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Customer Lifetime Value: A Data Science Approach for Hospitality Applications

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ABSTRACT
Segmentation of databases based on Customer Lifetime Value (CLV) is the cornerstone of Customer Relationship Management (CRM). To implement CRM strategies, the hospitality industry relies heavily on loyalty programs to track customer behavior. Despite the prevalence of loyalty programs, little attention has been given to CLV model formulation in hospitality. This paper reviews the extant literature discussing CLV modeling and formulates a model with hospitality-specific considerations. Based on the literature, a phased approach is proposed using cluster and Markov chain analyses, while incorporating a new metric based on a customer's expected trip cycle to identify lost customers in the non-contractual setting. The model is empirically tested on casino loyalty data to demonstrate the viability and robustness of the approach for hospitality sectors.

Keywords
hospitality, casinos, customer lifetime value, Markov chains, customer relationship marketing

INTRODUCTION

Consumer data has grown exponentially over the past few decades, leading to the application of data science across a variety of industries (Webb & Legg, 2021). Hospitality sectors of airlines and casinos were among the first to begin offering loyalty programs in the late 1990s (Law et al., 2018; Loveman, 2003). Over time, these programs grew into an essential service component and a data mining opportunity. Consistent with the growth of customer databases, the hospitality industry began to shift its strategic forethought from a transactional paradigm to a loyalty one (Bowen and Shoemaker, 2003; Shoemaker and Lewis, 1999). Within this evolution, service industries became more reliant on technologies, specifically those related to database marketing. This shift led to a rise in customer relationship management (CRM), where firms prioritize marketing resources to their most valuable customers (Kaul, 2017; Piccoli et al., 2003). From an industry perspective, CRM strategies and technologies continue to co-evolve as firms leverage customer data to create competitive advantages.

At the same time, research in hospitality discussing how to leverage this information has been rather limited (Yoo and Bai, 2013; Law et al., 2018).

Marketing is one of the primary fields that implement data science strategies. Firms use advanced algorithms to segment and target promotions to optimize-interactions with their customers (Nair et al., 2017). In hospitality, success is often derived from a loyal customer base that exhibits frequent re-patronage and long-term loyalty (Barsky and Tzolov, 2010; Legg and Hancer, 2020). For this reason, customer engagement is critical to firm viability, while analytics provide an opportunity to measure market size and growth through metrics such as customer lifetime value (CLV).

The concept of CLV has been well-documented (Gupta et al., 2006; Kaul, 2017); however, various issues arise when applying these methodologies in practice. Most notably, the hospitality industry operates in a non-contractual setting where consumers spend and visitation frequency is dynamic. Moreover, consumers have multiple competitors to choose from in their purchasing process. For example, a café customer can choose from a variety of competitors on their morning commute and may shift their visitation frequency and spend based on a variety of factors (time in traffic, wait times, new products, etc.). In this regard, it is particularly challenging to classify the activity status of each customer (active or inactive) and estimate their future value.

This article reviews CLV literature and provides a methodological approach that accounts for the dynamic purchasing habits within the hospitality industry. The article also provides a contribution to the CLV literature by presenting a novel approach to identify the activity level of customers in a non-contractual setting. The proposed methodology is tested on rated play from 331 patrons, sourced from a Las Vegas casino spanning 12 years.

The results show that lifetime value is a more effective approach for segmenting patrons who exhibit dynamic visitation and spending patterns compared to traditional industry metrics such as average daily theoretical (ADT), which is based on current value. As an underexplored topic, we are not aware of any other example of applying CLV within hospitality literature. Marketers who can more accurately classify the future value of their customers will be able to fine-tune their reinvestment strategies to increase the viability of their loyalty programs.

LITERATURE REVIEW

Customer Relationship Management (CRM)

The growth of digital consumer touchpoints has generated large-scale data points for hospitality organizations to track customer interactions through customer relationship management (CRM) systems. As a result, hospitality firms can observe guests' booking touchpoints (room inquiries, reservation dates), while also monitoring their activities and stay preferences (Eisen, 2018). Likewise, foodservice and casino firms leverage loyalty programs to track guests' purchases, visits, and spending preferences (Barr, 2018; Loveman, 2003; Marr, 2015; Solis, 2018). The availability of customer data has allowed hospitality firms to data mine their customer interactions to drive guest loyalty to support sustainable long-term growth (Provost and Fawcett, 2013). Moreover, by using CRM systems to drive guest loyalty, firms look to mitigate attrition and maximize their customers' lifetime value (Cheng and Chen, 2009; Provost and Fawcett, 2013). Although CRM systems have become common in recent years, minimal research has been conducted on the application of these methodologies in the hospitality industry.

CRM is broadly defined as "the strategic process of selecting customers that a firm can most profitably serve and shaping interactions between a company and these customers. The ultimate goal is to optimize the current and future value of customers for the company" (Kumar and Reinartz, 2018 p.5). For most firms, CRM is a central component within their marketing departments. Additionally, Piccoli et al. (2003) noted that the hospitality industry was well-positioned to leverage CRM due to the relational nature of reliance on interactions between guests and firms. Instead of focusing on attaining new customers and encouraging single transactions with one-way communication, CRM emphasizes developing comprehensive relationships that are built on multiple transactions and two-way interactions (Piccoli et al., 2003). Organizations that successfully integrate CRM with customer-centric strategies can develop deeper relationships to maximize their customers' values, while simultaneously cultivating loyalty (Peppers et al., 1999; Cheng and Chen, 2009; Khajvand et al., 2010).

The ability to collect customer-level data is often dependent on loyalty programs, which are extensively used by hospitality firms (McCall and Voorhees, 2010). Loyalty programs were developed to incentivize repeat guest patronage through usage of systematic rewards (Yoo and Bai, 2013). However, not all loyalty programs in the industry have been effective at driving guest loyalty (Legg and Hancer, 2020; McCall and McMahon, 2016). Factors influencing loyalty programs' effectiveness explored in research include how rewards are structured, how tiers are developed, and how much customers are driven to spend (Dekay et al., 2009; Legg, Webb and Ampountolas, 2021; Lucas and Nemati, 2020; Lucas and Spilde, 2017; McCall and McMahon, 2016; McCall and Voorhees, 2010; Tanford and Baloglu, 2013; Yan and Cui, 2016).

The effectiveness of loyalty programs also relies on optimal segmentation techniques that can provide robust insights on core customers (Goyat, 2011). However, a firm cannot simply assume that customer segmentation is a straightforward application that generates optimal return on investment (Tuma, Decker and Scholz, 2011). Segmentation schemes that are congruent with an organization's objectives along with formulation from relevant customer traits are more likely to generate positive returns (Yankelovich and Meer, 2006).

Marketing strategies and segmentation schemes must be aligned with the objective of profit optimization. CRM is used to incentivize repeat customer purchasing behavior, and the aggregate revenues of these purchases generated over the course of a customer's lifetime become potential value (Hosseni and Tarokh, 2011). Correspondingly, the cumulative incentives to customers and operational expenditures are the expenses. Rewards are structured to the highest valued customers to maximize profits while mitigating churn and protecting return on investments in CRM systems.

Proper structuring of incentives can also mitigate costs and optimize customers' lifetime value, which can be defined as "the present value of all future profits obtained from a customer over his or her life of relationship with a firm" (Gupta et al., 2006 pg2; Kumar et al., 2004). Even though lower CLV customers generate revenues, they are typically allocated lower priority. Conversely, loyalty programs that create value through prioritized incentives for their most valuable customers can raise switching costs that enhance a loyalty program's effectiveness (Bijmolt, Dorotic and Verhoef, 2010; Legg and Hancer, 2020; O'Brien and Jones, 1995). Value generated from loyalty programs becomes of greater importance for industries that offer similar products or services (Zakaria et al., 2014), such as the hospitality industry. It follows that by improving the identification of a firm's most valuable customers in a forward-looking manner (i.e. prediction models), organizations can appropriately allocate incentives to customers. Less accurate predictions can result in misclassification, which may prove detrimental to the long-term sustainability of businesses operating in a competitive environment (Malthouse and Blattberg, 2005).

Customer Lifetime Value in Hospitality and Gaming

In hospitality and gaming, CRM and CLV research has often focused on the concept of loyalty (Baloglu, 2002; Kandampully et al. 2015; Tanford, 2016; Tanford and Baloglu, 2016). To be competitive, firms must take control of future transactions by cultivating loyalty. These findings tend to align with studies outside the hospitality discipline which suggest loyalty and retention are the most critical components of CLV (Reichheld et al., 2000) and have a strong correlation between customer satisfaction and customer retention (Gupta and Zeithaml, 2006).

Studies in this area have largely ignored the formulation of CLV models for hospitality firms. Watson and Kale (2003) were the first to explore CLV in gaming with an aggregate model to segment Australian table games players. Their study used average revenues based on table games odds to classify customers. The approach did not use customer-level data; however, they were able to demonstrate the value of CLV calculations by projecting a segment's value over time. More recently, Coussement and De Bock's (2013) study of online gamblers showed that RFM variables known as recency (R), frequency (F) and monetary (M) values are significant predictors of customer churn.

It is important to consider how CLV modeling should be applied in hospitality. The high frequency of purchase along with dynamic timing of transactions presents a unique opportunity to explore CLV implementation strategies. Proper formulation of CLV can lead to a competitive advantage by prioritizing firms' most valuable customers while also identifying those with long-term potential through customer engagement. As data from customer interaction touchpoints continue to emerge, academia should explore CLV strategies to derive viable solutions.

Customer Lifetime Value (CLV) Modeling

Estimation of customer lifetime value has been employed in a variety of ways. In its most basic form, the gross contribution from customers is projected over a set number of periods (Berger and Nasr, 1998). The projection generally incorporates components of customer acquisition and retention, revenue and expenses, as well as a discount rate to determine the customer's *net present value* (Berger and Nasr, 1998). These estimates are expressed in a CLV table that can be used for decision-making. Gupta et al. (2006) provided an overview of CLV modeling techniques and highlighted the benefits of approaches incorporating RFM and probability into their estimates. Moreover, in optimizing CLV predictions, future customer spending patterns and timing do not translate well to linear techniques due to the inherit nature of spending variability.

1. *Segmentation*

Market segmentation is defined as breaking a large market into smaller and more manageable submarkets (Shani and Chalasani, 1992). Marcus (1998) noted that marketing to different customer types often meant differentiating strategies across various demographic characteristics. Using these strategies, firms can customize marketing campaigns by targeting specific segments to increase response rates and promotional efficiency. There are many different segmentation approaches with varying estimation procedures; however, they all revolve around the concept of splitting a large pool of customers into smaller subgroups. Multidimensional segmentation approaches based on demographics and behavioral attributes hold more robust applications (Marcus, 1998; Hwang et al. 2004; Kim et al., 2006; Ekinci et al., 2014). Specifically, behavioral attributes identify a customer's value, while demographic variables account for life-cycle characteristics.

Organizing customers into homogenous segments is a foundational component of CLV modeling (Gupta, 2006). Specifically, any projection of an individual customer's value is derived from the behavior of similar customers. Without segments, individual projections would exhibit small samples with large variance, while a group of similar customers reduces variability and increases reliability. The groups provide the basis for assessing the potential value of a customer based on their characteristics.

One of the more widely used behavioral segmentation strategies is the RFM model (Bauer, 1988; Hughes, 1996; Marcus, 1998). Since its introduction, the RFM methodology has been widely adopted across many industries (Marcus, 1998) and incorporated in a myriad of research (Cheng and Chen, 2009; Dursun & Caber, 2016; Fader, Hardie & Lee 2005; Khajvand et al., 2011; Miglautsch, 2002; Pfeifer and Carraway, 2000; Wu, Chang, & Lo, 2009). The three factors represent fundamental components to evaluating a customer's standing with the firm. As such, RFM has established itself as a foundational approach to behavioral segmentation (Miglautsch, 2000).

Segmentation and RFM applications have been applied in many instances within the hospitality and tourism sectors (Law et al., 2018). RFM has been used to examine destination revisiting intention and loyalty (Wong et al., 2006; Jang and Feng, 2007), as well as customer value and pre-purchase motivations (Lumsden et al., 2008). RFM techniques have also been applied to profile lodging guests for marketing purposes (Morrison et al., 1999; Guilding et al., 2001; Min et al., 2002; Tideswell and Fredline, 2004; Osman et al., 2009; Dursun and Caber, 2016). In general, segmentation provides hospitality firms with an actionable process for developing strategies to target customers with similar characteristics to grow brand loyalty along with predicting their value. Additionally, literature has shown that RFM attributes provide a robust application for segmenting customers by their behavioral attributes, which can lead to more precise CLV predictions.

2. *Customer Life Cycle and Markov Chains*

Incorporating life cycle into CLV predictions allows for the model to account for the life cycle of their customers and the variability within their dynamic spending frequency. Literature suggests different models dependent on life-cycle stages (e.g., an acquisition or retention phase) (Gupta et al., 2006). Furthermore, customer life cycles are generally split into two broad categories and vary based on industry. The first class is termed "lost for good," which estimates customer retention using hazard models (Gupta et al., 2006; Neslin et al., 2006). These models do not allow for defected customers to return. The second approach is the "always a share" perspective and can be modeled with Markov processes (Gupta et al., 2006; Pfeifer and Carraway, 2000). The application of Markov chains allows customers to transition through several paths and potential phases in their lifetime.

In hospitality, customers are rarely "lost for good." Entertainment, travel and dining behaviors tend to change based on life cycle events. For instance, familial status may influence travel choices (i.e., destination, room type, etc.). Similarly, health factors may influence dining preferences. Therefore, the frequency of transactions and potential for dynamic shifts in behavior make Markov chains an ideal approach for the hospitality industry.

3. *Classifying Customer Activity*

As customers transition over their life cycle, it is also important to classify which customers are active or inactive to properly use resources and monitor churn. Several studies have developed models in contractual settings where customer activity is known. These studies were conducted in telecommunications (Hwang, Jung, & Suh, 2004; Kim et al., 2006), financial services (Haenlein et al., 2007; Khajvand and Tarokh, 2011; Ekinci et al., 2014; Chang and Ijose, 2016), and streaming services (Jie et al., 2019), where customers hold accounts with the firm and are considered active as long as the accounts are open. These studies attempt to mitigate customer churn by predicting those most likely to lapse and suggest marketing strategies for retention to increase lifetime values (Neslin et al., 2006; Glady et al., 2009; Almana et al., 2014).

Unlike telecommunications and streaming services, the hospitality industry operates in a non-contractual setting where spending patterns and brand loyalty behaviors are more complex (Sander et al., 2016). In many cases, guests patronize competing locations (restaurants, hotels, casinos) on a weekly or even daily basis. This presents a unique challenge for hospitality managers to identify who is still an active customer (engaged with the firm). Specifically, firms must decide how long to wait before engaging a customer or reclassifying the customer as inactive. Understanding the importance of where a customer is in their life cycle is central to CLV forecasts and leads to potential issues when applying CLV applications to hospitality.

Research has attempted to correct the problematic challenge of classifying customer activity status in dynamic settings with a Negative Binomial Distribution (NBD) based on historical purchases (Schmittlein et al., 1987; Reinartz and Kumar, 2000; Jain and Singh, 2002). The challenge with NBD is that it requires various assumptions, numerous inputs and has been shown to provide misleading results (Reinartz and Kumar, 2000; Jain and Singh, 2002). A secondary approach is to generate utility preferences for each customer (Rust et al., 2004; Sunder et al., 2016). Rust et al. (2004) and Sunder et al. (2016) show how utility preferences can be applied to predicting the likelihood of switching brands within the retail and CPG sectors. In these settings, customer lifetime value can be successfully employed when the market purchase behavior of customers can be monitored.

In comparison, hospitality firms do not receive competitive information regarding their share of wallet in the marketplace. This makes the customer utility approach impractical. A simple solution is to define a subjective cutoff similar to Coussement and De Bock (2013), such as if a customer has not shown up for three months. The issue with this approach is that the predefined value may not apply to all customers. Some customers visit frequently while others visit sparingly, making it inappropriate to force the metric to accommodate one group over another. Therefore, we aim to identify a suitable approach that is mathematically supported to monitor customer behavior.

Model Development with Hospitality and Gaming Considerations

Unique industry challenges can hinder model performance of CLV estimations when they are not accounted for (Haenlein et al., 2007; Ekinci et al., 2014). Different industries present unique challenges to customer classification based on variances in the type of business or service provided. The objective of this study is to use the aforementioned literature to derive a data-driven approach that leverages loyalty data from a hospitality firm, while recognizing the inherent limitations in CLV predictions when behavioral variability exists. Informed by Kim et al. (2006), a phased design was applied using insights from one technique to apprise another. The literature suggests that model formulation contains segmentation of customers into homogenous clusters, while also providing flexibility for customers to transition between groups over time. In this paper, we develop a model that demonstrates the potential benefits of implementing data science techniques and strategies based on prior research.

METHODS

Data

A data set of 331 loyalty customers belonging to a Las Vegas casino over a 12-year period was used to estimate the proposed model. Demographic data sourced from the loyalty card included patrons' age, gender, and distance from the casino. From a behavioral perspective, the recorded trip date and theoretical value (expected win/loss) were provided for each player. Note that the data are both left- and right-censored, containing a mix of new and existing customers.

Model Development

Gupta et al., (2006) developed a general equation [1] to be applied at the segment level for estimating CLV in the dynamic setting. The equation, which we adopt to the casino data, requires transition probabilities denoted *P*, values for the customers in each segment denoted *R*, and *i* defined as the applicable discount rate. Each year the value of a customer in each segment can be determined from the transition probabilities and average spend for a customer in the segment. The individual calculations are then summed for each year *t* to generate a total value for a customer currently in segment *S* over *T* years. In other words, the outcome probability is multiplied by the corresponding revenue to calculate the expected value for a customer in year *t*, discounted to present day.

$$CLV_{ST} = \sum_{t=0}^{T}[(1+i)^{-1}P]^{t} * R \qquad (1)$$

For our study, customer segments were derived from the individual's demographic and behavioral characteristics. Specifically, K-means clustering was used to segment the customers based on its simplicity of implementation and its wide application in a variety of fields (Cheng and Chen, 2009; Wu et al., 2009; Khajvand et al., 2010). When developing the segments, the demographic variables included the patrons' age, gender, and resident distance from the casino. In addition, two RFM variables, the patrons' average daily theoretical win (ADT) and trips per year, were used. After several iterations, the final segmentation was reduced to include trips per year (frequency), ADT (monetary), and the players' initial age. Distance from the casino was highly correlated with frequency of purchase, and gender did not add any significant difference in the segmentation scheme.

The next step was identifying customer activity status in a dynamic setting. To counter the lack of feasibility of NBD models and utility curves for hospitality CLV applications, we used a new approach that addresses the problematic issues by incorporating confidence intervals as shown in equation [2]. For each patron, a difference in the number of days between visits is calculated as a random variable, with a given mean and standard deviation for each year. The mean and standard deviation were used to create an expected pattern of behavior for each customer to determine if individuals are designated as active or inactive. Specifically, the metric is similar to a 95% upper confidence interval for a customer's expected trip cycle. This metric is then multiplied by two; inferring that the customer has missed two expected trips based on *their* specific pattern. If the customer had not visited within two expected trips, they were classified as inactive. The development of the metric is grounded in the findings of usage analysis (number of trips), which assists in retention activities (Weinstein, 2002), while accounting for the number of days since their last visit (recency), which has been found to be the largest predictor of churn (Coussement & De Bock, 2013).

$$Trip\ Flag: (AvgTBT\ +\ 2 * stdTBT) * 2 \qquad (2)$$

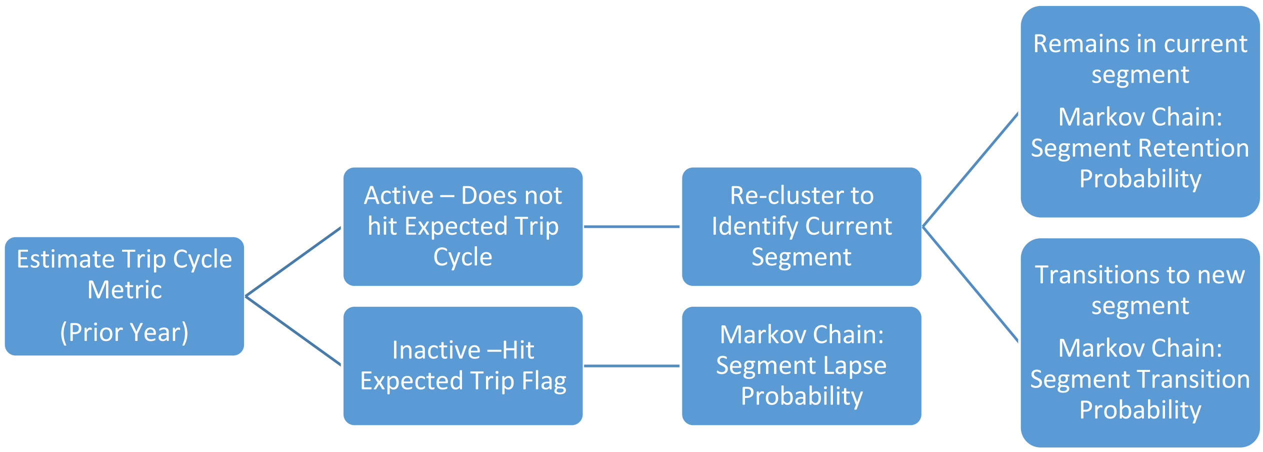
To meet the trip flag criteria, an individual must have made at least two trips in the prior year. If two trips were not made, these individuals were removed from estimation, as there were not enough data points to make an informed estimate regarding their trip behavior or lifetime value. After several iterations, many individuals had trip flags of less than a week due to very frequent visitation patterns. As discussed prior, life cycle events must be accounted for in CLV modeling. The model becomes problematic when events such as vacation or hospitalization occur, causing an individual to fall out of their expected behavior, even though a lapse may not be occurring. To mitigate life cycle occurrences and not actual changes in customer behavior, a minimum trip flag of 21 days was implemented. In other words, those with very frequent visitation patterns and expected trip cycle estimates of less than 21 days were reclassified to a trip cycle of 21 days. On the other hand, those with longer expected trip cycles (greater than 21 days) were assigned their calculated trip cycle value. The recalculated metric for a customer's expected trip cycle is provided in Equation 3.

$$Expected\ Trip\ Cycle: Max((AvgTBT\ +\ 2 * stdTBT) * 2\ , 21) \qquad (3)$$

Subsequently, trip flags were recalculated every year and used as the indicator for classifying a patron as active or inactive in the subsequent year. For example, a customer's trip flag for 2014 was used to determine if a customer lapsed in 2015. If an individual had lapsed, they were removed from their segment but had the ability to re-enter (or become re-active) in later years, thus beginning a new life cycle with its own visitation patterns.

The activity status of each customer provides only one component of the Markov chain probability matrix (inactive customers). Another key component for CLV estimations is projecting the migration patterns of active patrons longitudinally or over time. Incorporating migrations into CLV estimations allows organizations to strengthen relationships with customers who may transition over time into more profitable and higher value customers, while allocating fewer resources toward customers who may be nearing the end of their profitable life cycles. To identify the customer transitions, individuals were re-clustered each year based on the initial cluster seeds. If an individual was re-clustered into a new segment, then a transition between segments was identified. These movements specifically depict the dynamic nature of the hospitality field and account for changes in customer behavior over time. An overview of the process for determining the components of the Markov chain probabilities is depicted in Figure 1 and was reiterated each year. Additionally, an individual can make one of three movements in yearly increments: remain in their current segment, transition to another segment, or lapse from the model based on missing two expected trips or 21 days. The probability of each technique was calculated based on all the historical transitions. These estimates were aggregated across years to generate a homogenous Markov chain depicting the likelihood of a patron in any segment to transition in any given year.

Figure 1. CLV Estimation Cycle for One Year.



After the segments and transition probabilities were calculated, the customer lifetime value was determined. In reference to Equation [1], P is the Markov chain transition probabilities, R is the vector of the average yearly theoretical values for an individual in each segment, and i is the applicable discount rate. The calculations are summed for each year t to generate a total value for a customer currently in segment S over T years. In other words, the outcome probability was multiplied by the corresponding revenue to calculate the expected value for a customer in year t, discounted to present day.

RESULTS

The results of the segmentation are provided in Table 1. The table depicts the average number of patrons and their corresponding average gaming behavior in a given year. Specifically, the segments can be split into three overarching age brackets that help define their current life stage. The first group is characterized as young with three sub-segments. Each subgroup shows varying trip patterns and play behavior (ADT). The second group was characterized by middle-aged patrons and had four distinct player behaviors that mixed low and high ADT with low and high frequency of visit. Finally, the retired segment was characterized by players in their mid- to late 60s with three different patterns of behavior. In the last columns of the table, the yearly theoretical value per person was provided to highlight the worth of an individual in that segment per year, as well as a total segment value to account for segment size.

Table 1. Customer Segments.

Segment	Avg. # Customers	Avg. Age	ADT	Trips/Year	Theoretical per Person per Year	Theoretical Per Segment per Year
Young 1	5	40	43	188	\$8,084	\$40,420
Young 2	14	34	63	52	\$3,276	\$45,864
Young 3	5	35	147	65	\$9,555	\$47,775
Middle-Aged 1	33	51	50	64	\$3,200	\$105,600
Middle-Aged 2	13	54	54	184	\$9,936	\$129,168
Middle-Aged 3	17	53	157	45	\$7,065	\$120,105
Middle-Aged 4	17	48	111	147	\$16,317	\$277,389
Retired 1	44	69	40	115	\$4,600	\$202,400
Retired 2	16	67	107	195	\$20,865	\$333,840
Retired 3	17	67	136	56	\$7,616	\$129,472

The breakout of the 10 groups reveals that individuals in each segment have different theoretical values to the casino. These differences highlight the importance of understanding which customers are most valuable to the firm, while also stressing the importance of the firms' relationship with these customers. The Markov chain transition probabilities are displayed in Table 2 and provide insights into player progressions. To demonstrate the flexibility of the Markov chain approach, consider the following progression. A player in segment Young 1 has a 59.4% probability of remaining in the current segment, with a 3.1% probability of migrating to Young 2, and a 1.6%, 11.0% and 4.7% chance of transitioning to Middle-Aged 1, 2, and 4 due to a combination of age and behavioral change. This group also has a 20.3% chance of falling out of their expected trip pattern (based on their expected trip cycle). The estimated retention rates from the proposed trip flags are consistent with previous retention rates reported by Watson and Kale (2003) ranging between 66% and 89%. It is also important to note that not all segments can transition to other groups due to the dynamics of the segmentation variables. For instance, patrons in the Young cohort cannot transition to the Retired cohort directly, they must first move through the Middle-Aged segmentation cohort.

Table 2. Markov Transition Matrix

Markov Transitions	Young 1	Young 2	Young 3	Middle 1	Middle 2	Middle 3	Middle 4	Retired 1	Retired 2	Retired 3	Lapse
Young 1	59.4%	3.1%	-	1.6%	11.0%	-	4.7%	-	-	-	20.3%
Young 2	9.4%	51.3%	6.9%	1.3%	-	-	1.3%	-	-	-	30.0%
Young 3	-	5.6%	53.7%	-	-	-	1.9%	-	-	-	38.9%
Middle-Aged 1	0.5%	-	-	50.1%	7.0%	3.3%	3.3%	1.5%	-	0.8%	33.7%
Middle-Aged 2	2.0%	-	-	1.3%	60.7%	-	8.0%	4.0%	4.0%	-	20.0%
Middle-Aged 3	-	-	-	4.0%	-	64.7%	6.0%	0.5%	-	3.0%	21.9%
Middle-Aged 4	-	-	-	2.0%	4.0%	1.0%	66.5%	-	2.5%	-	23.6%
Retired 1	-	-	-	-	-	-	-	63.6%	4.6%	2.9%	28.8%
Retired 2	-	-	-	-	-	-	-	6.7%	76.2%	2.1%	15.0%
Retired 3	-	-	-	-	-	-	-	6.3%	5.3%	60.2%	28.2%
Lapse	-	-	-	-	-	-	-	-	-	-	100.0%

Note A: Trip Flag = -Max((Avg. TBT + 2Std)*2, 21 Days)
Note B: Not all segments can transition to all others due to dynamics of segmentation variables (Ex. Age: Young cannot transition to Retired)

The average spend, retention rates, and player transitions provide the fundamental components for constructing a customer’s lifetime value formulated in Equation 1. Specifically, the transition matrices (probability of movement) and the segment’s average theoretical value per person, per year, were multiplied together to generate an expected value of the customers over a specified timeframe. Following this calculation, the expected value of a player currently in these segments is projected for 5 and 10 years down the road as shown in Table 3. Note: The present value was calculated using an interest rate of 3%.

Table 3. Customer Lifetime Value Estimates

Segment	ADT	Trips/Year	Theoretical per Person per Year	5 Year CLV	10 Year CLV
Young 1	43	188	$8,084	$27,270	$35,788
Young 2	63	52	$3,276	$12,992	$17,115
Young 3	147	65	$9,555	$21,167	$23,394
Middle-Aged 1	50	64	$3,200	$13,065	$17,800
Middle-Aged 2	54	184	$9,936	$33,817	$43,912
Middle-Aged 3	157	45	$7,065	$23,390	$30,146
Middle-Aged 4	111	147	$16,317	$45,678	$55,161
Retired 1	40	115	$4,600	$16,486	$22,042
Retired 2	107	195	$20,865	$63,995	$80,769
Retired 3	136	56	$7,616	$23,484	$29,840

The results of the analysis stress the importance of viewing customers with a long-term, CRM-based relationship. From a short-term (transactional) perspective, guests would be valued based on ADT as casino marketing tends to gravitate to those who spend the most each visit. Classifying customers based on this metric would indicate that customers in Young 3, Middle-Aged 3 and Retired 3 are most valuable as shown in Table 1. However, when analyzing the customers based on their theoretical value per year (accounting for average spend and frequency of visit), Young 3, Middle-Aged 4 and Retired 2 are the most valuable customers. Further change in the most valuable customers occurs after accounting for customer behavior and the probability of transition. Young 1 becomes the most valuable segment in the younger demographic with Middle-Aged 4 and Retired 2. These differences in evaluation are derived from each group's migration patterns and inactivity rates based on their expected trip cycle. Accounting for these differences allows for a more complete picture of the value of each segment and the customers within.

DISCUSSION

Hospitality companies have begun to leverage consumer data to advance their understanding of their customers, identify customer preferences to enhance engagement, and make decisions to optimize their CLV. Despite these advances, there remains little research concerning strategic marketing and CLV estimation for hospitality. This study presented a practically viable approach to CLV estimations that industry practitioners can implement with the data they already collect.

The study applied a phased analysis for CLV modeling that accommodates the dynamic nature of customers in the hospitality industry. A novel data-science approach for estimating customer activity was introduced by identifying a customer's expected trip cycle to determine when a customer may deviate from their expected behavior. The technique provides a new metric to classify customer activity without using a fixed decision criterion (e.g. static 3 months), which may prove problematic in practical application.

In addition, the nuances and randomness in visitation patterns and player progressions bring into focus the idea that customer behavior is largely unpredictable. The presented model controls for this irregularity, while also allowing customers to progress through their life cycle with the use of Markov chains. This process is ideal for the hospitality industry as the model accounts for natural shifts in customer behavior and allows for new classifications to be made. The model results demonstrate how the outlined approach can decipher between a customer's transactional and lifetime value after accounting for customer activity and progressions over time.

Managerial

From an industry perspective, the presented approach provides hospitality firms with an outline to implement CLV modeling. Every location and industry will have its own challenges, but the fundamental structure of the modeling process will incorporate similar information regarding customer behavior over time. The current focus of leveraging big data and analytics to improve decision-making can be used to help firms identify customers that are most profitable from a long-term perspective. Similar to the arguments of Gupta et al. (2006), the presented model highlights the importance of finding which customers to target and identifying the correct balance. As was found in this study, the most valuable customers based on each interaction (ADT) were not the most valuable long-term. Similar results may help a firm generate a competitive advantage and better allocate marketing resources while observing how patrons progress through their life cycles over time. Kim et al. (2006) emphasized that CLV cannot solve problems itself but that it needs to coincide with an overall marketing strategy. Marketers at this location should test a variety of strategies to foster growth and observe if tactics can be used to increase the likelihood of transition into favorable segments or a decline in lapse rates. In the casino industry, this may be done through promotional offers such as free slot play, food and beverage offers, and free nights at a hotel, among others (Barsky and Tzolov, 2010).

Limitations and Future Research

This study has several limitations. First, the model was formulated with limited data from one casino. The data-driven results found here should not be generalized to other locations; rather, the modeling process outlines an approach to data mining that could generate insights at other locations. Specific market characteristics should be addressed on a case-by-case basis. There are also several data limitations. For instance, only rated play was observed for these customers; gaming patrons may choose to play without using their loyalty cards, and therefore the total spend may be different for each customer. A second limitation is that customer expenses were not considered in the evaluation as data regarding these expenses were not provided by the firm. The marketing expenses associated with acquiring and maintaining these players may make some segments more or less valuable. It is recommended that expenses be incorporated into CLV modeling under the value element R in Equation 1. In addition, only the theoretical value of each customer was observed. Although this metric is commonly accepted, the actual realized win or loss may be different for each customer.

It is also important to note that while our application spanned 12 years, more frequent estimation for firms that wish to implement these strategies may be warranted. In addition, firms may also want to consider other variables in their segmentation scheme. While our focus was on RFM components, other variables may provide insights unique to a specific location. Finally, it is encouraged for research and practitioners to explore the metric for expected trip cycle. While our model used a minimum trip cycle lag of 21 days to align with target churn rates of prior research (Watson and Kale, 2003), it is recommended that firms perform significant testing and select a target churn rate before implementation.

Despite the limitations, firms are encouraged to develop more sophisticated segmentation procedures that honor the foundations of RFM while recognizing that patterns of loyalty may vary, particularly in competitive environments with low switching costs. To this point, further exploration of the expected trip cycle may be an interesting endeavor for future research. In addition, further iterations of CLV modeling will continue to emerge with the advancement of data science in hospitality and tourism.

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