Sequence Effects in Service Bundles: Marketing and Operational Implications

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Service management scholars are interested in understanding the dynamics of successful service design, i.e., attributes and characteristics of a service that catch and hold the attention of decision-makers (e.g. customers). Additionally, operations management scholars have begun to investigate the impact that behavioral research has on standard assumptions of service design. Similarly, researchers in psychology and behavioral economics have shown that the sequence or ordering of events plays an important role in human perception. 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 perception. 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 predicting customer repurchase of season subscription ticket holders to determine if the temporal placement of events impacts repurchase. We investigate the presence of a peak effect, end effect, and sequence trend in order to introduce the discussion of the importance of sequence when determining service design and scheduling. These results have implications for effective service design for a wide range of industries.

1. Introduction

Effective service design involves developing a service concept that appeals to end users considering operational constraints (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 (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 order in which the service concept is delivered has any impact on the customers?

Recently, leading service management scholars (Chase and Dasu 2001, 2008, Cook et al. 2002) have suggested that the sequence of events within a service encounter can influence customer's overall perception of the service. Therefore, Chase and Dasu

(2001) argue that those interested in improving customer service should be aware of behavioral implications of service sequencing. They 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 there has been little empirical validation of the proposed ideas. Furthermore, 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 considered equal by the customers – i.e. there are different utilities for 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. In this paper, we investigate how the temporal placement or sequence of events within a service bundle impacts future customer repurchases behavior. Furthermore, we illustrate how the estimated utilities for sequence parameters can be used to make better operational decisions.

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. Some service bundles are created by bundling a number of different services that are intended to be used simultaneously, e.g., internet, cable television, and home telephone service sold together for one monthly charge. Others are created by placing similar discrete services together in a way that they have to be experienced across time, e.g., a course taught in 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 include a number of different events experienced across a season. Within this second type of service bundles, we observe that there are some bundles for which the sequence of events provides a logical constraint, e.g., the 5 day cruise typically visits islands in a physically linear fashion. However, there are other examples of service bundles for which the sequence is not assumed fixed or at least not entirely fixed, e.g., performing arts season subscriptions in which the schedule of performances can be altered. We believe that these types of service bundles provide ideal testing grounds for applying the sequence related behavioral research in the context of service design and scheduling. Using a rich multi-year ticket purchase database from a world-renowned performing arts venue, we test the impact of sequence on customer repurchase of subscription packages.

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, describe our research design and analysis approach; fourth, we present our results and associated discussion; and finally we discuss theoretical and managerial implications this research.

2. Literature Review

2.1 Service Bundling

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). It involves creating a product or service that is a mix of other products or services to be sold as one unit. The practice is common across many service industries, for example fast food industries offer meal packages, telecom 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. 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 such bundles. Thus operations management researchers to date have primarily concerned themselves with revenue management pricing issues surrounding product/service bundling (Bitran and Caldentey 2003, Bitran and Ferrer 2007, Aydin and Ziya 2008) and supply chain issues of supplier bundling (Schoenherr and Mabert 2008, Rosenthal et al. 1995). From an economic perspective, customers purchase bundles because their reservation price (the maximum price they are willing to pay) 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 highly demanded and lower demanded services. To reach global capacity maximization, managers would do best to spread out the most popular events across different subscription bundles spreading out the demand and reaching a higher capacity for the less popular elements. Leveraging highly popular elements is at the cornerstone of revenue management with bundled services.

Along similar research paths, procedures to find "optimal" product and service attribute profiles have been developed by both marketing and operations researchers. Studies have been conducted with objectives to find an attributes mix that maximizes sales or 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), and others taking into account 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 made contributed in understanding consumer choice of product and service attributes; however, none of the known research considers the sequence related attributes of service delivery.

2.2 Sequence-Related Behavioral Research

Researchers in psychology and behavioral economics have theorized on topics such as experiential memory (Eldridge et al. 2000), expectation effects (Wilson et al. 1989) , peak effects (Fredrickson and Kahneman 1993), duration effects (Ariely and Loewenstein 2000), recency effects (D.E. Broadbent et al. 1978), and end effects (Ross and Simonson 1991). Although well established in behavioral literature, these sequence effects have not been well tested within the context of service scheduling, design, and delivery. Applying these principles to the service concept theory involves service providers understanding how their concept is experienced overtime, how it is initially perceived, at which point the experience is at its most exciting or dull, and how it ends.

After reviewing past behavioral research, Chase and Dasu (2001) proposed that customers remember three points of a service experience:

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

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 last seems to impact the utility of the overall win. In a legal research article (Walker et al. 1972) , researchers have found that the order in which the evidence is presented impacts the overall judgment. Furthermore the sequences that start with weak evidence and end with strong evidence generally yield most favorable judgments.

Memory researchers suggest that humans relive their past experiences using "snapshots" not "videos" (Burt et al. 1995, Nguyen and Belk 2007). In other words, our minds are more prone to selectively capture and remember the snapshot of extreme high or low points (i.e. peaks) from a past experience. Furthermore, the researchers have found that 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 peak 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. Although researchers have generalized across both high peaks and low peaks, most research in this area has been about pain, implying extreme low points.

In a separate colonoscopy related research project (Redelmeier et al. 2003), researchers experimented with how patients reacted to extending the end of a procedure. An experiment was designed to prolong the less painful, yet still uncomfortable *end* of a procedure for some patients. Their assessment of pain was compared with other patients without the special treatment. The results showed that by extending the less painful portion at the end of the procedure, the overall pain assessment decreased; similarly, those patients whose most intense pain was closer to the end of the procedure reported higher overall pain. This "end effect", implies that while peaks are important, how an experience ends is also important (Kahneman et al. 1997).

In earlier behavioral literature, researchers labeled *serial position effects* as the effect that the order of items presented have on memory (Ebbinghaus 1902). Researchers have shown that when presented with a list of non-sense words to memorize, subjects displayed two types of serial position effects: first, *primacy*, or the ability to recall the first item on the list better than the items in the middle, and second, *recency*, the ability to recall the last items on the list better than those in the middle. Later, primacy and recency were found to be used to form impressions (Asch 1946, Anderson and Barrios 1961) , i.e., when subjects were given a set of adjectives to describe an individual, they placed more weight on the first and the last set of adjectives when asked to rate their impressions. More recently, researchers have found that subjects tend to 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).

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, peak and end effects have been less researched. In their seminal book *Service Breakthoughs: Changing the rules of the game* , Heskett, Sasser and Hart (1990) discuss the idea of "service bookend" and emphasize the need for not only a strong ending, but also a strong beginning mirroring the ideas of primacy and recency. As stated earlier, Chase and Dasu (2001, 2008) are the pioneering operations management scholars to suggest that the 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 is 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, but not for changes in the sequence of the process itself, i.e. the service process remained unchanged and only the performance levels of the different aspects of the process 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, Britan, Ferrer, and Oliveira (2008) further refine a conceptual framework of sequence and other behavioral aspects of service operations as it applies to profitability. They conclude by calling for more varying techniques of empirical based evidence across different industries and context.

Our research adds to the past literature by using an archival data source and econometric methods to test for the presence of sequence effect. Furthermore, our focus is not on the performance aspect of a fixed sequence, but instead we are interested in event placement of a service bundle for which the sequence is not assumed fixed, i.e., we hope to uncover the effect that a change in the *order* of events might have on customers, not just the change of the *performance levels* over time of a fixed process. Finally, we are attempting to find behavioral sequence effects in a service bundle that elapses over a long period of time while most previous studies focused on individual encounters providing insight on how sequence effects may be used in scheduling.

3. Theory and Hypotheses

Writers for good television series have an inherent sense for the importance of sequence effect and use it in creating tension in plot development and for building anticipation for further scenes. For example, a typical crime mystery plot often begins with a highly dramatic crime scene for which there are no easy answers for the protagonists. Throughout the episode, detectives discover evidence, some of which is shocking. Commercial breaks are strategically placed at high points in the episode to encourage viewers to sit through the commercials for fear of missing something important. Finally, the tension builds and the protagonists solve the mystery just in the nick of time, that is, just in the final few minutes. The hook at the beginning is interesting enough to keep viewers from channel surfing and the ebb and flow of the plot tension keeps us guessing until the very end. Television producers hope that the show was interesting enough to encourage viewers to return next week. The above example illustrates our first hypothesis. We propose that that by considering sequence effects within a service bundle, the customer re-purchase behavior can be predicted more accurately.

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

Extending the past work of sequence-related behavioral research we can assume that as a peak nears the end of a service bundle, its effect will remain salient in customer's minds and will result in a higher overall assessment. Therefore a time elapsed service bundles ending with a peak should result in higher overall assessment of the bundle, e.g., if the last event in a season subscription package includes an all-star cast of performers performing traditionally crowd pleasing pieces, then the customers will remember the event and give high marks to the entire subscription. On the other hand, if the all-star performance happened near the beginning of the season, the subsequent, less exciting events may diminish the utility of the peak experience thus lowering the overall assessment.

Based on the example provided above and past work in sequence-related behavior research, we propose that the placement of peak events within service bundles influences overall assessment of the bundle. In particular we propose the following hypotheses to test empirically:

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

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

H2c: Customers are more likely to repurchase as the time from the peak event to the time of last event shortens, i.e., as the peak event approaches the end.

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

Similarly, we are interested in knowing how variability of event utility within a bundle impacts customer assessment. As stated earlier, revenue management and capacity management principles would dictate that bundles should be created that mix both highly demanded events with low demanded events leveraging the highly demanded event to sell tickets to the lower demanded events. However, we suspect that customers know when a subscription is highly leveraged and may give it poor marks. Similarly, if a bundle includes one event that has a low utility (a valley) compared to others within the bundle, customers will take notice. To that end, we provide the following secondary hypotheses:

> **H3a:** Customers are more likely to repurchase as the events within the service bundle become more homogeneous in utility.
> **H3b:** Customers are more likely to repurchase if the service bundle includes a peak compared to those that include a valley.

Finally we propose that the customers who have experienced a service bundle in the past will be less effected by sequence effects.

> **H4:** Customers who have experienced a service bundle repeatedly are less impacted by the sequence of events.

4. Research Design

4.1 Data Description

We use an econometric model based on multi-year subscription ticket purchase database for an internationally renowned performing arts venue. This concert venue houses 5 different concert halls. The halls can be used simultaneously and therefore the venue can host up to approximately 700 events a year. Currently the venue hosts approximately 300 events per year and offers over 40 different subscriptions to its customers.

The database includes 6 years of ticket sales data from 2001 to 2007 including over 1 million individual ticket sales transactions for over 2,400 different events purchased by over 50,000 unique customers. The transactional ticket sales data includes the date and time of the ticket purchase, the price paid, membership status during time of purchase, general seating category (based on price category), and whether the ticket was

Figure 2: Tickets Sold per Genre 2001-07

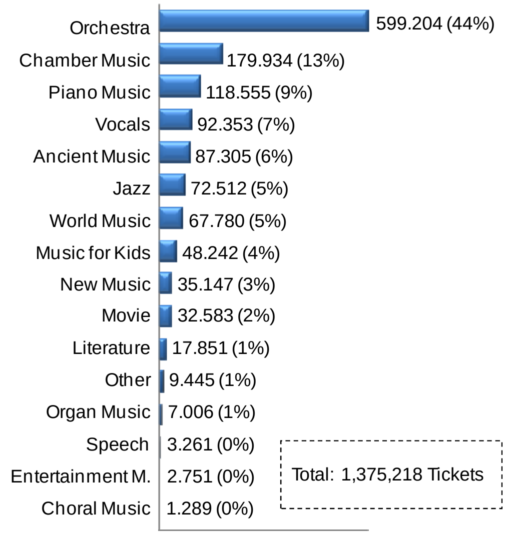
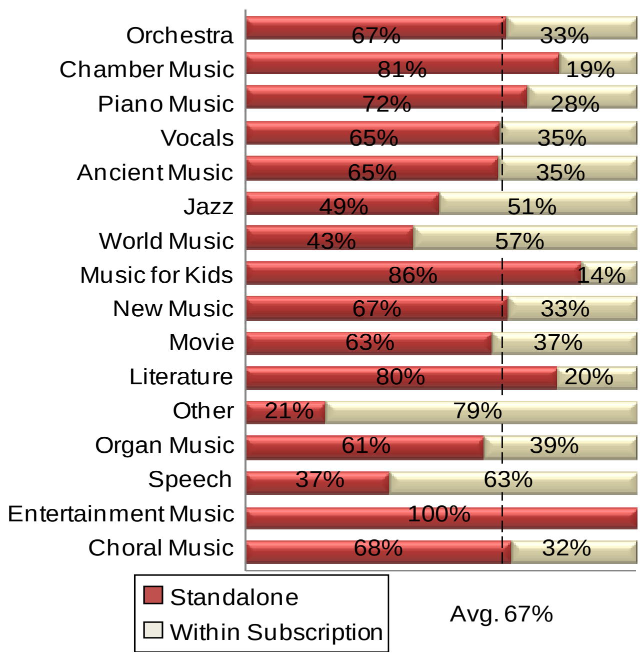


Figure 1: Share of Tickets Bought within Subscription 2001-07



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 percentage of tickets sold for each genre. Figure 2 shows the percentages of tickets sold as subscription for each genre.

Most subscription cycles offered are theme based, i.e., based on a certain genre or 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. Most of these subscription cycles are a continuation of a similar cycles offered the year before, i.e., the same theme is repeated year after year. That is not to say the same performances are repeated, but instead the same theme is kept and subscriptions can be linked year to year. 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, a *season* as the year of a given subscription, and a subscription *bundle* as a given year 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 years, but for reasons forthcoming, they are left out of the analysis.

4.2 Econometric Model

In order to test the proposed hypotheses we estimate a series of models that predicts probability that a customer who had purchased a given cycle for a given season, would again purchase the same cycle the subsequent year. The independent variables include customer characteristics (gender, loyalty status, etc), service attributes (genre, time of day, etc.) and sequence-related variables (e.g., placement of peaks and valley events within a bundle).

Specifically, for the set of customers $_i$ 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 subscription cycle the subsequent year. 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 follow the following form,

$$\ln\left(\frac{P(Y_{ij+1}=1)}{1-P(Y_{ij+1}=1)}\right) = \beta_{ij}x_{ij} + \epsilon \mid Y_{ij} = 1$$

where $Y_{ij+1} = 1$ represents a repurchase of the bundle j+1 (the next year's bundle for the same cycle) by customer i, x is a vector of predictors, β is the vector of coefficients, and ε are the errors. This model is estimated across all customers i who purchased bundle j. The model predicts the log-odds of repurchase given the set of independent variables using a maximum likelihood estimator assuming the distribution of errors follows a logit distribution.

4.3 Customer Specific Variables

In predicting repurchase, three general set of variables are considered: first customer specific attributes, second bundle specific attributes, and finally sequence specific variables as follows:

$$\ln\left(\frac{P(Y_{ij+1} = 1)}{1 - P(Y_{ij+1} = 1)}\right) = \varphi_{ij}x_{ij} + \theta_j x_j + \rho_j x_j + \epsilon$$

where φ_{ij} is a vector of customer i variables for bundle j, θ_j is a vector of bundle specific variables and ρ_j is a vector of bundle specific sequence related variables.

Customer specific attributes include gender, price category of tickets (seat placement), number of bundles purchased (for a given bundle, not globally) total number of bundles purchased (globally, within the season), days from purchase date to first event in the bundle (measure of how early a bundle was purchased), and membership status. Given 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. Hypothesis 4 states that customers who have experienced a service bundle repeatedly are less impacted by the sequence of events. To this end, 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.

Table 1: Customer Attributes Summary

	Non - Repurchasers	Repurchasers	All Customers
Days from purchase to first event*	115.72	130.70	126.41
Bundles Purchased*	1.94	1.73	1.72
Total Bundles purchased in the season*	1.74	2.16	2.10
Gender			
Male	3433	9304	12737
Female	4965	11794	16759
Unknown	710	1610	2320
Member	1860	2279	4139
Non-Member	7248	20429	27677
Experience			
Loyal	2143	15559	17702
Potential	332	364	696
Fickle	1472	2994	4466
New	5161	3791	8952
Price Category 1**	35%	27%	29%
Price Category 2**	16%	17%	17%
Price Category 3**	21%	18%	19%
Price Category 4**	17%	17%	17%
Price Category 5**	12%	12%	12%
Price Category 6**	11%	12%	12%
Price Category 7**	5%	5%	5%
Price Category 8**	1.2%	2.2%	1.9%
Price Category 9**	0.3%	0.4%	0.3%
Total	9108	22708	31816

* averages reported

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

** Percentage do not sum to 100% because some customer purchased from multiple price catagories

All other numbers are counts

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 only purchased the cycle for one season. By calculating the loyalty variable we set a limit on the data that can be used in the model. The first season that can be predicted is the fourth year 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 = 31,815 customers who had purchased a given cycle the previous season. Given the total size of the dataset and the resulting sample size for the empirical 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 observation to use to later validate the accuracy of the model as explained in Results section below. 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 Results section. Table 1 shows a summary of the customer specific variables.

4.4 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 thought of as 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).

Throughout this paper we have referred to an event's utility, but have not yet offered a way to measure event utility. Researchers have dissected a product or service 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 individual utility of each 8 events. 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 derived utility from a measure of both seat occupancy and ticket price: revenue per available seat (REVPAS). REVPAS is calculated by dividing the total revenue for each show by the total number of available seats in the concert hall. REVPAS is borrowed from the hospitality metric, revenue per

Table 2: Summary of Bundle Attributes

Total Subscription Bundles Considered	128	
	Average	Standard Deviation
Genre Mix*		
Ancient Music	3%	15%
New Music	4%	19%
Jazz	2%	15%
World Music	5%	21%
Children's Music	19%	39%
Literature	2%	15%
Organ Music	2%	14%
Piano Music	8%	26%
Chamber Music	23%	41%
Vocals	7%	21%
Choral Music	0%	1%
Orchestra	21%	37%
Film	3%	15%
Number of Genres in Bundle	1.33	0.74
Percentage of Events on Weekends	52%	33%
Percentage of Events in the Evening	80%	37%
Total Bundle Utility	149.13	87.37

* represents percentage of genre in all bundles

available room (REVPAR) which is calculated by diving total room revenue by the number of available rooms. REVPAR has been shown to be highly correlated to customer satisfaction (Davidson et al. 2001, Davidson 2003), service quality (Kimes 2001, 1999), and brand loyaty (H. B. Kim et al. 2003, H. B. Kim and W. G. Kim 2005). Hotels with higher REVPAR demand higher room rates and fill a higher percentage of their rooms because they provide a higher level of utility for their guests. Similarly, we believe that REVPA*S* 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). We assume that the venue has a good idea of the demand of individual events and sets ticket prices in order to maximize profit. Furthermore, we assume that patrons are also utility maximizing and will only purchase tickets if the expected utility of the performance is greater than or equal to the utility of the ticket price.

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. 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.

4.5 Sequence Variables

The sequence variables are of primary interest in this model as they will be used to test our hypotheses. We consider the utility of the highest utility or peak event within a subscription as well as the utility of the last event. Additionally, we measure the number of days from the peak event to the last event to determine the appropriate placement of the peak event. To consider the trend of the sequence of events, we calculate the slope for the line fit in ordinary least squared regression through event utilities and the number of days from the beginning of the bundle.

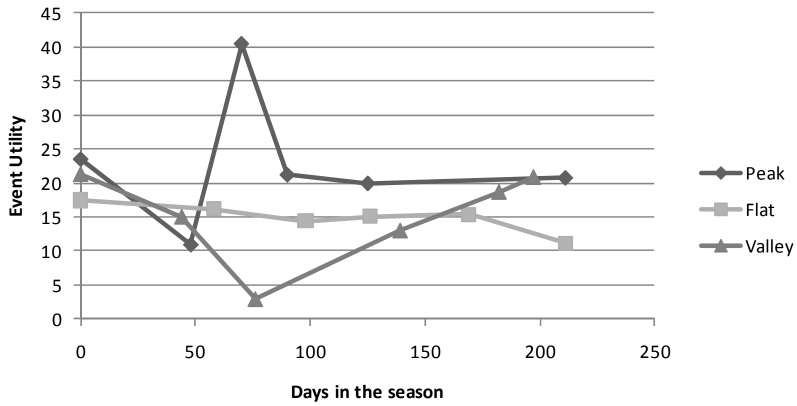
Table 3: Sequence Attribute Summary

	Average	Standard Deviation
Peak Event Utility	19.26	13.93
End Event Utility	14.49	9.96
Slope of Sequence	0.001	0.022

	Count of Subscriptions
Days from Peak Event to End Event	
0 Days	18
1 to 50 days	22
50 to 100 days	28
100 to 150 days	17
150 to 200 days	26
200 to 250 days	17
Flat Subscription	96
Peaked Subscriptions	27
Valley Subscriptions	5
Total Subscriptions	128

Finally, we have created variables to indicate if bundles include a true peak, a valley or if the events in the bundle are all 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; those bundles without a range of at least 10 were considered *Flat*. Next we calculated the average utility across all events for each bundle and compared this average utility 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 *Peak*. If the opposite was true, the bundle was coded *Valley*. Figure 3 shows an example of each of the three categories and Table 3 shows the summary of the Sequence Attributes.

Figure 3: Examples of Peak, Flat, and Valley Bundles



5. Results

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

Table 4: Logistic Regression Results

n = 28708

	Parameter	Model 1: Customer Attributes Model Estimate	Model 1 Std Err	Model 2: Customer and Bundle Attributes Model Estimate	Model 2 Std Err	Model 3: Customer, Bundle, and Sequence Attributes Model Estimate	Model 3 Std Err
Customer Attributes	Intercept	-0.71**	0.082	-0.1	0.135	-0.28*	0.141
	Days from purchase to first event	0.002**	0.0003	0.003**	0.0004	0.002**	0.000
	Subscriptions Purchased	0.02	0.02	0.1**	0.022	0.1**	0.022
	Total Subscriptions purchased in the season	0.02	0.012	0.04**	0.012	0.05**	0.012
	Gender M vs. F	0.06*	0.031	0.03	0.032	0.03	0.032
	Gender Unknown v F	-0.01	0.057	-0.03	0.058	-0.03	0.058
	Membership	0.35**	0.043	0.21**	0.045	0.18**	0.046
	Loyal vs. New	2.17**	0.035	2.02**	0.036	2.01**	0.042
	Potential vs. New	0.38**	0.084	0.36**	0.085	0.37**	0.036
	Fickle vs. New	0.97**	0.041	0.9**	0.042	0.9**	0.085
	Price Category 1	-0.3**	0.044	-0.06	0.051	-0.07	0.052
	Price Category 2	-0.11*	0.052	-0.09	0.056	-0.1~	0.056
	Price Category 3	-0.19**	0.047	-0.15**	0.051	-0.16**	0.052
	Price Category 4	-0.09~	0.05	-0.12*	0.053	-0.12*	0.054
	Price Category 5	-0.05	0.053	-0.04	0.057	-0.04	0.057
	Price Category 6	0.02	0.055	0.01	0.058	-0.003	0.059
	Price Category 7	0.05	0.079	-0.02	0.083	-0.03	0.083
	Price Category 8	0.39**	0.128	0.36**	0.131	0.37**	0.132
	Price Category 9	-0.07	0.272	-0.02	0.272	-0.01	0.272
Bundle Attributes	Ancient Music vs Orchestra			0.05	0.097	0.29**	0.108
	New Music vs Orchestra			0.15	0.116	0.39**	0.124
	Jazz vs Orchestra			-0.24**	0.079	0.02	0.098
	World Music vs Orchestra			-0.28**	0.091	-0.16	0.097
	Children's Music vs Orchestra			-1.54**	0.135	-1.44**	0.144
	Literature vs Orchestra			-0.47**	0.102	-0.37**	0.105
	Organ Music vs Orchestra			-1**	0.178	-0.66**	0.187
	Piano Music vs Orchestra			-0.45**	0.062	-0.3**	0.067
	Chamber Music vs Orchestra			-0.16*	0.063	-0.14*	0.065
	Vocals vs Orchestra			-0.02	0.072	-0.06	0.083
	Choral Music vs Orchestra			-0.37	1.176	-0.68	1.496
	Film vs Orchestra			-0.13	0.107	0.07	0.112
	Total Number of Genres in the Subscription			-0.2**	0.026	-0.21**	0.031
	Percent of events on weekend			0.03	0.069	0.11	0.074
	Percent of events in the evening			-0.62**	0.073	-0.8**	0.079
	Sum of all Events Utility			0.001**	0.0004	0.0003	0.001
Sequence Attributes	Peak Event Utility					0.01**	0.004
	Last Event Utility					0.01*	0.004
	Days from Peak event to Last Event					0.001*	0.0002
	Slope of event utility over time					2.6**	0.919
	Peak subscriptions vs. Flat subscriptions					-0.4**	0.072
	Valley subscriptions vs. Flat subscriptions					0.1	0.116

Testing Global Null Hypothesis: BETA=0	Model 1 (18 DF) Chi-Square	Pr > ChiSq	Model 2 (34 DF) Chi-Square	Pr > ChiSq	Model 3 (40 DF) Chi-Square	Pr > ChiSq
Likelihood Ratio	5878	<.0001	6333	<.0001	6396	<.0001
Score	5861	<.0001	6275	<.0001	6332	<.0001
Wald	4998	<.0001	5185	<.0001	5211	<.0001

Coefficients of Determination	Model 1	Model 2	Model 3
R-Square	0.185	0.198	0.200
Max-rescaled R-Square	0.265	0.283	0.286

Nested Model Comparison Statistics	Model 1 Intercept Only	Model 1 All	Model 2 Intercept Only	Model 2 All	Model 3 Intercept Only	Model 3 All
SC	34,424	28,731	34,424	28,440	34,424	28,438
-2 Log L	34,414	28,536	34,414	28,081	34,414	28,017

Predictive Accuracy - Calculated with observations excluded from model estimation: n = 3107	Model 1	Model 2	Model 3
Brier Score	0.165	0.163	0.162

Association of Predicted Probabilities and Observed Responses: Total pairs =168,619,627	Model 1	Model 2	Model 3
Percent Concordant	76.6	78	78.2
Percent Discordant	22.7	21.6	21.4
Percent Tied	0.7	0.4	0.4

Overdispersion Test	Model 1 Value/ DF	Pr > ChiSq	Model 2 Value/ DF	Pr > ChiSq	Model 3 Value/ DF	Pr > ChiSq
Deviance Chi Squared	1.05	<.0001	0.987	0.9349	0.985	0.9608
Pearson Chi Squared	1.00	0.331	1.004	0.3038	1.005	0.2966

Estimate Significance using Wald Chi Squared Test: ** Significant at alpha < 0.01 * Significant at alpha < 0.05 ~ Significant at alpha < 0.10

The results of the three models are shown in Table 4. The customer attribute model shows no real surprising 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 vs. Females are more likely to repurchase.
- Customers that are also Members are more likely to repurchase.
- 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 (Price 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:

- Compared to Orchestra, all genres (except for Ancient, New, and Jazz in the final model) 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 and positive in the 2^{nd} 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 looses significance indicating that total bundle utility can be better explained with the sequence variables.

Again, the results of the customer and bundle attributes in the final model all show similar signs and magnitude. The new variables of the final model are of primary concern in testing our hypotheses. First and foremost, our interest is in testing H1: including sequence variable will improve the model. Comparing across models using nested model comparison statistics we can see that the models improve as they are nested 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 testing if the added variables in the model add significantly to the model. Table 5 shows that comparing model 2 to model 1 there is evidence that the added

Table 5: Likelihood Ratio Test for nested model comparison

$$(-2 \text{ Log Liklihood}_{\text{model 1}}) - (-2 \text{ Log Liklihood}_{\text{model 2}}) \sim X^2$$

$$df = df_{\text{model 2}} - df_{\text{model 1}}$$

	Model 1: Customer Attributes	Model 2: + Bundle Attributes	Model 3: +Sequence Attributes
-2 Log Likelihood	28,536	28,081	28,017
DF	18	34	40
Likelihood Ratio		454	64
Degrees of Freedom		16	6
Pr > ChiSq		<.00001*	<.00001**

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

variables improved the model ($p < 0.00001$). Similarly, going from model 2 to model 3 there evidence that the sequence variables also improve the model's fit significantly ($p < 0.00001$) providing support for H1.

The remaining hypotheses can be tested by considering the estimates of the sequence variables:

- The coefficient for the Peak Event Utility is significant ($p < .01$), and is positive indicating that H2a (customers are more likely to repurchase a subscription as the utility of the peak event increases.) can be considered.
- The coefficient for the Last Event is significant ($p<.05$) and is positive indicating that H2b (customers are more likely to repurchase a subscription as the utility of the last event increase) can be considered.
- The coefficient for Days from Peak Event to Last Event is significant ($p< .05$) and is positive indicating that as the peak event is further from the last event, repurchase is more likely. This is opposite of H2c (Customers are more likely to repurchase a subscription as the time from the peak event to the time of last event shortens.)
- The coefficient for the bundle slope is significant ($p < .001$) and positive indicating that as the utility of events improve over time, (positive upward slope) repurchase probability increases providing support for H2d.

As we suspected, the effects of the relative peak event utility and the last event utility can play a significant role in predicting 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). However, this effect 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.

- 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 leveraged partially confirming H3a (customers are more likely to repurchase a subscription as the events within the subscription become more homogeneous in utility.) However, there is no evidence that repurchase probability differs between flat subscriptions and valley subscriptions.
- By changing the reference category from *Flat* to *Valley* we can test H3b (customers are more likely to repurchase a subscription that includes a peak

compared to those that include a valley) The coefficient for *Peaked* vs. *Valley* is significant (p<.01) and negative (-0.49) indicating that repurchase decreases for peak subscription compared to valley subscription disagreeing with our hypothesis.

- Finally, H4 (Customers who have experienced a subscription repeatedly are less impacted by the placement of peak events) is not explicitly tested in this model, however, by the nature of the underlying log odds function, we will show in the Discussion section that loyal customers are less impacted by the sequence variables than the other segments.

Before going into depth on the implications of these results, 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 squared 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 multicolinearity. 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 multicolinearity 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 showing 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.

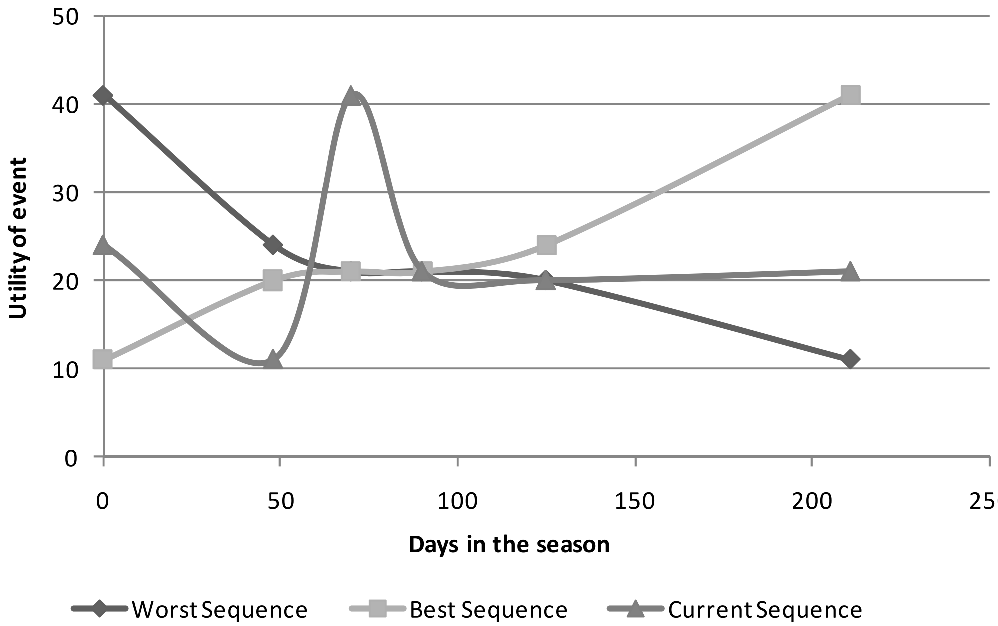
The overall models are significant shown by the Likelihood ratio, Score, and Wald test statistics indicating that at least one of the predictors has a beta not equal to zero for all three models. The R squared values are increasing across the three models. Predictive accuracy of the models was determined 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, 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.

6. Discussion

6.1 An illustration

To better explain the magnitude of the results, we present an example for illustration. 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 of repurchase and identify the best and the worst sequence. Figure 4 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

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

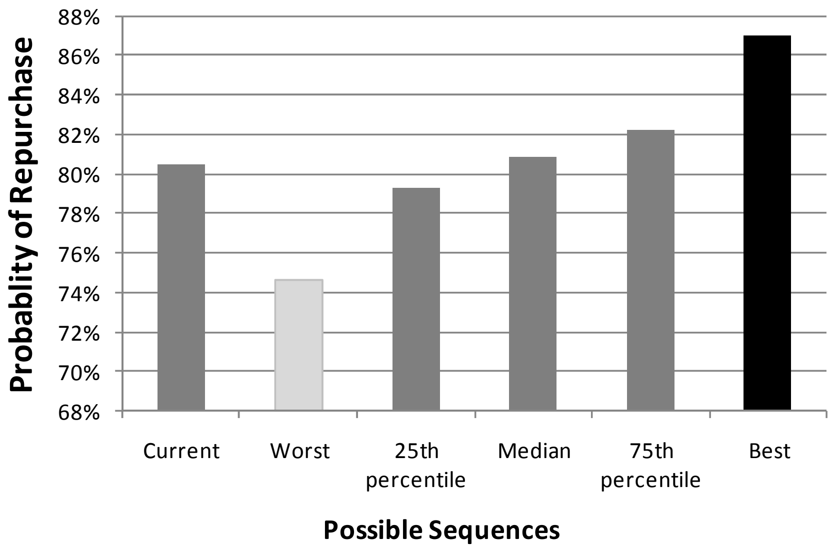


best sequence and at the beginning for the worst sequence.

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 given different scenarios of sequences from the current, worst, best and subsequent quartiles of probabilities using the coefficients estimated earlier. The increase in probability of repurchase from the current to the best sequence is 7% and from the worst to the best sequence is 12%(see Figure 5.) Following the same procedures, we have found optimal sequences for all the bundles with less than 8 events using brute force optimization, i.e. we solved for every permutation and found the best. Solving for the permutation of 8, 9 and 10 events proved to be too computationally intensive, and 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

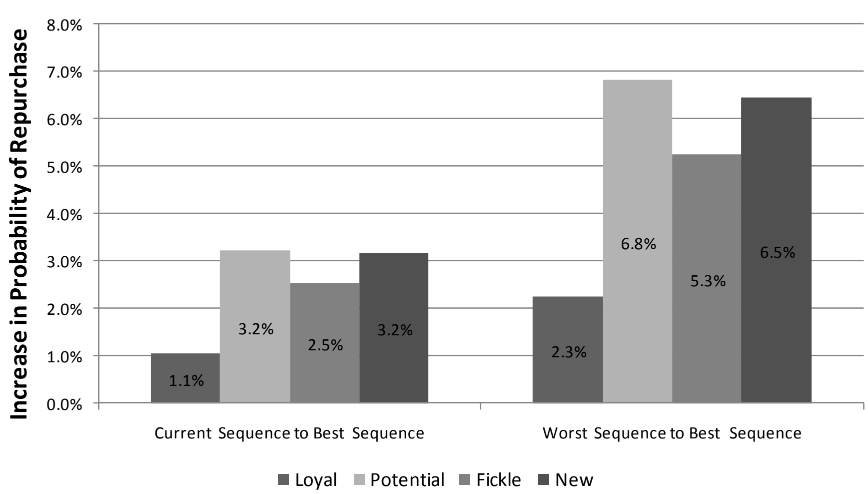
98 bundles for which we had found the probability of repurchase under the current sequence, the worst sequence, and the best sequence.

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



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 an much higher increase (see Figure 6)

Figure 6: Average increase in probability of repurchase



illustrating the impact that customer 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 probability of repurchase is greater than 50%, we believe that they will repurchase. Table 6 shows the results in the percentage of repurchases given the 50% cutoff for the worst, current, and best sequences. *Loyal* customers don't show any increase; 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 assumption, 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

Table 6: Percentage of repurchases given a cutoff value of 50% probability

	Customer Type				
	Loyal	Potential	Fickle	New	Grand Total
With the Worst Sequence	100.0%	41.1%	86.0%	13.5%	68.8%
With the Current Sequence	100.0%	55.2%	92.0%	19.1%	71.8%
With the Best Sequence	100.0%	70.9%	94.5%	28.2%	75.5%
Change from Current to Best Sequence	0.0%	15.8%	2.5%	9.1%	3.7%

sequence variables. On average, 3.7% representing 725 total customer 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.

6.2 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 have impacts on the repurchase behavior of customers, and that different customer segments may benefit more or less from efforts to implement event utility based sequencing into their schedule. The performing arts industry has relied on an aging loyal customer base which is not quickly being replaced by a younger segment. As a part of the experience economy (Pine and Gilmore 1998), the younger segment is in search of an experience that leaves an imprint; utility sequencing may prove to aid service providers in creating such experiences. 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, tour packages, etc 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 as stated earlier with the example of 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 show 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 later 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 at least 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

6.3 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, in may be important to consider the lifecycle of a cycle over many years and consider how sequence effect may impact an even longer view of the cycle. Except for the positive coefficient for *days from the peak to the end,* we found little evidence for primacy or anchoring (admittedly, we did not look hard), but 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. Return 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 of the season 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 it's "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.

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