these members rated an average of 24 songs on the last visit of their first certificate compared with 16 songs on the first visit of their second certificate (pairwise $t = 2.3$, $p < .05$).

Unobserved heterogeneity in goal-motivated acceleration. To rule out heterogeneity bias as an explanation for the quantity goal gradient, we calibrated the GDM on the data from completed certificates by simultaneously estimating unobserved heterogeneity in the goal-distance parameters, the constant, and the error variance. Although the BIC favored a one-class solution, we report the two-class solution. The size of the larger class was 97% ($\hat{\beta}_1 = -12.4$, $p < .01$; $\hat{\beta}_2 = -7.4$, $p < .01$), and the size of the smaller class was 3% ($\hat{\beta}_1 = -13.6$, $p < .01$; $\hat{\beta}_2 = 1.5$, $p > .7$). Thus, inconsistent with heterogeneity bias, both segments demonstrate acceleration in rating quantities as a function of goal proximity.

Tests of the Goal-Gradient Hypothesis with Persistence in Effort

In this subsection, we generalize the goal-gradient hypothesis to the domain of effort persistence. On the basis of the notion that the motivation to achieve a goal increases with its proximity, we predict that consumers will be more likely to persist in their effort when the reward is proximal, and equivalently, they will be more likely to cease their efforts when the reward is distal. In the context of the music-rating program, this prediction implies that the more songs the member has accumulated toward the 51-song goal (i.e., the smaller is d_t), the less likely the member will be to end an active song-rating visit.

To test the persistence version of the goal-gradient hypothesis, we model the probability of terminating a visit at any point in the song-rating process as a function of the distance to the goal, d_t, and other covariates. We use a logit model that accounts for unobserved heterogeneity in the baseline probability of ending a visit. The probability of

Table 4
THE TOBIT GDM OF QUANTITY

Model Parameters	*Estimate*
Intercept	29.9*
Variance (σ^2)	253.4*
Linear effect of goal distance, $\hat{\beta}_1$	–13.0*
Quadratic effect of goal distance, $\hat{\beta}_2$	–7.5*
Daily number of songs	.8
Total visits to earn certificate	–10.9*
Saturday–Sunday	–.2
Number of certificates already earned during the visit	–4.0*

*$p < .01$ (based on Wald test; two-tailed).

participant i terminating the visit t after rating q songs in that visit is given by

$$\text{(8)} \qquad \Pr_i(t, \mathbf{X}_{itq}) = \frac{\exp(g)}{[1 + \exp(g)]},$$

where $g = \beta_0 + \beta_1 d_{itq} + \beta_2(d_{itq} - \bar{d}_i)^2 + \beta_3 C_{itq} + \boldsymbol{\gamma}\mathbf{X}_{itq}$.

In Equation 8, we generalize the GDM to the domain of effort persistence and use the definition of proportional goal distance we used previously. In particular, $d_{itq} = (r - n_{itq})/r$, where r = 51 song ratings and n_{itq} is the number of songs accumulated by individual i toward earning the reward after rating q songs in visit t ($d_{itq} \in [.02, 1.0]$). The parameter β_1 captures the effect of goal distance on the probability of terminating a visit. We expect β_1 to be positive, indicating that a greater goal distance (d_{itq}) leads to a greater likelihood of defection (and, equivalently, a smaller d_{itq} leads to enhanced effort persistence). We used a dummy variable, C_{itq}, that we coded as 1 if the previous rating in the visit earned a certificate (i.e., if $d_{itq} = 1$) and 0 if otherwise. The goal-gradient hypothesis predicts an increased likelihood of visit termination (or RP defection) when d_{itq} reverts to 1.0, and therefore we expected β_3 to be positive. We estimated the effect of $d_{itq} = 1.0$ separately to guarantee that the hypothesized goal-gradient effect (captured by β_1) could not be explained solely on the basis of an increased likelihood of defection at $d_{itq} = 1.0$, that is, just after reward attainment. We also included a day-level control that captures daily variations in the total number of songs rated on the Jaboom Web site.

We calibrated the GDM on the entire data set, including ratings (and participants) that did not eventually earn a reward certificate. Thus, we jointly modeled visit termination and overall program defection. Table 5 displays the model estimates. Consistent with the goal-gradient hypothesis, the linear goal-distance parameter $\hat{\beta}_1$ was positive ($p <$ .01), indicating that members were more likely to defect when they were farther away from the reward goal (or, equivalently, they were more likely to persist when they were closer to the goal). Furthermore, as we predicted, $\hat{\beta}_3$ was positive ($p < .05$), indicating that the highest probability of terminating a visit occurred just after goal achievement, that is, when members were the farthest away from the (new) goal (at $d_{itq} = 1.0$). Figure 7 illustrates these results and shows that a majority (17% or 80/473) of all visit terminations occurred at $d_{itq} = 1.0$. The figure also shows that the percentage of visit terminations continued to decrease as a function of smaller distance to the goal. For example, among the 473 terminations we observed, 8.7% (41/473) occurred when only one song was accumulated toward the next reward (i.e., when $d_{itq} = .98$), whereas only .2% of visit terminations (1/473) occurred when as many as 50 songs were accumulated (i.e., when $d_{itq} = .02$).

The Music-Rating Program: Discussion

The Jaboom music-rating program enabled us to test the goal-gradient hypothesis in an empirical context that was different from the café RP, using an incentive system that is akin to a freelance employment contract. With this empirical application, we were able not only to replicate the finding of goal-motivated acceleration in visit rates (in the context of Web site rather than café visits) but also to extend the goal-gradient effect to the domain of quantity decisions and effort persistence. The various operationalizations of the goal-gradient hypothesis were examined with several generalizations of the GDM, which all relied on a common measure of goal distance, namely d_t. These varieties of the GDM included a hazard rate model of the timing of visiting the Jaboom Web site, a Tobit model of the quantity of ratings per visit, and a logit model of the probability of effort termination and program defection.

We found significant goal gradients even after we accounted for unobserved heterogeneity and statistically controlled for time trends in visit and song-rating frequencies. Moreover, we observed the phenomenon of postreward resetting, whereby members accelerated toward each of two subsequent rewards but exhibited a drop in their rating quantities after earning the first reward and starting to work toward the second (i.e., when d_t reverts to 1.0). The finding

Table 5

THE LOGIT GDM OF EFFORT PERSISTENCE AND DEFECTION

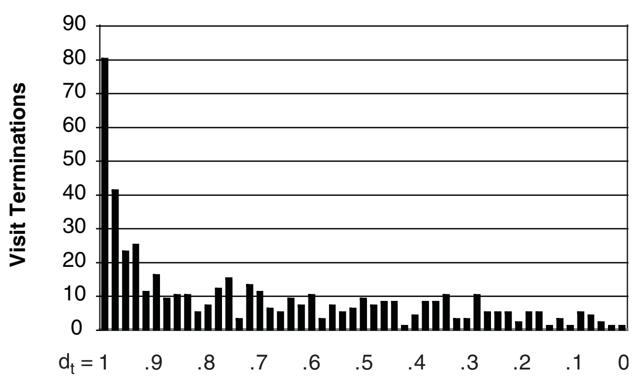
Latent Class-Level Parameters		
	Class 1	*Class 2*
Segment size (%)	94	6
Constant	–3.5**	–4.5**

Parameters Not Varying by Latent Class	
Acceleration Parameters	*Estimate*
Linear effect of goal distance, $\hat{\beta}_1$	.49**
Quadratic effect of goal distance, $\hat{\beta}_2$	.12*
Effect of certificate completed ($d_{tq} = 1$), $\hat{\beta}_3$	.27**
Covariate Parameters (i.e., Control Variables)	
Daily number of songs	–.05
Total visits to earn certificate	.40**
Saturday–Sunday	.05
Number of certificates already earned during the visit	.17*

*$p < .05$ (based on Wald test; two-tailed).
**$p < .01$ (based on Wald test; two-tailed).

Figure 7

NUMBER OF VISIT TERMINATIONS AS A FUNCTION OF GOAL DISTANCE



of postreward resetting is a key corollary of the goal-gradient hypothesis; it demonstrates that effort expenditure is a function of goal distance and rules out learning and other time-trend effects as well as a self-selection (or survivor) rival account. Self-selection is also inconsistent with the analysis of participants' entire sequence of ratings (including ratings that did not eventually lead to reward), which revealed significant goal gradients.[11] Next, we use individual differences to explore the relationship between the goal gradient and customer retention.

IMPLICATIONS OF THE GOAL GRADIENT FOR CUSTOMER RETENTION

Prior research with animals has shown that a steeper goal gradient was generated by an increased drive (e.g., hunger) to attain the reward (Hull 1934). This finding suggests that RP members who exhibit enhanced acceleration possess a stronger motivation to earn free rewards (e.g., due to a higher achievement motivation). If, indeed, the motivation to earn free rewards is related to the steepness of the goal gradient, individual differences in the tendency to accelerate (when we hold constant the overall program effort) should predict customer retention after attainment of the first reward. Specifically, we expect members who accelerate more strongly toward their first reward to be more likely to reengage in the program and earn a second reward. Relatedly, we expect stronger acceleration to lead to faster reengagement in the RP.

To examine these predictions, we recalibrated the GDM with unobserved heterogeneity in both the hazard rate and the goal-distance parameters, using a subsample of the café RP data that excluded subsequent cards. We used this model to obtain individual-level linear acceleration estimates based on the member's first coffee card. We calculated these estimates by multiplying the latent class parameters of goal distance (i.e., acceleration) by the individual-level probabilities of class membership. We then used the individual-level acceleration estimates as independent variables in predicting member reengagement in the café RP. Importantly, the tests we report subsequently included covariates that statistically controlled for the length of time it took participants to complete the first card (i.e., the participant's overall program effort and product liking) and the date of completion of the card. That is, we investigated the effect of individual differences in the slope of the goal gradient (the linear goal-distance parameter), holding constant the base hazard rate (i.e., the average interpurchase time) and possible seasonality (or right-censoring) effects.

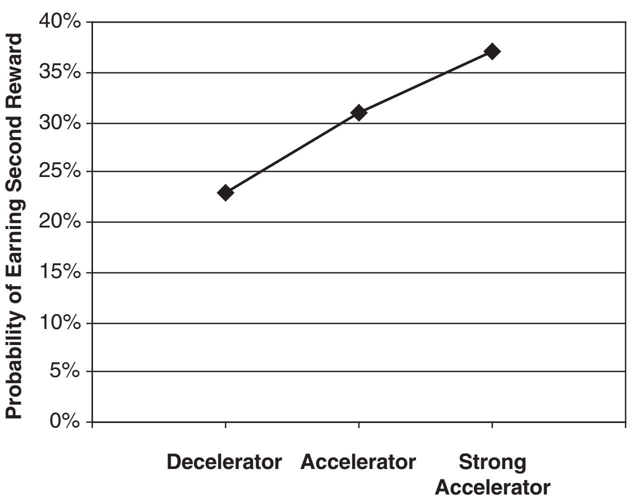
Retention Probability

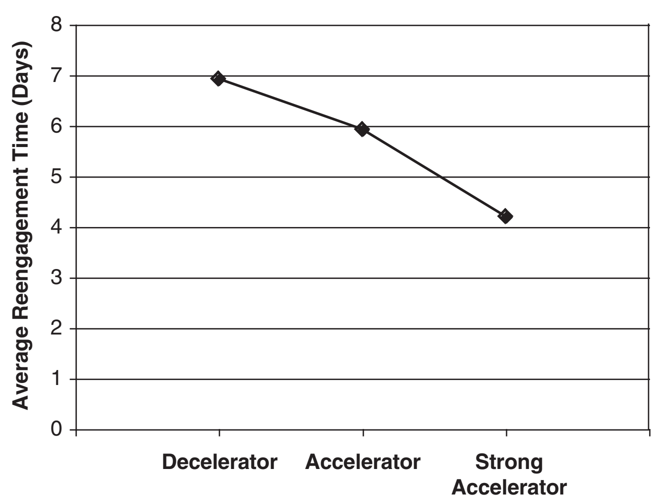
We used a logistic regression to test the prediction that members who accelerate more strongly toward their first reward will be more likely to earn a second reward. The (dummy) dependent variable received a value of 1 if the member earned a second reward and 0 if otherwise. The effect of the first-card individual-level acceleration estimate for the member was in the hypothesized direction ($\hat{\beta} = -.5$, Wald $\chi^2 = 5.3$; $p < .05$). In particular, members who accelerated more strongly toward their first reward were more likely to earn a second reward. To demonstrate this effect visually, we also split the sample on the basis of first-card estimated linear acceleration into three equally sized groups: decelerators (mean $\hat{\beta} = .1$), accelerators (mean $\hat{\beta} = -.05$), and strong accelerators (mean $\hat{\beta} = -.1$). Figure 8 (left panel) depicts the probability of completing a second card (based on the raw data) for each of these three groups.

[11]Detailed analyses that rule out the self-selection (survivor) account are available on request.

Figure 8

EFFECT OF FIRST-CARD ACCELERATION ON REENGAGEMENT PROBABILITY AND TIMING





Reengagement Time

To test the hypothesis that steeper acceleration predicts faster reengagement, we analyzed the subsample of 110 members who completed both a first and a second card. We computed reengagement time as the period between the last purchase on the first card and the first purchase on the second card. We fit a new (Weibull) hazard rate model that predicted the reengagement times using the individual-level estimates of first-card acceleration as an independent variable. We also included the covariates we used previously in the hazard rate model of interpurchase times and controlled for the duration and completion date of the first card. The effect of acceleration toward the first reward on the time to reengage in the program was in the hypothesized direction ($\hat{\beta} = -2.6$, Wald $\chi^2 = 13.8$; $p < .01$). That is, members who accelerated more strongly toward their first reward were faster to begin working toward their second reward (when we hold constant the base hazard rate, or the average interpurchase time, on the first card). Figure 8 (right panel) illustrates this result using the aforementioned tertiary split.

Implications for Customer Retention: Discussion

We posited that individual differences in the goal gradient capture variations in the motivation to earn free rewards. Consistent with this argument, we found that customers who accelerated more strongly toward their first reward subsequently exhibited greater retention and faster reengagement in the café RP. We replicated these effects in the context of the Jaboom music-rating program.[12] Given the previously reported findings of postreward resetting, our results cannot be explained as a simple continuation of the increased purchase rates of accelerators. Overall, the findings underscore the importance of incorporating the goal-gradient construct in the modeling and analysis of RPs.

GENERAL DISCUSSION

The goal gradient is one of the classic phenomena discovered in the animal-learning and behaviorism literature of the early twentieth century. It has important implications for achievement motivation and goal pursuit but, nevertheless, has been understudied in humans. This is particularly surprising, given that the goal-gradient hypothesis provides considerable insights into the psychology of rewards and the optimal design of customer, employee, and sales force incentive systems. In this research, we extended the goal-gradient hypothesis to the domain of consumer behavior and investigated its consequences for illusionary goal progress and customer retention.

The current research can be viewed as part of the ongoing (fruitful) attempt to bridge the consumer behavior and marketing science disciplines (e.g., Bell and Lattin 2000; Hardie, Johnson, and Fader 1993; Kivetz, Netzer, and Srinivasan 2004; Simonson and Winer 1992; Wertenbroch 1998; Winer 1986; for related discussion, see Wittink 2004). Such intradisciplinary endeavors often test behavioral theories with econometric modeling, secondary data, and/or field studies. In the current research, we built on prior analyses in behaviorism, social cognition, and behavioral decision research, and we used various modeling frameworks and empirical tests in the context of two real incentive systems. We primarily relied on field experiments and econometric analyses of actual multiperiod customer behavior. Such methodologies are crucial for the study of dynamic goal pursuit and intertemporal responses to RPs and other promotions (see, e.g., Gupta 1988; Simonson 1990; Van Heerde, Leeflang, and Wittink 2000). The alternative approach, whereby respondents are asked to assume a hypothetical state (e.g., "imagine that you have accumulated x points") provides an adequate test of lay theories and self-perception but not of the actual evolution of goal motivation and behavior.

Key Findings and Their Implications

We found that members of a café RP accelerated their coffee purchases as they progressed toward earning a free coffee. The goal-gradient effect also generalized to a very different incentive system, in which shorter goal distance led members to visit a song-rating Web site more frequently, rate more songs during each visit, and persist longer in the rating effort. Importantly, in both incentive systems, we observed the phenomenon of postreward resetting, whereby customers who accelerated toward their first reward exhibited a slowdown in their efforts when they began work (and subsequently accelerated) toward their second reward. To the best of our knowledge, this article is the first to demonstrate unequivocal, systematic behavioral goal gradients in the context of the human psychology of rewards.

For marketers, the goal gradient may provide profitable opportunities. In addition to facilitating segmentation, targeting, and promotions (we discuss this subsequently), the goal gradient may lead to a sales lift that exceeds the cost of the reward. For example, the results of the café RP imply that to earn one free coffee, customers bought two more coffees than they would have otherwise.[13] At the same time, consumers may derive pleasure from working toward future goals. This idea is consistent with the findings of an observational study, in which research assistants unobtrusively recorded the behavior and affect of the café customers. The results indicate that customers who participated in the RP (as opposed to customers who did not) were more likely to smile when buying coffee (3.8 versus 3.4 on a five-point scale; $p < .05$), chat for a few minutes with café employees (26% versus 7%; $p < .05$), say "thank you" (95% versus 87%; n.s.), and leave a tip (21% versus 3%; $p < .01$). Although these results should be interpreted with caution because customers self-select into the RP, they suggest that goal striving is intrinsically motivating beyond extrinsic rewards.

We posited that people are influenced by the proportional (or psychological) distance to the goal (i.e., $d_t = [r - n_t]/r$). Accordingly, we proposed that the illusion of progress toward the goal would enhance achievement motivation by reducing the perceived proportion of distance remaining to the goal. One test of this hypothesis involved a field experiment, in which customers who received a 12-stamp card

[12]Detailed results are available on request.

[13]Given the exclusivity of the café on campus, the observed purchase acceleration is likely a consequence of increased consumption rather than brand switching. Brand switching was not a possibility in the case of the music-rating program.

with two preexisting bonus stamps completed the ten required coffee purchases faster than customers who received a regular 10-stamp card. It is noteworthy that the goal-gradient and illusionary goal progress effects can be captured by a mathematically equivalent GDM, in which effort depends on the proportion of original goal distance already accomplished (i.e., $d_t = n_t/r$). Further research could explore the impact of framing goal progress in terms of completed versus remaining effort.

The illusion of goal progress and its boundary conditions merit further research. Beyond its theoretical importance, this phenomenon has substantial managerial implications for the design of RPs and other incentive systems. Currently, many RPs award bonus points to new members (e.g., American Express Membership Rewards Program, Hyatt Gold Passport). Given the rich, complex structure of such programs, it is easy for managers to increase the point requirements of rewards by an amount equivalent to the bonus, effectively creating illusionary goal progress.

Consistent with the notion that a steeper goal gradient implies a greater drive to achieve the reward, we found that stronger accelerators reengaged in the program faster and were more likely to earn a second reward. Relatedly, failure to persist in the effort stream and fulfill the requirements was associated with weaker acceleration and even deceleration. The relationship between the goal gradient and retention was also evident in the finding that just after reward attainment (when goal distance regressed to 100%), customers exhibited a drop in activity (postreward resetting) and were also most likely to defect. These findings have important implications for customer segmentation and the design of marketing interventions aimed at reducing churn. For example, it is particularly important to communicate with and motivate customers immediately after they earn a reward.

Extending the GDM. Using a common measure of goal distance (d_t) and logit, hazard rate, and Tobit frameworks, the GDM captured three forms of goal gradients: increased persistence, rate, and quantity of effort closer to the reward threshold. These three goal gradients predict increases in the *recency* of the last transaction, the average *frequency* of all transactions, and the average *monetary value* of these transactions; thus, the goal-gradient and its modeling have important implications for the widely used RFM approach.

Given the robustness and generality of the GDM, we believe that it can be applied to a broad range of goal-based motivational systems, including more complex incentive systems. Further research can employ the GDM to account for consumer and employee behavior in sophisticated incentive systems, such as those that airlines, retailers, and sales organizations use; in such programs, r and n_t are often expressed in terms of miles, points, and dollars or units sold. Such incentive systems often use rich, complex structures that offer a multitude of different rewards at various requirement levels. Customers can exhibit goal gradients in various ways, including purchase timing and quantity acceleration and increased retention and lock-in. However, the goal-gradient effect may be more difficult to detect in such complex incentive systems for the following reasons: First, a priori, the researcher cannot identify (or observe) the consumer's goal. Second, the observed *ex post* goal (based on the actual reward redeemed) is self-selected by the consumer, and thus it is difficult to draw causal inferences about differences in the behavior of consumers who redeem different rewards. Third, in the presence of multiple effort–reward combinations, the consumer's chosen goal may change during the program, thus complicating the investigation of the goal-gradient hypothesis. Finally, the issue of right censoring in observed behavior (compared with underlying motivation) that arises in the test of the music-rating quantity acceleration applies to complex RPs as well. This last problem can be solved with the Tobit version of the GDM. Despite the various challenges, we believe that capturing the goal gradient in more complex situations is a worthy endeavor, and the GDM can facilitate it.

The implications of the goal gradient for promotion, pricing, and competition. The goal-gradient effect has important implications, which merit further research, for key marketing variables. The findings suggest that goal proximity increases customers' responsiveness to credit-earning promotions and offers. For example, frequent flyers' willingness to purchase miles may increase closer to program goals. This hypothesis is consistent with the results of an unpublished study, in which we asked 329 respondents to imagine that they participated in a frequent-flyer program that offered a free domestic round-trip ticket for accumulating 25,000 miles. We told respondents that they had already accumulated either 13,000 or 23,000 miles (distant versus near goal, respectively; manipulated between subjects); we asked them to indicate whether they would agree to receive weekly marketing e-mails in return for 1000 bonus frequent-flyer miles. As we predicted, respondents in the near-reward condition were more likely than those in the distant-reward condition to accept the promotional offer (56% versus 38%, $\chi^2 = 10.7$; $p < .001$). Note that an increase in promotion sensitivity due to goal proximity could be attenuated when (1) the promotional effort is identical to the main program effort (e.g., "fly next week and earn triple miles") and (2) effort acceleration is subject to behavioral ceiling effects (e.g., frequent flyers cannot accelerate their flights beyond a certain point).

The goal-gradient effect has important implications for price sensitivity and competition. It suggests that the own- and cross-price elasticities of the RP sponsor are lower for members who are closer to the program's goals. Compared with nonmembers of the RP, members may be willing to pay a price premium or forgo convenience (e.g., purchase more expensive and/or layover flights), particularly when they near a program goal. In addition, the increased motivation to achieve RP goals may reduce competition and price wars by escalating customer lock-in and switching costs and enhancing consumption rates (i.e., expanding the category).

Conclusion

Building on the behaviorist goal-gradient hypothesis, we proposed that people working toward future rewards would accelerate their effort as they near the reward goal. Based on a wide range of empirical and modeling approaches, the findings we report in this article provide converging evidence for the impact and importance of goal gradients in the human psychology of rewards. Not only do customers accelerate toward rewards (in terms of timing, quantity, and persistence of effort), but their acceleration also predicts loyalty and future engagement with similar goals. The GDM unifies these results and predicts the effect of illusionary goal progress. On the basis of this research, we propose that the goal gradient and its modeling have important theoretical and practical implications for achievement motivation and goal behavior and for incentive systems and marketing promotions.

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