Keep Winning or Stop Losing?

The Effect of Consumption Outcomes on Variety-Seeking in Online Video Games

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Abstract

As consumers engage in experiential products, they may exhibit variety-seeking behavior by switching frequently between different options within the same category, or exhibit inertial behavior by consistently choosing the same option. The prior literature identifies three main reasons why consumers may be variety-seeking: external situations, satiation, and future preference uncertainty. We propose that consumers may also become variety-seeking in response to consumption outcomes, which indicate the quality of the consumer's experience for a specific consumption occasion. We predict that positive consumption outcomes lead to inertial preferences, while negative consumption outcomes lead to variety-seeking. We test our hypothesis within the novel context of an online video game, in which players choose between different map environments for each round of play and consumption outcomes can be measured objectively by a player's performance during the round. In our preliminary model, we extend upon classic models of variety-seeking that view the choices made between consumption occasions as a first order Markov process. We allow variety-seeking to be a function of time-varying factors, including satiation and consumption outcomes. We observe the effects of consumption outcomes on variety-seeking to be consistent with our hypothesis, which suggests in our context that firms should place players in a familiar environment in the next round of play if they are performing well, and introduce variety if they are performing poorly.

Keywords: *variety-seeking, inertia, video games, attribute satiation*

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1 Introduction

As consumers spend time engaging in experiential products, they may become satiated on certain product attributes and exhibit preferences for new experiences (variety-seeking), or they may become hooked on certain familiar features and prefer consistency (inertia). It is useful for firms to identify when consumers are variety-seeking or inertial when predicting purchase patterns and offering recommendations for future consumption occasions. Although there are multiple definitions of variety-seeking/inertial behavior, in the present research we are focusing specifically on how shoppers choose between different options across multiple consumption occasions within the same product category.

Researchers have proposed several reasons for why consumers exhibit variety-seeking behaviors, including response to external factors such as price promotions, satiation on product attributes over time, and exploration of different options to reduce future preference uncertainty (Kahn 1995). We propose that consumers may also become variety-seeking in response to consumption outcomes, which we define to be measures of the quality of the consumer's experience for a specific consumption occasion. We predict that positive consumption outcomes lead to inertial preferences, while negative consumption outcomes lead to variety-seeking.

For example, imagine that a Netflix user just started watching the Netflix Original Series Jessica Jones. After binge-watching 6 episodes, she gives the show 5 out of 5 stars, which indicates a positive consumption outcome and will likely lead to her continuing to watching the show or choosing to watch similar shows, like Daredevil, which shares several attributes with Jessica Jones, including being a gritty action series based on Marvel super hero characters. By the same logic, if the user really hated Jessica Jones and gave it 1 star, then it's likely that she would prefer to watching something completely different the next time she logs onto Netflix.

To test our hypothesis that positive consumption outcomes will lead to inertial preferences, while negative consumption outcomes will lead to variety-seeking preferences, we use data on individual player behavior in an online video game. Across 30 to 40-minute rounds of play, individual players choose which map they want to play on and experience consumption outcomes that can measured by their performance or points earned during the round. We find that better performance results in players choosing similar maps in subsequent rounds, while poorer performance results in players choosing maps with different attributes. Although we focus specifically on the context of online video games, our findings can be applied to the broader set of experiential products, including watching movies and dining at restaurants.

2 Literature

In this paper, we are specifically focused on decisions that consumers make when choosing between different options across consumption occasions within the same product category. Variety-seeking is defined to be when consumers switch frequently between options, while inertia (or reinforcement) is defined to be when consumers repeatedly choose the same option across multiple consumption occasions. We review the main reasons that researchers have identified for why consumers exhibit variety-seeking or inertial behavior, the most recent models that have been developed to capture variety-seeking, and the behavioral literature that supports our hypothesis that positive (negative) consumption outcomes lead to variety-seeking (inertial) behaviors.

2.1 Why Consumers are Variety-Seeking or Inertial

The concepts of inertia or reinforcement behaviors and variety-seeking were developed separately before researchers began to think of them as two ends of the same continuum, so much of the research that provides explanations for these behaviors focuses on one extreme. Early models used time-lagged variables to capture inertial choices and attributed them to “brand loyalty” (Jacoby and Kyner 1973; Guadagni and Little 1983). Researchers explored alternative explanations for inertial behaviors such as state dependence and habit persistence, which can be disentangled using more sophisticated utility models (Erdem and Keane 1996; Seetharaman 2004).

On the other hand, Kahn (1995) summarizes the three main reasons for why consumers may be variety-seeking: (1) external situations, (2) satiation, and (3) future preference uncertainty. External situations include marketing decisions made by firms. For example, different firms may promote in alternating weeks (Kahn and Raju 1991) or engage in price discrimination (Shaffer and Zhang 2000), driving consumers to switch between brands. Satiation is a well-studied phenomenon in both behavioral and quantitative research. Satiation may occur on brands or attributes and lead consumers to seek out products with new features (McAlister 1982; Inman 2001). Finally, forward-looking consumers may use variety-seeking as a way to resolve future preference uncertainty and learn about unknown choices (Walsh 1995; Erdem 1996).

2.2 Dynamic Discrete Choice Models

In the classic models of variety-seeking, the underlying assumption is that the consumer is making choices between options following a first-order Markov process (Jeuland 1979; Givon 1984; Kahn, Kalwani, and Morrison 1986). The key feature is that there is an explicit variety-seeking parameter that can estimated for each individual consumer. Brand choices are formulated as a standard logit model, but the first-order Markov property allows the probability of choice to depend on the brand that was chosen previously. The individual-specific variety-seeking parameter determines whether repeat choices or brand switching is more likely between subsequent consumption occasions.

There have been various extensions to this classic model to take into account variation across brands, consumers, and time. The brand choice probabilities can be revised to include brand-specific marketing variables (Seetharaman and Chintagunta 1998). The variety-seeking parameter can also vary within shoppers by assuming they come from a flexible distribution. For example, the Beta distribution allows for a bimodal pattern that can account for shoppers switching between inertial and variety-seeking states (Trivedi et al. 1994). Heterogeneity across individuals can be modeled as individuals receiving information that arrives according to a Poisson timing function (Roy et al. 1996). In our current model, we will demonstrate the advantages of attribute-based variety-seeking using a continuous distance between options (Chintagunta 1998). We also allow variety-seeking to change over time based on satiation and previously experienced consumption outcomes.

2.3 Effects of Consumption Outcomes on Variety-Seeking

Consumption outcomes are observable for a variety of experiential products. These include star ratings for movies or TV shows on Netflix, star ratings for restaurants on Yelp, thumbs up or down for videos on YouTube, and a player's score on a video game. We are going to focus on the context of video games, which has been mostly unexplored within the marketing literature. Player scores allow for a clean, relatively objective, and continuous measure of each player's consumption outcomes.

We hypothesize that positive consumption outcomes will lead to inertia, while negative consumption outcomes will lead to variety-seeking. Our model is also able to account for the magnitude of consumption outcomes in either direction, so the degree of variety-seeking or inertia also depends on how positive or negative the experienced outcomes are, relative to some reference point. Although we model the effects of consumption outcomes across a continuum, when we examine the behavioral work in support of our hypothesis, we focus on the valence of the outcomes (positive or negative) and how they might map to emotional responses. For example, for the Netflix TV show Jessica Jones, 5 stars would indicate a positive consumption outcome. For a military-based shooting game, positive net kills would be a positive consumption outcome. Likewise, a 1 star rating for Jessica Jones would indicate a negative consumption outcome, while a net of 15 deaths would indicate a negative consumption outcome for the shooter game.

Researchers in psychology and consumer behavior have long been interested in the effects of emotions on people's choice behaviors, but there is some disagreement on how positive and negative affect influences variety-seeking. Positive affect has been shown to increase variety-seeking behavior among enjoyable products, as long as they don't have any negative features (Kahn and Isen 1993). Positive moods seem to drive people to seek out more stimulation, but this pattern might break down at very extreme positive moods (Roehm and Roehm 2005). Other research shows that differentiation of positive and negative emotions of the experience slows the satiation process due to cognitive appraisal, and so focusing on negative emotions may result in more enjoyment of repeated experiences (Poor, Duhachek, and Krishnan 2012).

In contrast to this prior research, we focus on the affect generated by the same source as the choices being made, rather than an external manipulation of mood. We hypothesize that positive consumption outcomes should lead people to have more inertial preferences. This is consistent with literature that suggests that encountering high value rewards will intensify motivational states towards the same reward source (Berridge 2001) and positive rewards may "whet" the reward appetite (Wadhwa, Shiv, and Nowlis 2008). In our context, a video game player may experience a hot streak and expect continued positive outcomes from playing within the same or similar map environments. On the other hand, negative consumption outcomes lead to variety-seeking, which is consistent with the notion that helplessness and sadness result in people wanting to change their current state (Keltner, Ellsworth, and Edwards 1993; Lazarus 1991), and they may choose to do this through consumption choices (Lerner et al. 2004). A player may feel sad or frustrated after a tough loss, but a change of scene in the next round may boost their engagement in the game.

3 Model

The degree of variety-seeking may vary across product categories (Kahn et al. 1986) or across individuals (Givon 1984), but the model we develop is more appropriate for capturing how the degree of variety-seeking varies within individual consumers. Our model captures individual choices across multiple consumption occasions. In the base model, the probability of a consumer choosing option j depends on the individual's intrinsic preferences for option j's attributes x_j, which is given by the vector of attribute coefficients β. Although all variables are specified at the individual level, for simplicity we suppress the subscript for individuals. Without any time varying effects, the probability of each choice j is formulated by a standard logit:

$$P_j = \frac{\exp\{\beta x_j\}}{\sum_k \exp\{\beta x_k\}} \tag{1}$$

To capture how consumers respond to consumption outcomes over time, we specify choice preferences to be first-order Markov across rounds. So The probability of selecting map j depends on the option i that was selected in the previous round. This choice depends on the individual's intrinsic preferences for the attributes of option j and a variety-seeking parameter $VS \in [-\infty, +\infty]$ that determines how much weight is given to the distance d_{ij} between option j and the previous option i.

$$P_{j|i} = \frac{\exp\{\beta x_j + VSd_{ji}\}}{\sum_k \exp\{\beta x_j + VSd_{ki}\}} \tag{2}$$

To illustrate how the variety-seeking parameter VS comes into play, we note that the probability of repeating option j is different from the probability of switching from option i to option j:

$$P_{j|j} = \frac{\exp\{\beta x_j\}}{\sum_k \exp\{\beta x_k + VSd_{ki}\}} \tag{3}$$

$$P_{j|i} = \frac{\exp\{\beta x_k + VSd_{ji}\}}{\sum_k \exp\{\beta x_j + VSd_{ki}\}} \tag{4}$$

If $VS \geq 0$, then the player is variety-seeking, so the probability of switching $P_{j|i}$ is higher. On the other hand, if $VS \leq 0$, then the individual and so the probability of staying with the previous option $P_{j|j}$ is higher. These probabilities also depend on the distance between the options. So a variety-seeking player is also more likely to switch to options that are farther away, while an inertial player is more likely to choose options that are closer to the previously chosen option.

We allow each individual's variety-seeking parameter to vary across consumption occasions t as a function of the number of occasions that have passed so far, how satiated individuals are on each option, and the consumption outcome experienced at the previous consumption occasion $t-1$.

$$VS[t] = \gamma_0 + \gamma_1 \log(t) + \gamma_2 \text{Satiation}[t\text{-}1] + \gamma_3 \text{Outcome}[t\text{-}1] \tag{5}$$

Satiation is calculated by assigning a satiation level s_n to each attribute n. We allow attribute satiation to accumulate by 1 if the attribute was experienced in the previous round $t-1$ and to to decay over time by λ. The total satiation for each option is a combination of the attribute satiation, and we assume that all attributes are weighed the same.

$$\begin{cases} \lambda \mathrm{s}_n[t\text{-}1] + 1, \text{if attribute } n \text{ experienced at } t\text{-}1 \\ \lambda \mathrm{s}_n[t\text{-}1], \text{otherwise} \end{cases} \tag{6}$$

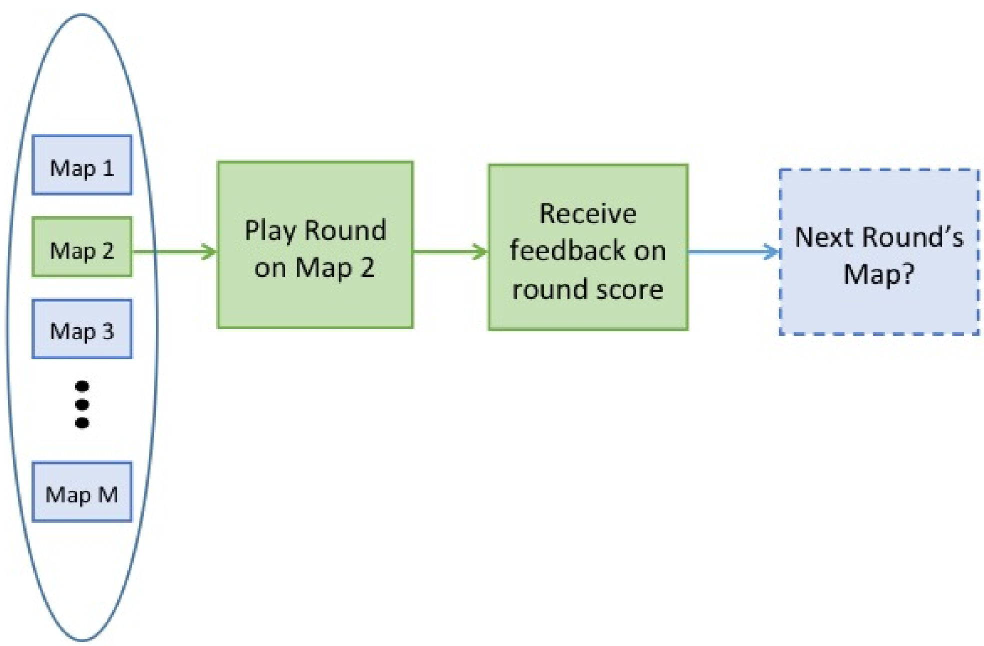
$$\text{Satiation}[t] = \sum_n \mathrm{I}_{n,j} \mathrm{s}_n[t] \tag{7}$$

4 Data

Our dataset was awarded through the Wharton Customer Analytics Initiative (WCAI) from a large video game developer. We have data on the activity of 1,309 frequent players of an online multiplayer first-person shooter video game. Players engage in campaigns averaging 20 minutes in length in two competing teams. We focus on the rounds played on the firm's public servers and exclude the rounds played on player's private servers. There are on average 20 players involved in each round, and people rarely play with the same player twice. We have each player's daily rounds played across two years, starting from the game's release. The players in our sample had a median of 682 rounds total across the data collection period.

Figure 1 illustrates a player's actions before and after each round of play. Each round is considered to be a particular consumption occasion t. During each round, players are allowed to choose what map they want to plan on. The map is basically a game environment with a set of attributes and features. The choice we are interested in the player's map choice. Players are presented with a set of M maps (which may vary over time with the release of expansion packs). The player then chooses a map and is dropped into a server by the firm's matching algorithm with other players to play a round. After the round, the player is shown his/her individual round outcomes, which might include the number of kills, number of deaths, individual points earned for completing certain tasks in the round, etc. In the next round, the player will again have the opportunity to select a map.

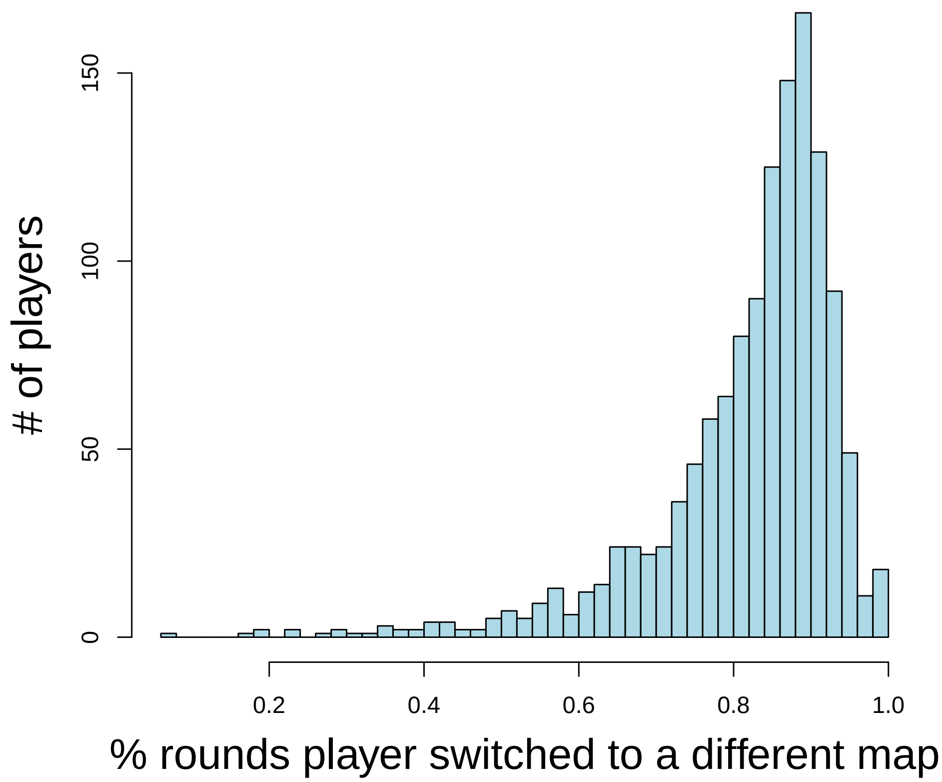
Figure 1: Outline of a player's sequence of actions for each round of play.



5 Descriptive Analysis

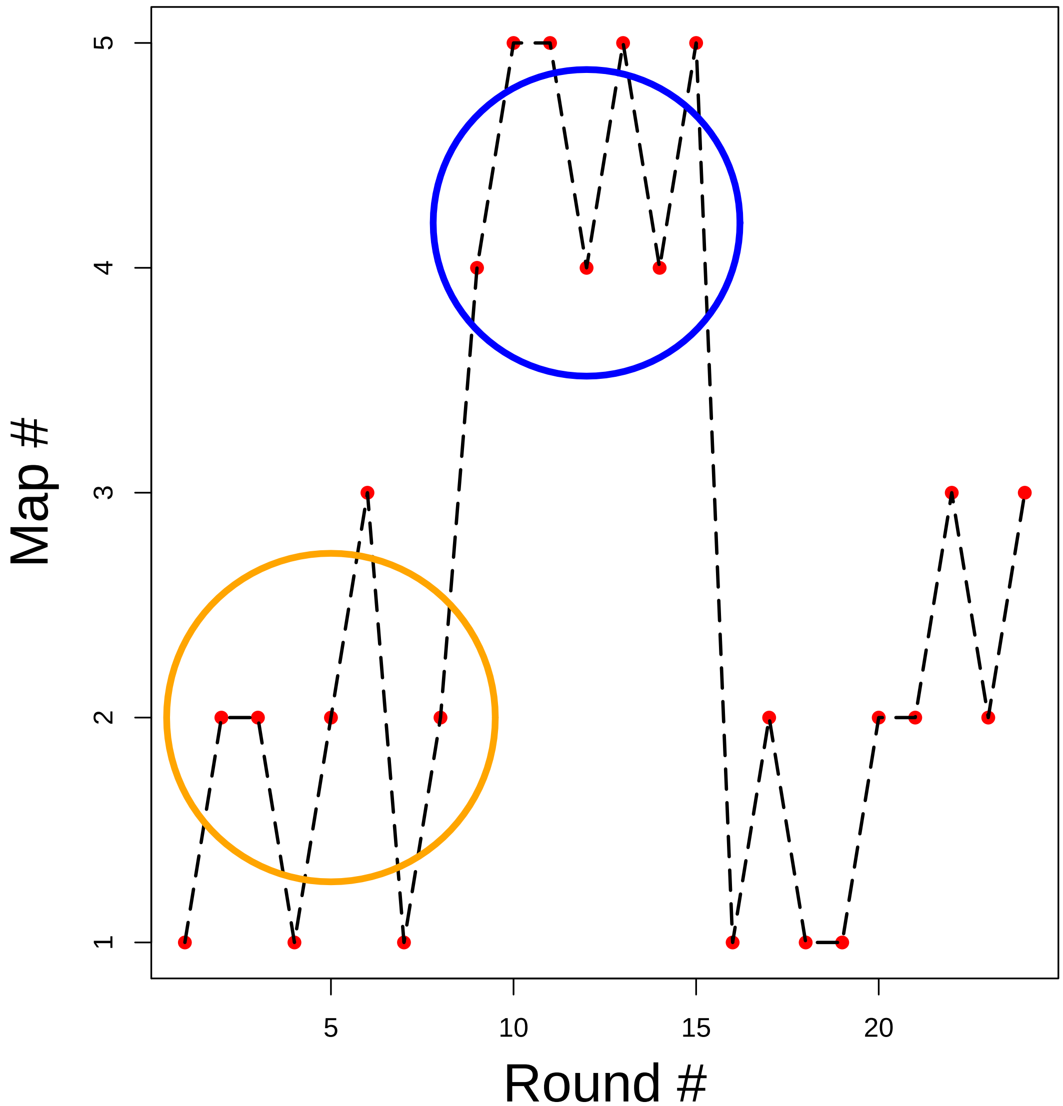
To examine at the surface-level how "variety-seeking" players are with respect to their map choices, we can look at how often players switch between maps. For each player, we calculate the percentage of rounds where they switched to a different map from the previous round. We see that the average switching rate is about 80%, so it would appear that players are very variety-seeking because they are switching between maps very often (see Figure 2).

Figure 2: Players switch often between maps.



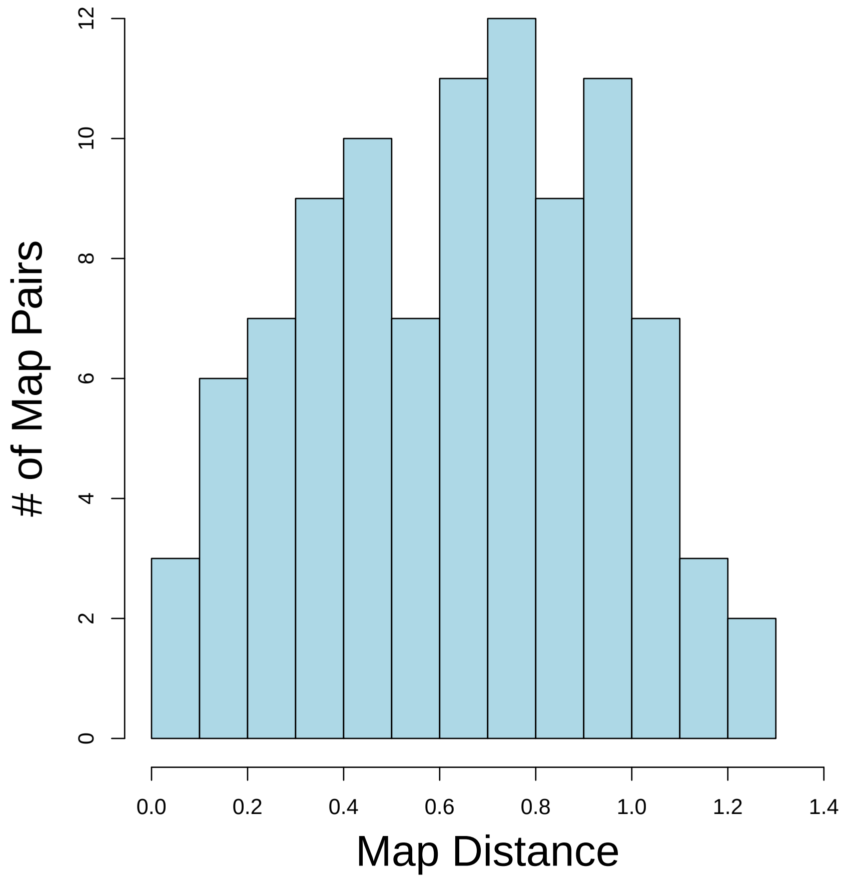
However, one important extension of the classic brand switching variety-seeking model is the use of attribute-based variety-seeking. To illustrate, we might for example see a player's pattern of rounds played and conclude that they are very variety-seeking because they are switching maps nearly every round (see Figure 3). But if maps 1, 2, and 3, are actually very similar to each other, while maps 4 and 5 are very similar to each other, then the player might be less variety-seeking than at first glance because he/she is actually switching occasionally between two clusters of maps.

Figure 3: Sample sequence of maps. The orange and blue circles represent potential clusters of similar maps.



In order to quantify the similarity between any two maps, we created a measure of map distance. We have 29 maps total, and they possess 14 different binary attributes. To calculate the distance between any two maps, we simply take the correlations across the maps and subtract them from 1. The map distance can fall anywhere between 0 and 2. The distance between any map and itself is 0. The range of map distances in our dataset falls between 0 and 1.4 (see Figure 4).

Figure 4: Distribution of attribute-based map distances.



If we rank the maps from most played to least played for each player, and look at the cumulative percentage of rounds played on these maps, we see that most players spend most of their time playing on just a few maps (see Figure 5). The top 10 favorite maps make up on average about 90% of a player's rounds. If we plot the average distance from the favorite map (see Figure 6), then we see that the most commonly played maps are also more similar to each other.

Figure 5: Cumulative frequency of maps played, ranked from most to least played.

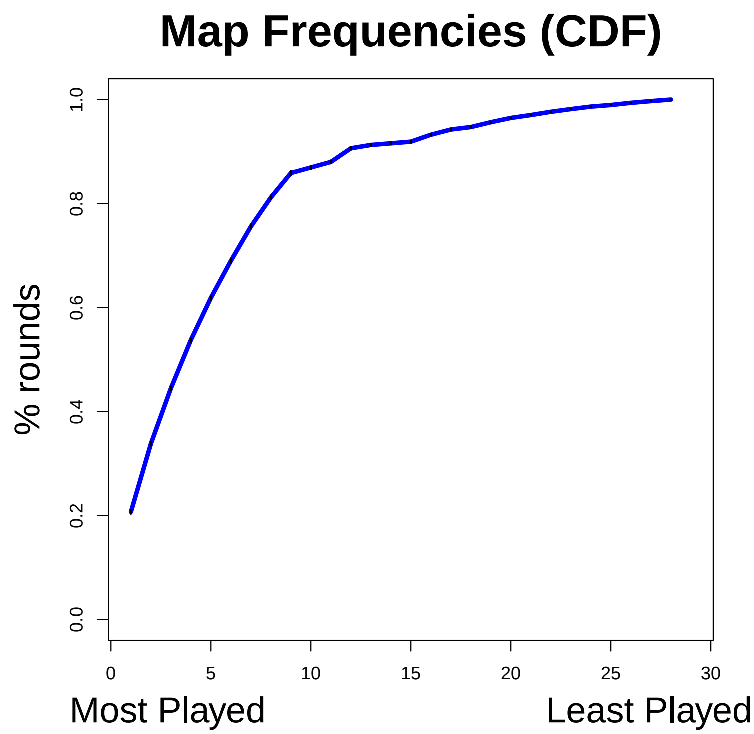
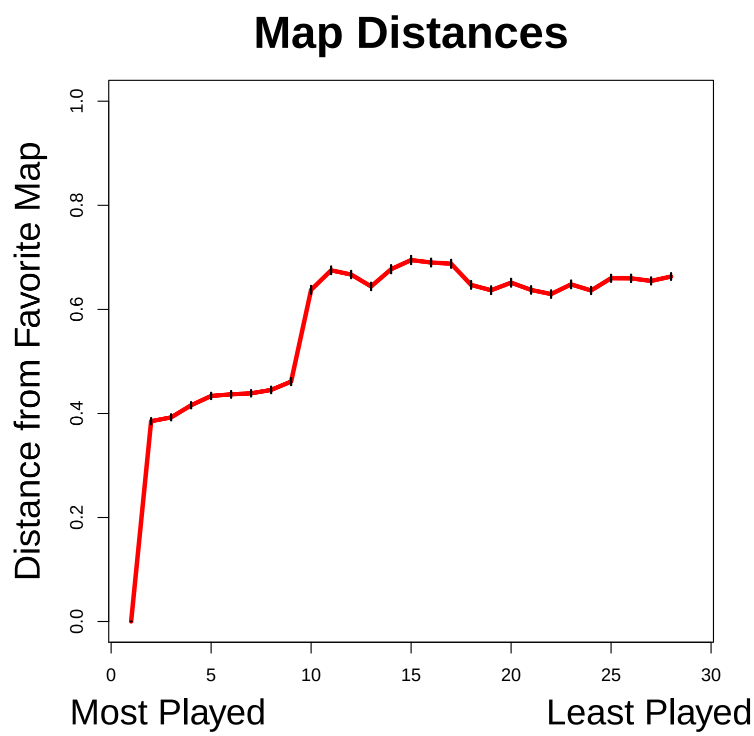
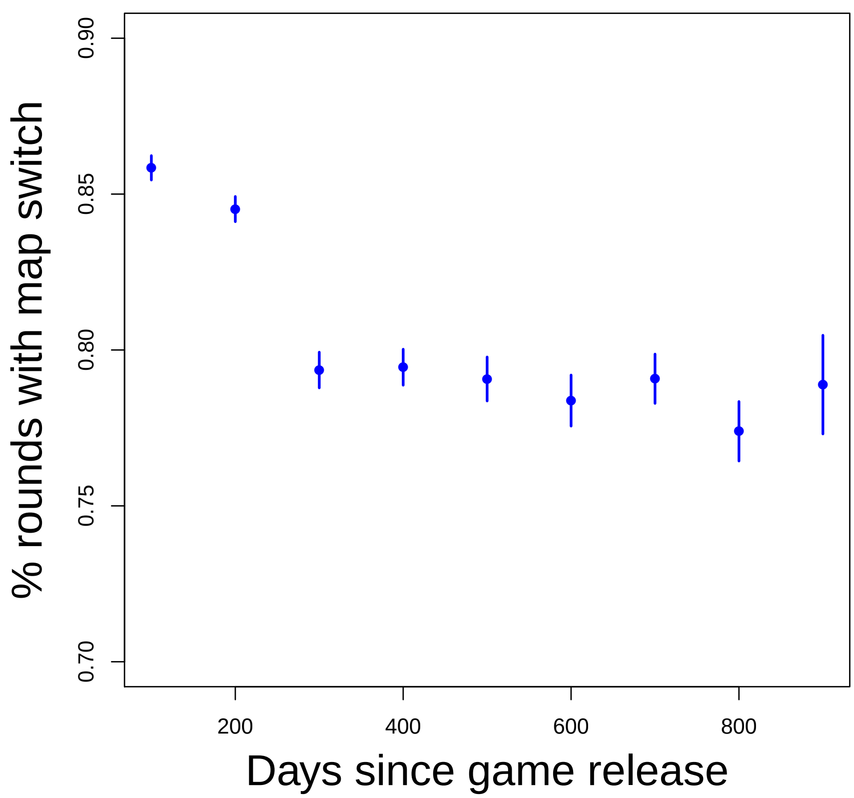


Figure 6: Distance from favorite maps, with maps ranked from most to least played.



Over time, the average rate of map switching across the entire player sample seems to decrease slightly over time (see Figure 7). There are two explanations for this pattern. One is that at the individual else, players are first exploring the different map options, and eventually settle on playing a smaller set of their favorite maps. The second explanation is that this pattern arises from the heterogeneity across players. It is possible that players who adopt early on are more variety-seeking, while players who enter later are less variety-seeking and bring down the average switching rate.

Figure 7: Players switch between maps less over time.



After each round, the player experiences a set of individual consumption outcomes. These include Total Points, Combat Points, Kills, Deaths, and Net Kills. These variables are all pretty highly correlated (see Figure 8), so we use Kills, which is generally the primary and most salient objective of the game.

Figure 8: Individual consumption outcomes.

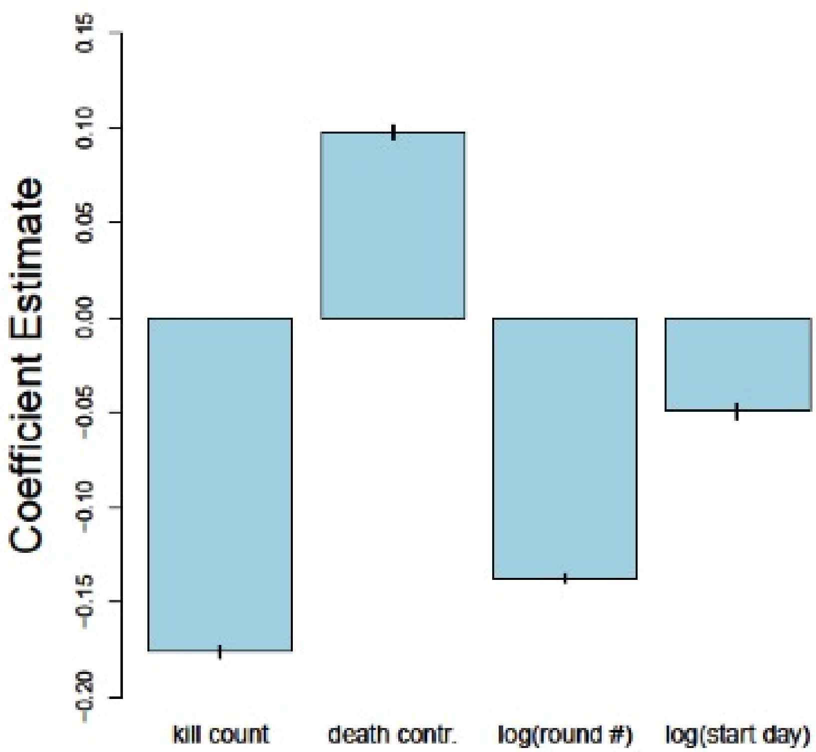
	Total Points	Combat Points	Kills	Deaths	Net Kills
Total Points	1				
Combat Points	0.79	1			
Kills	0.73	0.84	1		
Deaths	0.47	0.59	0.66	1	
Net Kills (Kills – Deaths)	0.44	0.44	0.57	-0.24	1

As preliminary evidence in support of our hypothesis that positive consumption outcomes lead to inertia and negative consumption outcomes lead to variety-seeking, we ran a binary logit with the dependent variable as whether the player switched maps between rounds (see Figure 9). The independent variables were kill count, death contribution, log of the round number, and log of the start day.

Kill count has a negative effect on map switching, consistent with our hypothesis that better outcomes lead to less switching. We couldn't directly use death count, since it was highly correlated with kill count, so we used death contribution, which is the number of deaths the player had relative to the total number of deaths experienced by both teams. Death contribution is a negative consumption outcome and has a positive effect on switching.

We also included the round number and the day that the player started playing to capture any temporal effects. Round number has a negative effect on map switching, so individuals gradually switch less over time (consistent with Figure 8). The start day also has a negative effect on map switching, which suggests that later adopters generally switch less as well. So this is evidence in support of both explanations for the general decrease in variety-seeking over time: within-player trends and across-player heterogeneity.

Figure 9: Results of Binary Logit on Map Switching.



6 Model Estimation Results

In order to model each individual's sequence of map choices, we estimate our model using a standard hierarchical Bayes method (Gelman et al. 2003). The set of parameters $\{\beta_i, \gamma_i\}$ is assumed to follow a multivariate normal prior distribution with $\{\beta_i, \gamma_i\} \sim \text{MVN}(\mu, \Lambda)$. Let μ follow a conjugate multivariate normal with $\mu \sim \text{MVN}(\mu_0, \Lambda_0)$, and let Λ^{-1} follow a conjugate Wishart distribution with ρ degrees of freedom and an inverse scale matrix R. The hyper parameters are chosen as identity matrices for Ω_0 and R^{-1}, a zero vector for μ_0 and the dimension of the covariance matrix for ρ to make it proper (the number of parameters plus 3). We use Markov Chain Monte Carlo iterations until sufficient convergence of the chains. To ensure our model is specified correctly, we did a simulation of 100 players with 200 rounds each and the 95% confidence intervals of the posterior estimates covered the true parameters.

Table 1: Results of hierarchical Bayes estimation on 100 players

Parameter	Est. Mean, 95% CI	Est. Var, 95% CI
γ_0 (Intercept)	-1.13 [-2.6, 0.9]	3.8 [1.1, 6.5]
γ_1 (log Round)	-0.4 [-0.9, -0.1]	0.6 [0.3, 0.9]
γ_2 (Satiation)	-0.5 [-0.9, -0.2]	0.9 [0.6, 1.3]
γ_3 (Outcome: Kills)	-1.0 [-2, -0.2]	5.6 [1.6, 9.6]

Table 1 gives the posterior results of the hierarchical Bayes estimation of the γ vector for 100 randomly chosen players from the sample. The negative intercept indicates that people are generally inertial. The negative coefficient on kills confirms our hypothesis that better performance leads to less variety-seeking. The number of rounds has a negative effect, as expected from the results of our descriptive analyses (see Figures 8 and 9). Interestingly, we also find that satiation also has a negative effect, so the more players experience certain attributes, they more they are inclined to choose maps with those attributes, which suggests that there may be a habituation or addiction element involved.

If we normalize the Kills to be relative to some reference point, like the mean Kills for each individual player, we can break up the effect of Kills on variety-seeking for Kills above and below the reference point. If the reference point is 0, then we see that the effect of kills is much steeper below than above 0 (see Figure 10).

Figure 10: Effects of consumption outcomes on variety-seeking below and above reference point.

7 Discussion

We built a descriptive model that allows for an individual-specific variety-seeking parameter to vary over time. Variety-seeking depends explicitly on time, satiation, and consumption outcomes. The results from our analysis lends support to our hypothesis that positive consumption outcomes lead to inertia, while negative consumption outcomes lead to variety-seeking. Although our analyses were conducted within the context of player map choices within an online video game, our model and findings can be extended to other domains of experiential products, including TV shows and restaurants.

There are several extensions that could be made to our current model. Currently we are assuming that all attributes contribute equally to the distance between maps, but this assumption could be relaxed and we could potentially estimate a different weight for each attribute. Since our data begins at the game's release, we could also incorporate how players are learning map attributes or map distances over time. Finally, we are assuming that players are simply maximizing of the utility for each map, but they may actually be trying to fill some goal or quota of gameplay, which would change the way we formulate their utility function.

For managers, this research will provide a method for determining individual customer preferences and how these preferences change over time based on consumption outcomes, as well as when customers might be more susceptible to the release of new products and whether they should be novel or similar to existing products.

Within the specific context of online campaign-based video games, consumption outcomes in each round of gameplay may be defined by the performance of the player. The firm may use these performance metrics to determine whether players are becoming bored or frustrated with the current playing experience and prefer a change of scene, or are on an exciting winning streak and want to continue with the same experience. This provides an opportunity to enhance the firm's current matching algorithm by suggesting that the player's consumption outcomes affect their preferences over time.

In the general context of experiential products, understanding whether consumers are variety-seeking or inertial may allow firms to provide better recommendations to consumers by taking their ratings on prior purchase or consumption occasions into account as a measure of their consumption outcomes. Net Promotor Scores have become an increasingly popular way for marketing practitioners to classify consumers based on whether or not they would recommend a firm's products to others, and our findings suggest that it might be effective for a firm to target satisfied customers with products that are similar to those they consumed in prior occasions, but target dissatisfied customers with products that are very different.

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