Researchers in psychology and behavioral economics have shown that the sequence of events plays an important role in the way we evaluate experiences. They have shown that the perception of the peak event, the last event, and the general trend of the sequence are important in predicting overall memory of an experience. Building on multi-disciplinary streams of past research, we investigate whether the sequence schedule of discrete events within a service bundle impacts customer repurchase behavior. Using a unique archival data source provided by a renowned performing arts venue, we build and test an econometric model to predict season ticket subscription repurchase and to determine if the temporal placement of events impacts repurchase. We find evidence of peak, end, trend, and spread effects and discuss the importance of sequence in determining service design and scheduling. These results have implications for effective service design for a wide range of industries.
1. Introduction

Scholars have suggested that the sequence of events within a service encounter can influence customer’s overall perception of the quality and satisfaction associated with the service (Chase and Dasu 2001, 2008, Cook et al. 2002). Specifically, Chase and Dasu (2001) suggest various strategies for service sequencing including placing the lowest point or bad news at the beginning of the encounter, ending the service on a high note, and improving the experience over time. While these ideas have intuitive appeal, to our knowledge they have not been empirically validated. The value of service sequencing on future customer behavior (e.g. repurchase) or operations (e.g. scheduling of events; capacity planning) have also not been explored.

In a related research stream, it has been shown that not all attributes of a service are equally considered by the customers, i.e., customers place different weights on various elements of a service (Verma et al. 1999). However, the past research has not explored if the temporal aspects of a service (i.e. sequence) also have unequal utility. Consumer behavior scholars have theorized that the underlying values of consumption of a service or product include not only functional values, but also conditional, and emotional values (Sheth et al. 1991). Behavioral research suggests that temporal sequencing influences these non-functional attributes in such a way as to significantly influence perception.

Effective service design involves developing a service concept that appeals to end users considering operational constraints (e.g. Verma et al. 2001). Furthermore, past research has emphasized that operations management’s role in designing a service concept involves understanding “what” should be done and “how” it should be done (e.g. Goldstein et al. 2002). While the methods and frameworks to accomplish the “how” of a service concept are in abundance, the often unasked questions within “how” is “when” i.e., does the delivery sequence of the service concept have an impact on customers’ experiences?

In this paper, we investigate how the temporal placement or sequence of events within a service bundle impacts future customer repurchases behavior. Using a rich multi-year ticket purchase database from a world-renowned performing arts venue, we test the impact of event sequence on customer repurchase of subscription packages. Specifically we identify that the placement of high-utility events and the trend of the event utilities impact the probability of subscription repurchases. Furthermore, we illustrate how the estimated weights for sequence parameters can be used to make better operational and marketing decisions.

The rest of the paper is organized in the following manner: first, we provide a review of literature related to service bundling, and sequence-related behavioral research; second, we present our theoretical framework and hypotheses; third, we describe our research design and
analysis approach; fourth, we present our results and associated discussion; and finally we discuss theoretical and managerial implications of this research.

2. Literature Review

2.1 Service Bundling

We address the temporal sequence of events within the context of a service bundle, i.e., a combination of a number of different services sold in one package. Product and service bundling is a heavily researched topic in marketing (e.g., Guiltinan 1987, Harlam et al. 1995, Stremersch and Tellis 2002, Gaeth et al. 1991). The practice is common across many service industries, for example fast food industries offer meal packages, telecommunications and cable companies offer packages with several different services at one price, and performing arts venues sell season subscriptions that include tickets to a number of events. Some service bundles are created by bundling a number of different services that are intended to be used simultaneously, or concurrently. For example, for one monthly charge telecommunication firms provide internet, cable television, and home telephone service as a service bundle that is typically used concurrently. Other service bundles are created by placing similar discrete services together in a way that they have to be experienced across time or sequentially. For example, a course taught over 12 weeks may have 12 separate class sessions, a cruise ship package includes 5 days of separate experiences to different locations, or season ticket sales for performing arts or sporting events includes a number of different events experienced across a season. Within this second type of service bundles, the event sequence of some bundles is constrained, e.g., the 5 day cruise typically visits islands in a physically linear fashion. However, in other service bundles the sequence is not assumed fixed or at least not entirely fixed, e.g., the schedule of performances within a performing arts season subscription can be altered. These types of service bundles provide ideal testing grounds for applying sequence related behavioral research in the context of service design and scheduling because the sequence of the discrete segments can be changed.

Different hierarchical levels of bundling effectively act as a pricing rate fence, for example a cell phone company that bundles phone, IM, and internet access can charge different prices for different combinations of bundles. Thus, operations management researchers to date have primarily concerned themselves with revenue management or pricing issues surrounding product and service bundling (Bitran and Caldentey 2003, Bitran and Ferrer 2007, Aydin and Ziya 2008) and supply chain issues of supplier bundling or product mix purchasing (Schoenherr and Mabert 2008, Rosenthal et al. 1995). From an economic perspective, customers purchase bundles because their reservation prices for all individual elements are met, i.e., the actual price
for highly demanded elements is lower than the reservation price so the surplus is transferred to the less desired element of the bundle. Revenue management principles suggest that in order to optimize revenue on bundled services, the bundle should include both high demand and low demand services. To reach overall capacity maximization, managers would do best to spread out the most popular events across different bundles reaching a higher capacity for the less popular elements. Leveraging highly popular elements is at the cornerstone of revenue management with bundled services.

In a related research stream, a number of procedures to find “optimal” product and service attribute profiles have been developed to find an attribute mix that maximizes sales, market share (Green and Krieger 1989, Shocker and Srinivasan 1979, Ho and Zheng 2004), or profit (Green and Krieger 1991, Morgan et al. 2001, Moore et al. 1999, Raman and Chhajed 1995). Other researchers have developed attribute mix optimization models while considered operating constraints such as capacity (Pullman and Moore 1999), production costs (Moore et al. 1999), waiting time and labor scheduling (Pullman et al. 2000), and operational difficulty (Verma et al. 2001). This stream of research has contributed to an understanding of consumers’ choice of product and service attributes; however, to our knowledge, none of the optimization models have considered the sequence related attributes of service delivery.

2.2 Sequence-Related Behavioral Research

Based on a review of past behavioral research, Chase and Dasu (2001) proposed that among over things, customers remember three aspects of a service experience:

1. The trend in the sequence of pleasure and pain
2. The high and low points
3. The ending

These three aspects have been researched heavily in psychology and behavioral economics and are called Trend Effects, Peak Effects, and End Effects respectively.

Trend Effects

Generally speaking, people prefer a sequence of events that improves over time (Loewenstein and Prelec 1993). For example, Ross and Simonson (1991) demonstrated that gamblers prefer to first lose $15.00 then subsequently win $85.00 over first winning $85.00 then losing $15.00. Although the net gain is the same, the trend in the sequence of winning seems to impact the utility of the overall win.

In a legal research article (Walker et al. 1972) researchers found that the presentation sequence of different pieces of evidence impacts the overall judgment. The sequences that start with weak evidence and ends with strong evidence generally yield the most favorable judgments.
In another study, Loewenstein and Prelec (1993) describe an experiment which asks participants to choose between visiting a good friend one weekend and an abrasive aunt another weekend. A majority choose to postpone the (good) friend and visit the (abrasive) aunt first. They explain this behavior as a tendency to want to *savor* good outcomes by postponing them and quickly get through bad outcomes to eliminate a feeling of *dread*.

Similarly, other studies have shown that, all else being equal, an increasing wage profile is preferred to a declining or flat one (Loewenstein and Sicherman 1991). Ariely (1998) describes an experiment in which participants were asked to rate their pain under different pain sequence profiles inflicted with the aid of a calibrated vice squeezing the participant’s hand at different pressures. Profiles that started with high pressure and decreased over time rated much lower (56 out of 100) than those that started low and increased over time (75 out of 100). As we begin to adapt to the most recent stimulus, an improvement feels like a gain while a worsening move can feel like a loss. According to prospect theory, we tend to be more sensitive to a loss than a gain hence a preference for upward trends (Kahneman and Tversky 1979).

**Peak Effects**

Researchers studying memory have found that our minds are more prone to selectively capturing and remembering the snapshot of extreme high or low points (i.e. peaks) from a past experience rather than recording every detail of our lives (Burt et al. 1995, Nguyen and Belk 2007). Furthermore, the intensity and sequence of an experience seem to be more important than the *duration* of the experience. For example, Redelmeier and Kahneman (1996) discovered that the overall pain experienced by a patient is highly correlated with the highest degree of pain for patients during colonoscopies regardless of duration, e.g., patients whose colonoscopy lasted 1 hour compared to those whose colonoscopy lasted 15 minutes experience similar overall pain highly correlated to the peak pain felt.

In situations with multiple high points, Loewenstein (1987) identified a *spreading effect* explained by a preference to spread out preferred outcomes in a sequence. When participants were asked to choose between sequences with two good outcomes and one mediocre outcome (2 fancy dinners and one dinner at home), a majority choose to separate the good with the mediocre.

In a follow up study, Lowenstein and Prelec (1993) asked subjects to schedule 2 future weekends to use a pair of hypothetical $100 coupons to a restaurant. When subjects were told they had two years to use the coupons they spread out their plans using the first, on average, at week 8 and the second on week 31. Thaler and Johnson (1990) showed that people think they will be more happy if two positive events are temporally separated than if the same two events are temporally close (winning 2 lotteries on the same day vs. separated by a week). Chase and Dasu (2001)
recommend that service businesses consider segmenting pleasurable aspects of an encounter and combine the painful segments. They state that most people would prefer to win two $5 gambles as opposed to one $10 gamble essentially spreading out the winning episodes. The spreading effect ensures that a sequence is well “covered” by positive events.

Serial position effects explain that the presentation sequence impacts memory (Ebbinghaus 1902). Researchers have shown that when presented with a list of nonsense words to memorize, subjects displayed two types of serial position effects: primacy, or the ability to better recall the first items, and recency, the ability to better recall the last items. Primacy and recency have been found to form impressions and influence decision making (e.g., Asch 1946, Anderson and Barrios 1961). More recently, researchers have found that subjects rely heavily on their initial reference point in decision making. This effect has been termed an anchoring effect because the initial reference acts as an anchor that is not often or easily adjusted (Tversky and Kahneman 1974, Ariely et al. 2003). Recency, primacy, and anchoring suggest that what is remembered and used to form impression is at the beginning or the end.

End Effects

In a clinical trial Redelmeier et al. (2003) prolonged the less painful, yet still uncomfortable end of colonoscopy procedure for some patients and compared the assessment of pain for these patients against the those of other patients. The results showed that the overall pain assessment was lower for the experiential group. Similarly, those patients whose most intense pain (peak) was near the end of the procedure reported higher overall pain. Similarly, in his calibrated vice experiment, Ariely (1998) found that pressure profiles that started low and ended high, resulting in lower total pressure, had statistically equivalent ratings as a control group that had a consistent high pressure. This end effect reveals that the end of an experience impacts remembered utility (Kahneman et al. 1997).

Marketing researchers have used the above ideas in explaining how customer expectations are formed and how satisfaction with a product or service is expressed (e.g., Oliver 1980, Parasuraman et al. 1985). Within the operations management literature, sequence effects have been less researched. In their seminal book Service Breakthroughs: Changing the rules of the game, Heskett, Sasser and Hart (1990) discuss the idea of “service bookend” and emphasize the need for services to provide not only a strong ending, but also a strong beginning mirroring the ideas of primacy, recency, anchoring, and spreading effects. As stated earlier, Chase and Dasu (2001, 2008) are the pioneering operations management scholars to suggest that behavioral research ought to be considered in service design; however, they do not provide any additional
empirical evidence. They, however, propose that an upward trend and a strong ending are more
important than a strong beginning (Chase 2004). Other researchers have shown through
experimentation (Hansen and Danaher 1999) and service content analysis (Verhoef et al. 2004)
that an upward trend of sequence performance leads to higher perception of quality and
satisfaction; however, these studies only tested for a change in performance level across a fixed
sequence, not for changes in the sequence of the process itself, i.e. the service process remained
unchanged and only the performance levels changed. Other scholars (Bolton et al. 2006) have
shown that more recent service encounters as well as “extra mile” or extremely favorable
experiences influence system support service contract renewals. More recently, Britran, Ferrer,
and Oliveira (2008) further refine a conceptual framework of duration in a service encounter and
how it applies to profitability. They cite behavioral literature as it applies to duration and the
sequence of an encounter and conclude by calling for more varying techniques of empirical based
evidence across different industries and context.

Our research adds to the past literature by testing the presence of sequence effects in a
rich archival data source and by econometric modeling. Furthermore, we are interested in
temporal event placement within a service bundle i.e., we hope to uncover the effect that a change
in the sequence of events might have on customers, not just the change of the performance levels
over time of a fixed process. Finally, we provide insight on how sequence effects may be used in
event scheduling by searching for sequence effects in a service bundle that elapses over a long
period of time.

3. Theory and Hypotheses

The sequence literature reviewed above suggests that the sequence of events ought to
impact customer evaluation of a service. The decision to repurchase a repeating service bundle is
based largely on the evaluation of the previous experience with the service (Bolton 1998) In
evaluating a service bundle, customers evaluate their preferences, their satisfaction with the
bundle, the quality of the bundle and the value of the service (Zeithaml 1988, Parasuraman et al.
1985) in this study we are attempting to find evidence to support the theory that sequence effects
impacts customer behavior, but we are less interested in the complete causal path. At a highest
level, we propose that sequence effects influence customer evaluations of service bundles which,
in turn influences customer behavior.

Sequence Effects ➔ Evaluation of Service ➔ Customer Behaviors
The link from sequence effects to customer evaluations may be through customer satisfaction, service quality, or by adding value, but we leave the complete causal model to future research. However, we posit that sequence effects should be a proxy for customer evaluations and so should influence customer behaviors in predictable ways that will be outlined in our hypotheses.

Within consumer behavior research there is a proposed model of consumption that identifies multiple independent product and service attributes that lead to utility. These include functional, conditional, and emotional attributes. Functional value is gained from the functional or utilitarian aspects of the physical attributes. Conditional value is added when the conditions are right for consumption of the product or service. Finally emotional value is added by arousing feeling or affective states. Sequence effects may increase value through conditional means by scheduling the right event at the right time, i.e. an event in a non-ideal time slot will not add value as much as it would in a more appropriate time. Similarly, sequence effects can influence emotional values by more positively influencing the affective state of an individual through considering trend, peak and end effects.

Choice modeling determines the utility of an alternative based on the characteristics of individual choosers and the functional attributes of the alternatives. By modeling a population's choice behaviors, we understand what functional attributes significantly led to making the choices. The traditional choice model can be expressed like this:

\[
\text{Prob}_i = f(\text{customer's attributes, alternative's functional attributes})
\]

In words, the probability of choosing alternative \( i \) is a function of the customer's attributes and the alternatives (or product and service functional) attributes. In this manner, service design researchers have shown that service providers can gain valuable information about what type of customers are drawn to their offering and what these customers prefer.

When predicting a repurchase of a service, we assume that including the evaluation of the service in addition to customer attributes and product and service attributes will improve the prediction. Since we believe that sequence effects should proxy customer evaluations we theorize that including sequence effect attributes into a probabilistic choice model will improve the model's fit. We propose that an econometric prediction of customer repurchase will be improved with the inclusion of variables that represent the sequence of the utility of discrete events within

8
the bundle. This hypothesis can be tested by comparing nested models, i.e. comparing the fit of an estimated model that lacks sequence related variables against a model that includes them.

**H1:** Prediction of customer repurchase will improve significantly by considering sequence attributes above and beyond just considering customer characteristics and product (goods and/or service) features.

This first hypothesis is our primary concern, simply put, we hope to find the sequence of events matters in the repurchase decision. We follow up this primary research question with less general hypotheses that investigate specific sequence theories.

The colonoscopy related research (Kahneman et al. 1993, Redelmeier et al. 2003) found that a patient’s perception of overall pain was influenced significantly by the peak pain level suggesting that as the peak event increases in utility, its impact is more pronounced. These lines of research suggest that the peaks are more remembered and influence customer’s evaluation more than other events which leads to our next hypothesis. Note that we consider the event with the highest utility to be the peak, i.e., our notion of “peak” is positive (utility) instead of negative (pain), but we expect similar results.

**H2a:** Customers are more likely to repurchase as the peak event utility increases.

Similarly, the colonoscopy research found that the pain level at the end of the procedure also significantly impacted overall perception. The end effect suggests that the last event of a sequence impacts customer evaluation, and so we predict that as the utility of the last event increases its effect will remain salient in customer’s minds and will result in a higher overall assessment.

**H2b:** Customers are more likely to repurchase as the last event utility increases.

Combining the peak and end effects, colonoscopy research found that by extending the end of the procedure so that the peak pain was further from the end led to improved pain evaluations. Similarly, procedures that ended shortly after the peak pain had worse evaluations. In our case, we expect that the placement of the peak event near the end of a sequence should positively influence assessment. A bundle ending with a peak should result in a higher overall assessment of the bundle, e.g., if the last event in a season subscription package includes an all-
star cast of musicians performing traditionally crowd pleasing pieces, then the patrons will remember the event and give high marks to the entire subscription. On the other hand, if the all-star performance occurs further from the end of the season, the subsequent, less exciting events may diminish the utility of the peak experience thus lowering the overall assessment.

**H2c:** Customers are more likely to repurchase as the peak event nears the end of the sequence.

Finally, Chase and Dasu (2001) suggest that as a sequence improves over time the feeling of loss is avoided and customer evaluations improve. We predict that an upward trend of event utility should impact customer evaluation positively.

**H2d:** Customers are more likely to repurchase as the trend of the events utility over time increases.

4. **Research Design**

In order to test the proposed hypotheses we estimate a series of econometric models that predicts probability that a customer who had purchased a given service bundle for a given time period, would again purchase a bundle from the same cycle the subsequent time period. (In this paper we refer to purchase of each service bundle as a “cycle” and a time-period as a “season”).

Specifically, for the set of customers $C$ who bought cycle $j$ season $t$, we are interested in predicting whether or not each customer will buy cycle $j$ season $t+1$, i.e. the same cycle the subsequent season. The unit of analysis is individual customers who purchased a given cycle the previous season and our dependent variable is binomial: 1 if the customer purchased the same cycle the subsequent year, 0 if they did not. Since our dependent variable is binary, we have chosen to model the data using logistic regression. Our econometric model uses the following form,

$$\ln \left( \frac{P(Y_{cjt+1} = 1)}{1 - P(Y_{cjt+1} = 1)} \right) = \beta X + \epsilon$$

where $Y_{cjt+1} = 1$ represents a repurchase of bundle $j$ in season $t+1$ (the next season’s bundle for the same cycle) by customer $c$, $X$ is a vector of predictors, $\beta$ is the vector of coefficients including an intercept, and $\epsilon$ are the errors. This model is estimated across all customers $i$ who purchased bundle $j$ in season $t$. The model predicts the log-odds of repurchase
given the set of independent variables using a maximum likelihood estimator assuming the
distribution of errors follow a logit distribution. Described in more detail below, the independent
variables include customer characteristics, service attributes, and sequence-related variables.

4.1 Data Description

To test the proposed hypotheses we use a multi-year subscription ticket purchase
database for an internationally renowned performing arts venue located in Europe. This concert
venue houses 5 concert halls that can be used simultaneously. The venue hosts approximately 300
events per year and offers over 40 different subscriptions to its customers. The database includes
6 years (seasons) of ticket sales data from 2001 to 2007 including over 1 million individual ticket
sales transactions for more than 2,400 events purchased by over 50,000 unique customers. The
database includes the date and time of the ticket purchase, the price paid, membership status of
the customer during time of purchase, general seating category (based on price category), and
whether the ticket was purchased as a part of subscription. Additionally, we are given details
about all the events such as the date and time of the event, the genre of the event (out of 16
possible genres), and the specific concert hall used for the event. Finally, we have limited
customer specific information that is optional when creating an account with the venue: gender,
title, degree held, postal code, etc. Figure 1 shows the percentages of tickets sold as subscription
for each genre.

The subscriptions offered by the venue are theme based cycles offered year over year.
Most cycles are based either on a certain genre or are specific to a particular ensemble. Themes
based on genre alone include Jazz, Classical Symphony, Music and Film, Piano, Children’s
Music, etc. Other themes include Rising Stars, International Orchestras, International Quartets,
Beethoven, Original compositions, etc. The cycling nature of the subscriptions allow us to link
subscription bundles year to year to determine if a given customer repurchased the same cycle the
next season. For the purpose of terminology we will now refer to a subscription cycle as a theme
based subscription that can be tracked year over year over several seasons and a subscription
bundle as a specific season in a subscription cycle. In the six years of data we find 41 subscription
cycles that can be tracked for all six seasons for a total of 246 subscription bundles. There are
other subscriptions cycles that do not span over all six seasons, but for reasons forthcoming, they
are left out of the analysis.

4.2 Customer Specific Variables
In predicting repurchase, three general sets of variables are considered: first customer specific attributes, second bundle specific attributes, and finally sequence specific variables. We are not primarily interest in customer and bundle specific attributes, but they are included in the model to act as control variables. Additionally, our main hypothesis states that by including sequence attributes our model should improve; therefore, we will be comparing models that include sequence variables with those that do not.

Customer specific attributes include gender, seating category of tickets (seat placement), number of bundles purchased (for a given bundle, not across all bundles) total number of unique bundles purchased for the season, days from purchase date to first event in the bundle (measure of how early a bundle was purchased), and membership status. Since we are predicting the purchase of cycle \( j \) season \( t+1 \), we will derive the above mentioned variables from ticket sales data for season \( t \). Additionally, we have created a variable to determine the customer’s loyalty with the bundle. We have classified customers into four groups and subsequently predict that the groups can be thought of as ordinal in their likelihood to repurchase. The first group consists of those customers who have purchased the given subscription cycle for the past 3 seasons; we named these customers *Loyal*. The second group consists of customers who have purchased a given cycle for the past 2 seasons, but not 3 seasons; we name these *Potential* as in “Potentially Loyal”. The third group is named *Fickle* and is made up of customers who have purchased a given cycle one season ago and three seasons ago, but not two seasons ago. They are fickle because they are not consistent in repurchasing. Finally the last group is called *New* and is made up of those customers who have purchased the cycle for only one season. By calculating the loyalty variable we set a limit on the data that can be used in the model. We begin with predicting the fourth season \( (t=4) \) since season 1 would be season \( t-3 \), season 2 would be season \( t-2 \) and season 3 would be season \( t-1 \). Still, with this restriction we are left with data for seasons 4, 5, and 6 for which have 44 cycles giving us 128 bundles (40 cycles with 3 seasons + 4 cycles with 2 seasons). Within those 128 bundles we find a total sample size of \( n = 31,816 \) customers who had purchased a given cycle the previous season. Given the total size of the dataset and the resulting sample size for the model, we are satisfied with reducing the data in order to derive the loyalty variables.

In our final estimation of the logit model, we excluded a random 10% of the observations to use to validate the accuracy of the model as explained in the Appendix section. Further, we identified and excluded 1 outlier observation that proved to be a significant influence on the model estimation, again described in more detail in the Appendix section. Table 1 shows a summary of the customer specific variables.
4.3 Bundle Specific Variables

Both marketing and operations management researchers consider product/service mix as an important aspect of customer satisfaction, perception, intention, and subsequent choice processing. Product and service mix is the set of attributes for a given product and service, e.g. a hotel property might include an exercise facility, a pool, a restaurant, wireless internet, and concierge service; a credit card might have fraud protection, online account access, automatic bill pay and cash back rewards; a car might have good gas mileage, 5 cup holders, moon roof and Bluetooth capability. Service providers have to choose what attributes to include in their offering in order to entice the right customer to purchase. In the case of the concert venue, management must create bundles of subscriptions that include attributes such as the number of events in the bundle, the genre mix of the events, and the percent of events on weekend (Friday – Sunday) vs. weekday, and the percentage of non-matinee events vs. matinee (before 5 pm). Adding to the list of bundle specific variables, we include a measure of total bundle utility calculated as the sum of all the individual event utilities - event utility calculations are described in the next section. This variable can be thought of as a measure of the total number of events within the bundle as well as the relative popularity of the subscription as a whole. Table 2 provides a summary of the bundle specific attributes.
4.3.1 Determining the Utility of an Event

Researchers have dissected a service’s utility into the individual parts and attributes of the service. In our context, we would like to determine the utility that customers receive from each event within a subscription, e.g., if there are 8 events within a subscription we want to determine utility of each event. Perhaps the most appropriate measure of utility would come by asking each customer to rate the performance at the end of each show, but unfortunately we do not have access to such data. Instead, we have formed two measures that we use independently to represent event utility at an aggregate level.

Table 1: Descriptive Statistics of Customer Attributes Variables

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<td>Bundles Purchased*</td>
<td>1.94</td>
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<td>Unique Bundles Purchased*</td>
<td>1.74</td>
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Seating Category 8**

<table>
<thead>
<tr>
<th></th>
<th>1.2%</th>
<th>2.2%</th>
<th>1.9%</th>
</tr>
</thead>
</table>

Seating Category 9**

<table>
<thead>
<tr>
<th></th>
<th>0.3%</th>
<th>0.4%</th>
<th>0.3%</th>
</tr>
</thead>
</table>

Total

<table>
<thead>
<tr>
<th></th>
<th>9108</th>
<th>22708</th>
<th>31816</th>
</tr>
</thead>
</table>

* Averages reported

** Percentage of customers who purchased subscriptions from a given price category.

** Percentage do not sum to 100% because some customers purchased from multiple price categories.

** Seating Categories start with lowest priced seats (category 1) and ascend to highest price seats (category 8).
The first measure of event utility that we use is the event’s average ticket price. As a part of the essential “P’s” of marketing, price communicates to customers the company's intended value for its product or service. From a customer's perspective, the price of the product must exceed or at least equal any expected value derived from the product or service. It is, therefore in the company's best interest to set its price in relation to the value delivered and perceived by its customers. If the price is set too high the customer will not buy and if it is set too low the company is foregoing potential profits. It is for this reason, we assume that the concert venue does a fair job at pricing the events such that its price close to the value customers expect to experience from the event.

Kotler explains that as customers get a feel for the actual quality as opposed to perceived quality of a product the price plays a smaller role representing quality. However, as an actual measure of quality is unknown to a customer, the price is the primary signal used to determine expected quality. In the case of concert events, it may be difficult for customer to assess the quality of a specific event especially if it is an artist or performance that is unknown to the customer.

The second measure of utility is a measure of both seat occupancy and ticket price: Revenue per Available Seat (REVPAS). REVPAS is calculated by dividing the total revenue for each event by the total number of available seats for the event.

\[
ticket price_{ce} = \text{the price that customer } c \text{ paid for event } e. \\
available seats_{e} = \text{the number of available seats for event } e.
\]

\[
REVPAS_{e} = \frac{\sum c ticket price_{ce}}{available seats_{e}} \tag{2}
\]

REVPAS is borrowed from the revenue management field for which some measure of revenue per available unit is maximized. For example, revenue per available room (REVPAR) is used widely in the hotel industry and has been shown to be highly correlated to customer satisfaction (Davidson et al. 2001, Davidson 2003), service quality (Kimes 2001, 1999), and brand loyalty (Kim et al. 2003, Kim and Kim 2005). This research suggests that hotels with higher REVPAR provide more utility to their customers. Similarly, we believe that REVPAS is an appropriate measure of an event’s overall utility because it takes into account the price at
which tickets are sold, the number of tickets sold, and the occupancy (or the number of tickets left unsold).

Our data does not provide us with the means to derive an individual customer level measure and so we choose to test our hypotheses with aggregate measures. Certainly this is a weakness of our model from an individual customer's perspective and is not ideal in deriving a choice model; however, from the stand point of the service provider, an aggregate measure is needed to implement a scheduling methodology based on our results. We assume that event schedulers forecast aggregate demand for each event and set prices accordingly. The forecasts are based on a combination of past attendance data and industry trend knowledge. Because the forecasts are derived from the same data we use in deriving event utility, they can then be used to sequence the events according to the results of our model.

Similarly, an individual level utility measure can also be rolled up to make aggregate forecasts, and its advantages include being able to create bundles that target a specific segment for which the aggregate utility represent poorly. We leave for future research target market bundle creation based on individual utility measures, but with this exploratory research we are content with assuming that the aggregate measure reflects a fair starting point in investigating the presence of sequence effects in our context. Table 2 show descriptive statistics for bundle variables.

4.4 Sequence Variables

The sequence variables are of primary interest in this model as they will be used to test our hypotheses. Recall from the previous section that we have two measures of utility that will be calculated for each event. We identify the event with of the highest utility within a subscription and capture its utility as the peak event utility. Additionally, the last event’s utility is considered. Additionally, we measure the number of days from the peak event to the last event. To consider the trend of the sequence of events, we calculate the utility slope for the line fit in ordinary least squares regression through event utilities and the number of days from the beginning of the bundle.

Finally, we have created variables to indicate if bundles include a true peak, a valley or if the events in the bundle are relatively homogenous in utility. To determine these categories we plotted the event utilities across time for each subscription and coded bundles that appeared to have a peak, a valley or neither. After coding, we observed that those with a peak or a valley had a range of utility that was at least greater than 10 (with REVPAS); 10 corresponded closely to the 75th percentile of ranges for all bundles. Those bundles with ranges less than the 75th percentile where then coded Flat. For the remaining bundles, we calculated the average utility within a
bundle and compared it to the peak event utility and the valley event utility. If the difference from the peak to the average was greater than that from the valley to the average, then the bundle was coded as \textit{Peak}. If the opposite was true, the bundle was coded \textit{Valley}. Figure 2 shows an example of each of the three categories and Table 3 shows the summary of the Sequence Attributes.

Table 3: Summary of the Sequence Attributes

<table>
<thead>
<tr>
<th>Genre Mix*</th>
<th>Average</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ancient Music</td>
<td>3%</td>
<td>15%</td>
</tr>
<tr>
<td>New Music</td>
<td>4%</td>
<td>19%</td>
</tr>
<tr>
<td>Jazz</td>
<td>2%</td>
<td>15%</td>
</tr>
<tr>
<td>World Music</td>
<td>5%</td>
<td>21%</td>
</tr>
<tr>
<td>Children’s Music</td>
<td>19%</td>
<td>39%</td>
</tr>
<tr>
<td>Literature</td>
<td>2%</td>
<td>15%</td>
</tr>
<tr>
<td>Organ Music</td>
<td>2%</td>
<td>14%</td>
</tr>
<tr>
<td>Piano Music</td>
<td>8%</td>
<td>26%</td>
</tr>
<tr>
<td>Chamber Music</td>
<td>23%</td>
<td>41%</td>
</tr>
<tr>
<td>Vocals</td>
<td>7%</td>
<td>21%</td>
</tr>
<tr>
<td>Choral Music</td>
<td>0%</td>
<td>1%</td>
</tr>
<tr>
<td>Orchestra</td>
<td>21%</td>
<td>37%</td>
</tr>
<tr>
<td>Film</td>
<td>3%</td>
<td>15%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Total Bundles Considered</th>
<th>128</th>
</tr>
</thead>
</table>

Number of Genres in Bundle | 1.33 | 0.74 |
Percentage of Events on Weekends | 52% | 33% |
Percentage of Events in the Evening | 80% | 37% |

<table>
<thead>
<tr>
<th>Total Bundle Utility</th>
<th>REVPAS</th>
<th>Average Ticket Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>93.23 (72)**</td>
<td>133.82 (75)**</td>
<td></td>
</tr>
</tbody>
</table>

* represents percentage of genre in all bundles
** average (standard deviation)

Figure 2: Examples of Peak, Flat, and Valley Bundles
Due to the large number of variables available to predict repurchase, we have chosen to create 3 models nesting the three main variables types: customer specific, bundle specific, and sequence specific. Nested model comparisons can be used to determine if adding additional variables leads to an improved fit. The flowing three models were estimated:

Model 1: Customer Specific Variables
Model 2: Customer Specific and Bundle Specific Variables
Model 3: Customer Specific, Bundle Specific, and Sequence Variables.

Since we use two measures of event utility, and variables derived from event utility are found both in bundle specific and sequence specific variables, models 2 and 3 will be estimated twice – once for each utility calculation. Because of the panel nature of our data (same customer over several time periods) we include a fixed effect for season by adding two dummy variables for seasons 4 and 5. This will control for unobserved homogeneity within each season. To control for unobserved homogeneity within customers, we estimated the model in several ways: using customer ID as a random intercept and alternatively using Huber White Robust (sandwich) errors.
clustered on customer ID. Neglecting to account for the intercorrelation of observations within panel data leads to a fear that the estimated variances will be inflated leading to improper interpretations of significance; however, in our case neither the random intercept nor the clustered errors approach yielded differences in the significance of any coefficient. We have chosen to report the result from a regular logistic regression with fixed effects across seasons, but without random intercept or clustered errors for customers. This approach is taken for two reasons: for the sake of parsimony and because the statistical comparison of nested models is established when the models are estimated with maximum likelihood (logistic regression) as opposed to a bootstrap, jackknife, or method of moments estimator (random intercept, clustered errors). Since our primary hypothesis is tested by comparing nested models and because the individual coefficient significances are not changed, we choose to present the simpler model.

The results of the models are shown in Table 4 and the model specifications are discussed in the Appendix.

Recall that the customer and the bundle attributes are not the primary concern for this study. We are interested in Model 1 and 2 primarily in comparison to Model 3. Therefore, we will only briefly discuss their results. The customer attribute model shows intuitive results:

- The coefficient for the number of days from purchase to the first event is positive indicating that customers are more likely to repurchase if they buy their tickets early.
- The more subscriptions purchased (both within the subscription and across the season) the more likely the customer is to repurchase.
- Males are more likely to repurchase compared to females.
- Customers that are also Members are more likely to repurchase than non-members.
- Compared to New customers, Loyal, Potential, and Fickle customers are all more likely to repurchase. Surprisingly Fickle customers are more likely to repurchase than Potential customers.
- Customers who purchase higher priced seats (Seat Categories) have a higher likelihood of repurchase.

The customer attributes in the second and third model retain their sign and general magnitude. The new variables introduced in the customer and bundle model show the following results:
### Table 4: Logistic Regression Results

<table>
<thead>
<tr>
<th>Event Utility Measure</th>
<th>All</th>
<th>REVPAS</th>
<th>Average Ticket Price</th>
<th>REVPAS</th>
<th>Average Ticket Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.702**</td>
<td>-0.062</td>
<td>0.083</td>
<td>-0.279~</td>
<td>-0.296~</td>
</tr>
<tr>
<td>Season 4</td>
<td>-0.028</td>
<td>-0.017</td>
<td>-0.026</td>
<td>0.007</td>
<td>0.012</td>
</tr>
<tr>
<td>Season 5</td>
<td>0.014</td>
<td>0</td>
<td>-0.003</td>
<td>-0.013</td>
<td>0.031</td>
</tr>
<tr>
<td>Days from purchase to first event</td>
<td>0.002**</td>
<td>0.003**</td>
<td>0.003**</td>
<td>0.002**</td>
<td>0.002**</td>
</tr>
<tr>
<td>Subscriptions Purchased</td>
<td>0.02</td>
<td>0.098**</td>
<td>0.098**</td>
<td>0.102**</td>
<td>0.103**</td>
</tr>
<tr>
<td>Total Subscriptions purchased in the season</td>
<td>0.018</td>
<td>0.046**</td>
<td>0.045**</td>
<td>0.048**</td>
<td>0.046**</td>
</tr>
<tr>
<td>Gender Mvs. F</td>
<td>0.061*</td>
<td>0.028</td>
<td>0.028</td>
<td>0.028</td>
<td>0.03</td>
</tr>
<tr>
<td>Gender Unknown v F</td>
<td>-0.014</td>
<td>-0.034</td>
<td>-0.033</td>
<td>-0.03</td>
<td>-0.029</td>
</tr>
<tr>
<td>Membership</td>
<td>0.351**</td>
<td>0.203**</td>
<td>0.216**</td>
<td>0.183**</td>
<td>0.188**</td>
</tr>
<tr>
<td>Loyd vs. New</td>
<td>2.175**</td>
<td>2.022**</td>
<td>2.033**</td>
<td>2.015**</td>
<td>2.028**</td>
</tr>
<tr>
<td>Potential vs. New</td>
<td>0.386**</td>
<td>0.358**</td>
<td>0.359**</td>
<td>0.376**</td>
<td>0.368**</td>
</tr>
<tr>
<td>Fickle vs. New</td>
<td>0.974**</td>
<td>0.902**</td>
<td>0.908**</td>
<td>0.858**</td>
<td>0.911**</td>
</tr>
<tr>
<td>Seating Category 1</td>
<td>-0.296**</td>
<td>-0.063</td>
<td>-0.078</td>
<td>-0.073</td>
<td>-0.053</td>
</tr>
<tr>
<td>Seating Category 2</td>
<td>-0.112*</td>
<td>-0.086</td>
<td>-0.095*</td>
<td>-0.099*</td>
<td>-0.074</td>
</tr>
<tr>
<td>Seating Category 3</td>
<td>-0.186**</td>
<td>-0.145**</td>
<td>-0.152**</td>
<td>-0.163**</td>
<td>-0.122*</td>
</tr>
<tr>
<td>Seating Category 4</td>
<td>-0.092*</td>
<td>-0.115*</td>
<td>-0.123*</td>
<td>-0.121*</td>
<td>-0.103*</td>
</tr>
<tr>
<td>Seating Category 5</td>
<td>-0.046</td>
<td>-0.032</td>
<td>-0.037</td>
<td>-0.044</td>
<td>-0.013</td>
</tr>
<tr>
<td>Seating Category 6</td>
<td>0.019</td>
<td>0.006</td>
<td>0.001</td>
<td>-0.012</td>
<td>0.015</td>
</tr>
<tr>
<td>Seating Category 7</td>
<td>0.047</td>
<td>-0.014</td>
<td>-0.024</td>
<td>-0.028</td>
<td>-0.01</td>
</tr>
<tr>
<td>Seating Category 8</td>
<td>0.391**</td>
<td>0.365**</td>
<td>0.355**</td>
<td>0.363**</td>
<td>0.351**</td>
</tr>
<tr>
<td>Seating Category 9</td>
<td>-0.062</td>
<td>-0.016</td>
<td>-0.017</td>
<td>-0.001</td>
<td>-0.016</td>
</tr>
<tr>
<td>Ancient Music vs Orchestra</td>
<td>0.044</td>
<td>0.009</td>
<td>0.009</td>
<td>0.275*</td>
<td>0.168</td>
</tr>
<tr>
<td>Jazz vs Orchestra</td>
<td>0.141</td>
<td>-0.007</td>
<td>0.013**</td>
<td>0.159</td>
<td></td>
</tr>
<tr>
<td>World Music vs Orchestra</td>
<td>-0.249**</td>
<td>-0.334**</td>
<td>0.024</td>
<td>-0.266**</td>
<td></td>
</tr>
<tr>
<td>Children's Music vs Orchestra</td>
<td>-1.539**</td>
<td>-1.697**</td>
<td>-1.46**</td>
<td>-1.479**</td>
<td></td>
</tr>
<tr>
<td>Literature vs Orchestra</td>
<td>-0.478**</td>
<td>-0.578**</td>
<td>-0.37**</td>
<td>-0.422**</td>
<td></td>
</tr>
<tr>
<td>Organ Music vs Orchestra</td>
<td>-1.007**</td>
<td>-1.174**</td>
<td>-0.681**</td>
<td>-0.948**</td>
<td></td>
</tr>
<tr>
<td>Piano Music vs Orchestra</td>
<td>-0.454**</td>
<td>-0.515**</td>
<td>-0.297**</td>
<td>-0.451**</td>
<td></td>
</tr>
<tr>
<td>Chamber Music vs Orchestra</td>
<td>-0.156*</td>
<td>-0.241**</td>
<td>-0.142*</td>
<td>-0.157*</td>
<td></td>
</tr>
<tr>
<td>Vocals vs Orchestra</td>
<td>-0.021</td>
<td>-0.071</td>
<td>-0.061</td>
<td>-0.021</td>
<td></td>
</tr>
<tr>
<td>Choral Music vs Orchestra</td>
<td>-0.288</td>
<td>-0.217</td>
<td>-0.197</td>
<td>-0.571</td>
<td></td>
</tr>
<tr>
<td>Films vs Orchestra</td>
<td>-0.13</td>
<td>-0.27*</td>
<td>0.064</td>
<td>0.026</td>
<td></td>
</tr>
<tr>
<td>Total Number of Genres in the Subscription</td>
<td>-0.204**</td>
<td>-0.222**</td>
<td>-0.204**</td>
<td>-0.219**</td>
<td></td>
</tr>
<tr>
<td>Percent of Events on Weekend</td>
<td>0.029</td>
<td>0.047</td>
<td>0.119</td>
<td>-0.023</td>
<td></td>
</tr>
<tr>
<td>Percent of Events in the Evening</td>
<td>-0.613**</td>
<td>-0.59**</td>
<td>-0.806*</td>
<td>-0.72**</td>
<td></td>
</tr>
<tr>
<td>Sum of all Events Utility</td>
<td>0.001**</td>
<td>0.001</td>
<td>0</td>
<td>0.001*</td>
<td></td>
</tr>
</tbody>
</table>

| Coefficients of Determination             |           |               |                     |               |                     |
| Pseudo R-Squared                          | 0.185     | 0.198         | 0.198               | 0.200          | 0.199               |
| Max-scaled R-Square                       | 0.265     | 0.283         | 0.283               | 0.286          | 0.285               |

| Nested Model Comparison Statistics        |           |               |                     |               |                     |
| SC                                        | 28,751    | 28,463        | 28,476              | 28,459        | 28,494              |
| -2 Log L                                  | 28,536    | 28,083        | 28,096              | 28,017        | 28,052              |

| Predictive Accuracy - Calculated with observations excluded from model estimation: n = 3107 |           |               |                     |               |                     |
| Brier Score                                | 0.1649    | 0.1615        | 0.1617              | 0.1614         | 0.1619              |

** Estimate Significance using Wald Chi Squared Test: ** Significant at * Significant at alpha < 0.05  ~ Significant at alpha < 0.10
• Compared to Orchestra, nearly all genres have negative estimated coefficients indicating lower likelihood of repurchase.
• As the number of genres in a bundle increases, repurchase likelihood decreases indicating that on average, mixed genre bundles do not fare as well as single genre bundles.
• As the percentage of weekend events in a bundle increases, repurchase is more likely.
• As the percentage of evening events in a bundle increases repurchase is less likely.
• Total bundle utility (sum of all event utility) is significant (with REVPAS) and positive (with both measures of utility) in the 2nd model, indicating that as the total bundle utility increases, repurchase likelihood increases. However, when the sequence variables are introduced in the 3rd model, the total bundle utility variable loses significance, indicating that total bundle utility can be better explained with the sequence variables.

5.2 Hypotheses Testing and Discussion

Our primary hypothesis, by including sequence variables the model will improve, can be tested by comparing nested model comparison statistics. We can see that the models improve as they progress as the Schwarz Criterion (SC) and the -2 log likelihood are decreasing as more variables are added. Using the difference in degrees or freedom across the models we can create a hypothesis test to determine if the added variables in the model significantly add to the fit of the model. Table 5 shows that comparing Model 2 to Model 1 there is evidence that the added variables improved the model (p < 0.00001). Similarly, going from Model 2 to Model 3 (within utility type) there is evidence that the sequence variables also improve the model’s fit significantly (p < 0.00001) providing support for H1.

This conclusion indicates that the sequence variables, as a whole, significantly impact

\[
(-2 \text{ Log Likelihood}_{model 1}) - (-2 \text{ Log Likelihood}_{model 2}) \sim \chi^2
\]

\[
df = \text{df}_{model 2} - \text{df}_{model 1}
\]

<table>
<thead>
<tr>
<th>Table 5: Likelihood Ratio Test for nested model comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>(-2 Log Likelihood _model 1) – (-2 Log Likelihood _model 2) \sim \chi^2</td>
</tr>
<tr>
<td>df = df _model 2 – df _model 1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model 1: Customer Attributes Model</th>
<th>Model 2: + Bundle Attributes</th>
<th>Model 3: +Sequence Attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td>All _2 Log Likelihood 28,536 20</td>
<td>Revaps 28,083 36</td>
<td>Average Ticket 28,096 36</td>
</tr>
<tr>
<td>DF</td>
<td>REVPAS 28,017 42</td>
<td>Average Ticket 28,052 42</td>
</tr>
<tr>
<td>Likelihood Ratio</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Degrees of Freedom</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pr &gt; ChiSq</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* comparing Model 2 with Model 1
** comparing Model 3 with Model 2

21
the repurchase behavior of the customers in our dataset regardless of the utility measure that is used. As discussed in the hypotheses development section, we believe that the sequence of a service will contribute to its value in turn impacting its evaluation and ultimately the behavior of the customer. In our dataset, we had no direct measure of customer evaluation, but this result implies that by impacting repurchase decisions, the sequence variables can act, at some level, as a predictor of perceived value and customer evaluations and hence are an important aspect of service design.

The remaining hypotheses can be tested by considering the estimated parameters of the sequence variables. The coefficient for the Peak Event Utility is significant (p < .01) and positive under both REVPAS and average ticket price, indicating that H2a (customers are more likely to repurchase as the peak event utility increases) is supported. The coefficient for the Last Event is significant for REVPAS (p<.05) and positive, indicating that H2b (customers are more likely to repurchase as the last event utility increases) is supported. The coefficient for Days from Peak Event to Last Event is significant (p< .05) and positive for both REVPAS and average ticket price, indicating that as the peak event is further from the last event, repurchase is more likely. This result contradicts H2c (Customers are more likely to repurchase a subscription as the time from the peak event to the time of last event shortens) and is discussed in detail in the next paragraph. The coefficient for the bundle slope is significant with REVPAS (p < .001) and positive, indicating that as the utility of events improve over time (positive upward slope) repurchase probability increases, providing support for H2d.

5.3 Managerial Implications

As it was proposed, the effects of the relative peak event utility and the last event utility can play a significant role in predicting repurchase, mainly that as the utility of the peak event and last event increase, so too does repurchase. The non-trivial finding is that the likelihood of repurchase does not increase as the peak event nears the end, rather the likelihood increases as the peak event gets further from the end (or closer to the beginning). This can be explained by considering the spreading effect that has been found to be present in sequences with more than one desirable event. When asked to plan two nights in the future to eat at a fancy restaurant, most people would prefer to separate the dinners over time. The same seems to be occurring in our case, mainly that the last event should have high utility and that the peak event (highest utility event) should be near the beginning, spreading out the two desirable events. In the sequence of pain literature, the peak or highest amount of pain was best placed further from the end as well; the explanation was that the highest pain would be less-remember if it was further from the end.
In our case, the peak is best suited further from the end for reasons of savoring pleasure across a longer period of time.

The spreading effect that we have found is bounded by the positive coefficient for the slope, i.e. if an early peak placement creates a negative slope, the probability of repurchase will decrease instead of increase. This means that a peak event should be placed as far away from the end so as to maximize marginal benefit from the spreading effect without decreasing the benefit derived from the trend (slope) effect. In our data, this usually means that the ideal spot for the peak event is rarely the first event, but can often be the second or third event (see illustration of scheduling optimization in appendix for an example). This suggests two things, first that the trend or momentum that is inherent in progressively increasing event utility lead to improved sequences, and second that the first event and hence first impressions do not need to be the climax of the bundle. Intuitively it would be ideal to set the initial expectation as low as possible by placing a low utility event first followed closely by the peak event with a drop in utility after building up to a high ending. This structure allows the customer’s expectations to be surpassed, it allows for the spreading of high events (peak and end), and allows for an overall all positive trend.

Of interesting and unexpected note, the coefficient for Peak Subscriptions vs. Flat Subscriptions is significant (p<.01) and negative, indicating that customers are more likely to repurchase a bundle that is homogenous as opposed to one that has a peak. However, there is no evidence that repurchase probability differs between flat subscriptions and valley subscriptions. By changing the reference category from Flat to Valley the coefficient for Peaked vs. Valley is significant (p<.01) and negative (-0.49 for REVPAS), indicating that repurchase decreases for peak subscription compared to valley subscription. The result that “peaked” bundles fared worse than “flat” bundles adds further complexity to our findings. Just as the number of days from peak was bounded by a preference for positive slopes, the preference for high peak and end utilities is bounded by the preference for bundles made up of relatively homogenous events in terms of utility. This suggests that customers are not impressed by highly leveraged bundles that include one event that is highly popular bundled with less popular events. This strategy may improve short term occupancy and ticket sales numbers; however, it does not appear to lead to sustainable repurchase rate. To the extent that highly popular events occur, we provide two suggestions: 1. Bundle all high utility events together or 2. Spread out high utility events to bundles two at a time and spread them out in order to optimize the peak, end, trend, and spreading effects.

6. Conclusion
6.1 Theoretical Contributions

At the highest level, this research has provided a degree of empirical support for the peak, end, and trend effect theories set forth by previous researchers. Uniquely, we find evidence that these effects can be found in long sequences that elapse over an entire subscription season while past research has been focused on single interactions. Additionally, the model shows that scheduling sequence decisions may impact repurchase behavior of customers. Although our research may not be completely generalizable, we believe that the effect of utility based scheduling can be realized outside the context of performing arts; certainly scheduling sporting events, conferences, courses, and tour packages have similar bundling attributes that make them akin to scheduling based on estimated utilities. This type of scheduling is already well used within the entertainment industry, take for example television programming: for a given show across a season, the writers of most shows try to create some sort of upward trend that will climax at the season ending episode in order to encourage watchers to return to watch their show the next season. Service providers can learn from the entertainment industry and add value to their offering by attempting to schedule their services accordingly.

The best sequence shown in the first illustration above was simply the one that had the highest slope; it started with the lowest utility event and placed the remaining according to their sorted utility. However, the trivial highest slope solution is not always optimal because of the positive coefficients of the days from peak to first will try to pull the peak away from the last event. This happens generally under two conditions: first, the range of the utility in bundle is small, i.e. it was a flat bundle, or second, the utility of the events is bimodal in nature with two (or more) events that both act as peaks. In the latter case, the optimal sequence was one in which the bundle ended on the second highest utility event while the peak was pulled back in time just enough to maintain an optimal slope. This leads us to conclude that the sequence effect is not always a linear relationship, and that there may be room for opposing views on where the peak ought to be placed in time. Further it leads to managerial recommendations to create bundles that are bimodal in order to capitalize on the advantages of ending on a high note and placing a peak earlier in the bundle. Our results indicate that once a peak is reached, the schedule will do best to maintain the level of utility rather than drop down dramatically; an early climax is acceptable so long as the level can be maintained for the remainder of the bundle. Additionally, instead of simply considering a linear slope, a quadratic interpretation of the sequence utility may be more appropriate.
6.2 Limitations, Future Research, & Conclusions

The illustrative example that was provided above was useful in showing the impact that the sequence of events has on the model; however, in reality creating subscription bundles and scheduling an entire season of events is not as trivial as picking up one event and putting it in a different place in time. Some events have constraints placed on them by the performers (e.g. a guest artist in town) and others may be seasonal by nature (e.g. a Christmas show). In our illustration, we were able to easily find the local optimum given a set of events, but the more challenging problem is to solve a global optimum across all the bundles and events given that bundles can be made up of a much larger set of events across many different days. This problem is left for future research, most likely solved with heuristic optimization methods.

Our model is limited in that it predicts only one year of repurchase given the attributes of the previous year’s bundle. Instead, it may be important to consider the entire lifecycle of a cycle over many years and consider how sequence effect may impact an even longer view of the cycle. Although we found little evidence for primacy or anchoring, research on expectations shows that once an expectation is set, it is difficult for a service provider to lower its standard again. Does this imply that if a season ends on a high note, but the next season begins on a much lower note, customers will experience more disconfirmation because expectations are very high? Also, does the impact of the first show provide an anchor for which all other shows are judged? If so, then does a peak need to be more or less intense in order to be effective?

In considering peak and end effects it is not a stretch to think of an offering as a series of nested sequences all of which include some sort of peak and end effect. Returning to our television programming example, television writers consider the lifetime cycle of a show over perhaps 5 seasons and plan plot developments across the 5 seasons. The first season certainly has to catch the interest of an audience in order to provide continuance for the show and each season progressively becomes more intense as character development becomes more complex and plots become more and more interesting peaking with the final season. Within each season the episodes follow a similar sequence and even within each show segments follow a similar pattern. Similarly a subscription to 8 different musical performances can be considered as a series of nested sequences. At the highest level we have the events scheduling within the subscription as addressed in this paper, next the musical song sequence (how do you choose the order of the songs within a given concert), and finally each piece of music itself invokes peaks and valleys by creating tension and dissonance and release and harmony. Composers use volume, rhythm, tempo, timbre, and chord progression to evoke a sense of movement in which a peak is found and the end is achieved. At the highest level is the subscription cycle over its lifetime across several
seasons for which the general trend of each season may benefit from an upward trend building up to a peak.

We do not consider this study to be a “peak” in this field of research and certainly not its “end”. Business scholars can most certainly learn much from those experiences around us that perhaps unknowingly evoke the power of the peak and end effect. Drawing from other industry practices, business scholars can begin to understand how genuine peaks are created and how the lowest most level of the nested sequences may drive the peaks of the higher levels.

7. Appendix

7.1 Model Specifications

It is prudent to discuss the appropriateness of the econometric method in estimation. The assumptions for a logistic regression are relaxed compared to those of an ordinary least squares regression due to the fact that we use a maximum likelihood estimator. For a logistic regression we are primarily concerned with independence of the error term and a lack of multicollinearity. To test for the latter, we calculated variance inflation factors (VIF) for the final model showing that none of the variables have a VIF of higher than 10 with the highest of 8.3 and only three variables with VIF greater than 3. Similarly, by nesting the models and observing very little changes in previously estimated variables, we can conclude that multicollinearity is not severe in the models. Certainly there is correlation between observations as we often have the same customer over several seasons and across different cycles; similarly, there are many observations for each bundle and each cycle. A more complicated hierarchical mixed model could be more appropriate for the data, but we chose to present the empirical test of this model with normal logistic regression. To determine if the correlation between the observations is causing excessive overdispersion, in effect inflating the variance estimates, the Deviance and Pearson Chi Squared statistic were calculated. Both showed that there is no evidence of excessive overdispersion (Model 3: Value/df = .98, 1 p = 0.96, 0.29). Additionally, we estimated an alternative random intercept model that was customer specific, i.e. a random variable influencing the intercept for each individual customer was estimated, essentially controlling for the correlations within customers. Under this model, the estimated coefficients were nearly identical compared to the normal logistic model validating the earlier findings that overdispersion is not significantly influencing our results. For the sake of parsimony, we reported the results of the normal logistic model.
By plotting the Deviance difference and the Pearson Chi squared difference against the predicted probability, we were able to identify 1 observation that had a high level of influence on the model. Upon investigation, the observation was from a customer who had purchased 40 bundles for the same season subscription. This outlier proved to be a significant influence on the model and was removed from the final results since a purchase of 40 subscriptions for the same bundle was not typical (mean = 1.7) and did not represent a normal customer. No other single observations were left as significant influencers.

The overall models are significant shown by the Likelihood ratio, Score, and Wald test statistics indicating that at least one of the predictors has a beta not equal to zero for all three models. The R squared values are increasing across the three models. Predictive accuracy of the models was determined by calculating the probabilities of repurchase for the excluded 10% and calculating a Brier score (the average of the squared difference between the prediction and the outcome). Brier Scores range from 0 for a perfect prediction to 1 for a perfectly incorrect prediction, so a smaller score indicates an improved prediction. The scores for the 3 models improve across models (0.165, 0.163, and 0.162). By excluding a random set of observations in estimation, we were able to avoid bias that would result in using the same data to test the model as was used to fit the model.

7.2. An illustration

In this section we illustrate the impact that the sequence has on the probability of repurchase. First, we show what the probability model predicts under different event sequences of specific bundles for one customer. Next, we show average repurchase probability changes for different events sequences across a large population of customers and bundles.

A subscription bundle found in the dataset consists of the following events with utilities on the appointed day: on day 0 utility 23, day 48 utility 11, day 70 utility 41, day 90 utility 21, day 125 utility 20, and day 211 utility 20. If we keep the day of the event constant we can optimize the impact that the coefficients of the sequence variables will have on the overall probability.

**Figure 3: An Illustration: Best, Worst, and Current Sequences**

“Peak” Bundle

![Graph of the Peak Bundle](image)
probability of repurchase and identify the best and the worst sequence by using exhaustive search optimization, i.e. we solved for every permutation and found the sequences that maximized and minimized the effects of the sequence variable coefficients found in our estimation of Model 3. Figure 3 shows the current, best and worst sequence plotted. We notice that in this example there is a clear peak (utility = 41) and the peak is placed at the end under the best sequence and at the beginning for the worst sequence.

For comparison, we can imagine a separate bundle that has events on the same days, but with different event utilities: 23, 17, 25, 21, 20, and 21. The event utilities are more homogenous and the bundle would be classified as “flat”. When we find the optimal sequence for this set of event utilities we see a different story. Figure 4 shows that rather than the peak event being placed at the end, the best sequence places the peak event (utility = 25) as the second event. These two examples illustrate that different solutions can be reached based on the different mix of the events within the bundles. In the first example, a clear peak was placed at the end of the sequence magnifying the end effect and the trend effect. With the second example, there was no clear peak, but in fact the two top events with relatively close utilities (25 and 23) get spread out across the sequence magnifying the days from peak to end impact. In the first example we can see evidence of the peak & end effects, while in the second we see the spreading effect.

**Figure 4: An Illustration: Best, Worst, and Current Sequences**

“Flat” Bundle

Within the dataset we find an individual customer with unknown gender who has purchased 3 bundles from only this one cycle 72 days before the first event all in the price category three, who has not purchased a membership, but is a loyal customer who has purchased the same cycle the past 3 years. For this customer we can show the probability of repurchase for the worst, current and best sequence using the coefficients estimated earlier. Figure 5 shows the probabilities under the three sequences for both the examples used above, the “peak” bundle from
Figure 3 and the “flat” bundle of Figure 4. The increase in probability of repurchase from the current to the best sequence is 7% for the “peak” bundle, but only 2% for the “flat” bundle. It appears from this example that an improvement in the sequence for a “peak” bundle is much more impactful than an improvement in a “flat” bundle.

**Figure 5: Probability of Repurchase under Different Sequences for One Customer**

![Bar chart showing probability of repurchase for peak and flat bundles under different sequences.]

Following the same procedures, we have found optimal sequences for all the bundles with less than 8 events. Since solving for the optimal sequence was not the objective of this paper, we stopped at bundles with 7 events leaving us with a total of 19,606 observations from 98 bundles for which we had found the probability of repurchase under the current sequence, the worst sequence, and the best sequence.

Across this sample, we experience an average increase of 2% of repurchase probability from the current sequence to the best (68% to 70%) and 4% from the worst sequence to the best (66% to 70%). Among loyal customers, the increase is smaller, 1% and 2%, but for the remaining segments we see a much higher increase (see Figure 6) illustrating the impact that customer

**Figure 6: Average increase in probability of repurchase**

<table>
<thead>
<tr>
<th>Segment</th>
<th>Current Sequence to Best Sequence</th>
<th>Worst Sequence to Best Sequence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loyal</td>
<td>1.1%</td>
<td>5.3%</td>
</tr>
<tr>
<td>Potential</td>
<td>3.2%</td>
<td>6.5%</td>
</tr>
<tr>
<td>Fickle</td>
<td>2.3%</td>
<td></td>
</tr>
<tr>
<td>New</td>
<td>3.2%</td>
<td></td>
</tr>
</tbody>
</table>
loyalty has on sequence effects predicted in H4.

To further illustrate, we arbitrarily choose a cutoff point of probability for which we believe that a customer will repurchase. For illustration we choose 50% as our cut off, i.e. for any customer whose predicted probability of repurchase is greater than 50%, we believe that they will repurchase. Table 8 shows the results in the percentage of repurchases given the 50% cutoff for the worst, current, and best sequences. On average, 3.7% representing 725 total customers move from not repurchasing to repurchasing by moving from the current sequence to the best sequence. This number is purely illustrative, since the cutoff that we chose may not be appropriate; however, it illustrates the impact that the sequence has on the probability of repurchase in our model. *Loyal* customers don’t show any increase; i.e., there are no *loyal* customers who have a probability of repurchase lower than 50% even with the worst possible sequence. However, among potentially *loyal* customers, only 55% will purchase under the current sequence while nearly 71% will purchase under the best sequence. Under these assumptions, H4 (customers who have experienced a subscription repeatedly are less impacted by the sequence of events) seems to hold since *loyal* customers have high probabilities regardless of the measured sequence variables.

<table>
<thead>
<tr>
<th>Customer Type</th>
<th>Sequence Type</th>
<th>Worst</th>
<th>Current</th>
<th>Best</th>
<th>Change from Current to Best Sequence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loyal</td>
<td>Flat</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>Potential</td>
<td>Peak</td>
<td>41.1%</td>
<td>55.2%</td>
<td>70.9%</td>
<td>15.8%</td>
</tr>
<tr>
<td>Fickle</td>
<td>Valley</td>
<td>86.0%</td>
<td>92.0%</td>
<td>94.5%</td>
<td>2.5%</td>
</tr>
<tr>
<td>New</td>
<td>Flat</td>
<td>13.5%</td>
<td>19.1%</td>
<td>28.2%</td>
<td>9.1%</td>
</tr>
</tbody>
</table>

Customers in *flat* bundles show an increase of 1.9%, but *peak* and *valley* bundles show a much higher increase(9.3% and 8.1%) illustrating again that homogenous bundles do not benefit from an improved sequence as much those with more variability in event utility.

8. Bibliography


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