Can You Get a Ticket? Adaptive Railway Booking Strategies by Customer Value

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Abstract

This paper integrates a customer segmentation method with a discrete event simulation model to bridge the gap between identifying customer behaviors and using this knowledge to respond to customers and make the best use of resources. Three strategies are proposed and examined to improve the operation efficiency of a ticket-booking system. Their objective is to assist high-value customers in obtaining the tickets they want and/or reduce cancellations and failure-to-pays from low-value customers. Our simulation results demonstrate that the high-value, customer-friendly strategy beats all in assisting high-value customers and simultaneously improves railway operation performance. Additionally, the indirect, low-value customer abandonment strategy also has improved slightly in all aspects. Applying these strategies is expected to result in a decrease in complaints regarding booking system rejections and an increase in high-value customer satisfaction. On the other hand, the direct abandonment strategy to reject all low-value customers does not make any improvement.

Keywords: *Railway, Booking, Simulation, Customer value, Customer segmentation, Customer relationship management*

Introduction

Railway companies, with the popularity of e-booking systems, now have access to information on individual customer behaviors. This advantage can enable railway companies to initiate customer relationship management, or CRM, for improved profitability and resource allocation (Venkatesan and Kumar 2004; Kumar and Peterson 2005). According to Stringfellow et al. (2004), the intention of CRM is "understanding customer needs and leveraging that knowledge to improve a company's long-term profitability." Railway companies, due to traveler anonymity and the public nature of railway services, had no way to record customer purchase history in the past and could not differentiate their treatments to customers. Currently, with an e-booking system to retain individual customer data, railway companies can analyze each customer's value and allocate resources accordingly.

Utilizing individual customer purchase data to predict quantities of cancellations and no-shows has been confirmed effective in the field of airline research, as illustrated in the work of Lawrence et al. (2003), Garrow and Koppelman (2004), Neuling et al. (2004), Gorin et al. (2006), and Illiescu et al. (2008). Similar research has been conducted in the railway system, but as far as the authors are aware, there are only the works of Cirillo et al. (2011), Hetrakul and Cirillo (2013), Piening et al. (2013), Hetrakul and Cirillo (2014), and Chen and Wang (2013). However, these two fields are still focused on applying their results to decide the amount of seat overbookings and the allocations of seats among different fare classes, rather than identifying an individual's value to decide how to respond to the individual's request.

Train seating is a valuable resource to a railway company. When a ticket is booked but not yet paid for, the slot is blocked from booking for other customers. Although loyal customers always pay for their booked tickets during the advance ticket-booking period, some ticket holders often hold their reservations for a period of time, frequently cancelling them subsequently. More than 40% of railway ticket bookings ultimately are cancelled in India, Taiwan, and China, according to Bharill and Rangaraj (2008), Chen and Wang (2013), and *China Review News* (2013), respectively. Not only does this high-cancellation situation affect the booking system's operational efficiency, it also incurs complaints about people's inability to book tickets (Zhang et al. 2007; Von Martens and Hilberts 2011). If a customer's booking is rejected because slots are fully booked, yet some or part of those booked slots are eventually cancelled and later booked by others, the customer may be resentful. A loyal customer, frustrated by repeated booking failures, might switch to a competing provider to make his journey possible. This becomes a "lose-lose" situation for both customers and the railway company.

A company should recognize the profitability of loyal customers from the CRM perspective and attempt to know their functional and emotional needs (Stringfellow et al. 2004): they need tickets, and they think they have a priority in making reservations. On the other hand, the company should consider abandoning those who consume a railway company's resources and damage its performance, who may be labeled as "troublemakers" (Van Raaij 2005; Haenlein and Kaplan 2009; Haenlein and Kaplan 2011). The direct abandonment of troublemakers may cause most companies to hesitate; yet, some indirect abandonment strategies can lead to less severe reactions from customers, such as increasing prices and decreasing service levels (Haenlein and Kaplan 2011; Haenlein and Kaplan 2012).

This study aims to use individual-level booking data to implement CRM strategies to improve the performance of a railway ticket booking system. Customers are segmented into three groups, based on a Taiwanese railway agency's ticket booking database. Three strategies then concentrate on assisting high-value customers to obtain tickets, applying an indirect abandonment policy to low-value customers, and using a direct abandonment policy to reject low-value customers in comparison with a base scenario to evaluate their effectiveness. The remainder of the paper is organized as follows: First, literature on passenger name record (PNR) applications in ticket booking, customer value analysis, and customer management is reviewed. Next, the development of customer segmentation and ticket booking simulation models is introduced. Finally, the implementing of models and conclusions are presented.

Using PNR in Ticket-Booking Services

Early ticket booking papers in railway and airline services primarily utilize aggregated booking data to forecast demand, predict cancellations and no-shows, and allocate seats to various legs and classes. With an increasing number of customer booking databases and improvements in computer calculation speed, a new trend involves utilizing PNRs to increase prediction accuracy (Garrow and Koppelman 2004; Morales and Wang 2010). A PNR is generated when a ticket booking is made. Its typical information includes time of service, time of booking, time of cancellation, ticket type/fare by class, membership, payment status, origin and destination, reservation channel, group size, day(s) of travel, and number of travel legs, for air travel providers. By using PNRs, customers are heterogeneous agents with their own features, and they interact with others to exhibit aggregate behavior (Khouja et al. 2008).

The application of PNR in ticket booking can be classified into three categories. The first category uses discrete choice models that originate from Talluri and Van Ryzin's (2004) research. Garrow and Koppelman (2004) developed a multinomial logit (MNL) model for the airline industry to predict the percentages of show, cancellation, no-show, and standby for each potential traveler. They concluded that the incorporation of passenger information can improve forecasting accuracy. Iliescu et al. (2008) described a booked ticket's cancellation as a survival process, and the survival percentage of each booking relied on the reservist's characteristics. Graham et al. (2010) used a discrete-time proportional odds model to predict the conditional probability of a ticket surviving from one period to the next. Similar techniques are also applied in the railway industry. Hetrakul and Cirillo (2013) applied three logit-based ticket purchase timing models and compared their suitability to three market segments with different travel distances. Additionally, Piening et al. (2013) analyzed customer choices to upgrade, downgrade, or cancel their ticket discount cards when their cards were due. Their hazard model identified several CRM practices that would affect the discount cards' renewal.

The second category applies data mining techniques to explore meaningful relationships in the customer-booking database. Lawrence et al. (2003) demonstrated that their three data-mining models employing PNRs were superior to a historical model in forecasting airline no-shows. Neuling et al. (2004) introduced how Lufthansa German Airlines applied a decision tree-based model to forecast no-show probabilities. Morales and Wang (2010) tested three decision tree-based models using hotel booking data and found that compared to several traditional statistical methods, they could reduce a 20% forecast error. Its application in the railway industry was developed by Chen and Wang (2013), who used a two-stage clustering model to predict customer values and recommended loyalty program strategies for each customer group.

The final category employs combinatorial methods to forecast customer behavior. Gorin et al. (2006) developed a cost-based, PNR-adjusted approach to find optimal no-show rates for the airline industry. Their objective was to minimize the cost of seat overselling and underselling, while adjusting its no-show probabilities for different customer segments using historical booking data. They concluded that the new approach could improve revenue by up to 10% compared to traditional average no-show rate methods. Cirillo et al. (2011) established an MNL model for the railway industry to explain passengers' choice of booking time, and combined it with a linear-regression demand function to find optimal fares. Hetrakul and Cirillo (2014) further used their logit and demand models to jointly decide optimal ticket prices and seat allocations.

It can be asserted from the above reviews that PNR studies in ticket booking are limited, and the purpose of these studies is primarily to aggregate predicted individual behaviors as parameters to estimate total number of demands, cancellations, or no-shows. The premium benefit of analyzing PNR is not only to predict what might occur, but also to guide a company's actions (Lavalle et al. 2011). The evident link between identifying customer behaviors and using this knowledge to respond to customers is still lacking in ticket-booking literature.

Customer Value Analysis and Customer Management

Several innovative companies have acknowledged that providing differentiated services to customers based on their profitability can be more beneficial, as resources are limited and valuable. For example, investing in the top 1% of customers could earn 50% of a company's revenue, but serving the bottom 20% could cost the company money (Ziethaml et al. 2001; Van Raaij 2005). Therefore, identifying customer value and treating them appropriately is an important avenue for becoming a top performing company.

Customer value can be assessed either by solely using past purchase history or by forecasting future cash flow. The former can be calculated by applying recency, frequency, and monetary (RFM), activity-based costing, past customer value, and share-of-wallet methods (Kumar 2006). The latter is based primarily on the customer lifetime value (CLV) concept proposed by Jackson (1989), a prediction of the net discounted profit obtained from a customer over his or her lifetime with a company. This considers when and how much the customer will purchase, and how the company will invest its resources. A prediction of CLV can be obtained via different types of models, such as the negative binomial distribution (NBD)/Pareto model, the beta-geometric/NBD model, and hazard models (Fader et al. 2005; Gupta et al. 2006).

The RFM method has been used the most frequently among these methods for decades to select customers (Bijmolt et al. 2010). Its fundamental rationale is that those who have recently made purchases, make more repeated purchases, and spend more money are a company's best customers (McCarty and Hastak 2007). Variables other than the original R, F, and M are incorporated in extended studies. For example, Wei et al. (2012) added "relation length" and Khajvand et al. (2011) proposed "count item" in their models. Although CLV is an effective tool to measure direct, or transactional contributions, it overlooks the non-monetary benefit or harm that customers may carry. As this paper considers customer cancellation and no-show (or failure-to-pay, in the railway scenario) behaviors, an extended RFM model is utilized to segment customers. Therefore, in this study, customer value is defined as the direct and indirect contributions brought by a customer to a company during a period of time (von Martens and Hilbert 2011).

Once customers are categorized by their values, companies can allocate resources differently by group. For example, Reinartz and Kumar (2002) segment customers into four types—true friends, barnacles, butterflies, and strangers—and suggest that companies should implement differentiated strategies for these groups. These strategies include communicating consistently and finding ways to increase the loyalty of "true friends"; promoting up- and cross-selling or controlling costs for "barnacles"; preparing to cease investment in "butterflies"; and making no investment in "strangers." Likewise, First Union, a US bank, provides extra customer service support to its profitable customers, but it does not grant special favors, such as waiving bounced checks, to those who are unprofitable (Zeithaml et al. 2001). In 2007, Sprint Nextel terminated wireless services to approximately 1,000 customers for making "too many" service calls, with some amounting to hundreds per month (Mittal et al. 2008). Filene's Basement, a retailer, curtailed all further service to two sisters in 2003 because of their chronic complaints and returning of goods (Haenlein and Kaplan 2009). These cases demonstrate that halting resources, or even abandoning unprofitable or low-value customers, exists in practice.

Although abandoning a customer is not an easy decision for any company, it is considered based on the following reasons: customer profitability, employee productivity, capacity constraint, and target market (Mittal et al. 2008). If a company must abandon a customer, there are direct and indirect abandonment strategies. A direct abandonment strategy refers to a situation in which a company explicitly expresses the intention to end the relationship with the customer, such as the Sprint Nextel and Filene's Basement cases. On the other hand, a company may choose an indirect abandonment strategy, which terminates the relationship with a customer without explicitly communicating this to the customer (Haenlein and Kaplan 2011). According to Haenlein and Kaplan (2011; 2012), divesting unprofitable or low-value customers can prevent future losses and may improve a company's image among some types of current customers. However, in the meantime, the company may risk negative word-of-mouth (WOM). Therefore, carefully designing abandonment strategies and managing potential reactions become important.

Model Development

Customer Segmentation Model

Two models were developed during this research for identifying customer values using PNRs and measuring the effectiveness of booking strategies for a railway ticket booking system in Taiwan. The ticket booking system stores personal ID, date and time of booking, train number, trip origin, trip destination, order quantity, and status, such as purchased, cancelled, or failure-to-pay, for each booking record. Six variables were extracted from these booking data to constitute an extended RFM model.

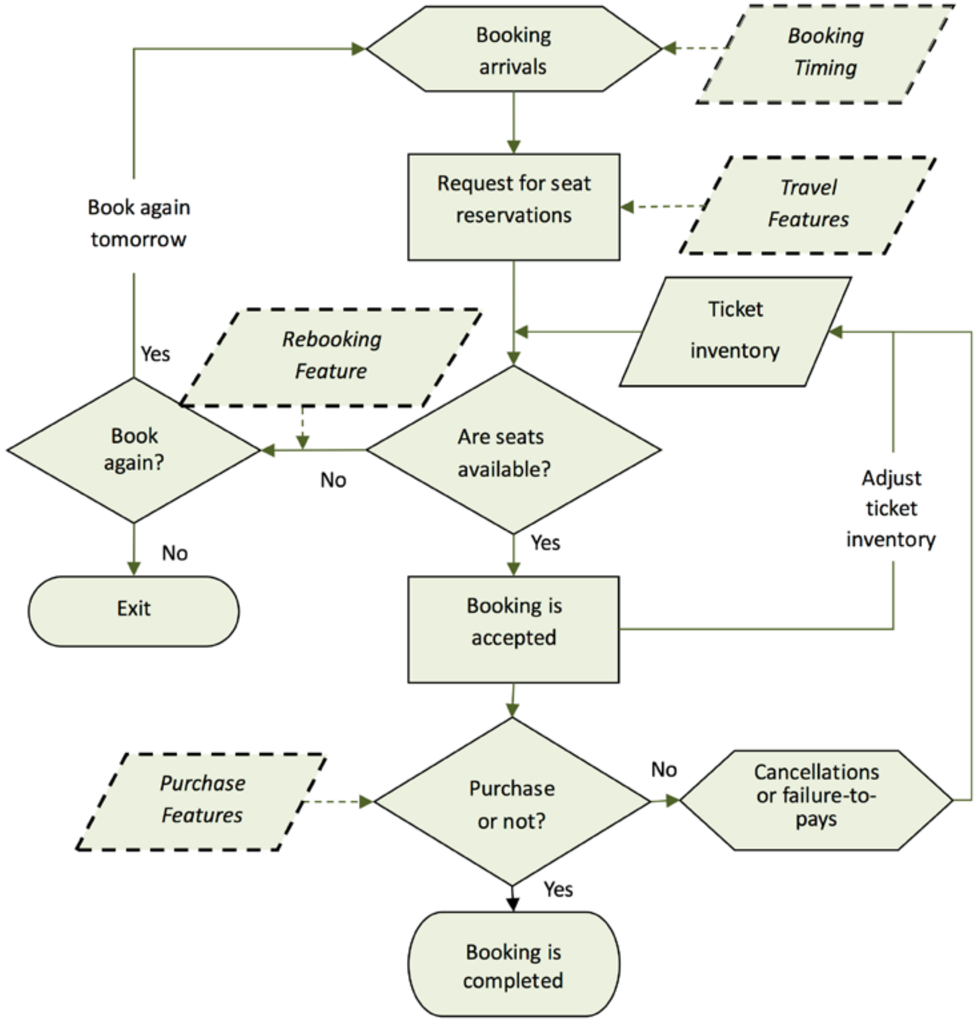
1. Recency (R) – the interval between when a customer last booked and the end of a specified period of time.
2. Frequency (F) – the number of bookings during a specified period of time.
3. Monetary (M) – the average amount of money a customer spends for each booking during a specified period of time, not including cancelled and failure-to-pay bookings.
4. Total Mileage (TM) – the total mileage traveled during a specified period of time, not including the mileages of other passenger(s) travelling along with the customer.
5. Purchase Rate (PR) – the purchase rate of a customer's total bookings during a specified period of time.
6. Average Status Score (ASS) – the average status score of the bookings from a customer during a specified period of time (5 points for a purchased booking, 3 points for a cancelled booking, and 1 point for a failure-to-pay booking).

The customers in the booking database are assigned a number from 5 to 1, according to their rankings for each of the three variables, using the procedure proposed by Hughes (1994). These customers are then grouped by their summed scores. The higher a customer's summed score, the more beneficial the customer is to the company in terms of their loyalty in making repeated purchases and paying for their booked tickets. On the other hand, those who have low scores are labeled as "troublemakers" who consume booking resources and block other customers' reservations but seldom pay for their bookings.

Ticket Booking Simulation Model

A discrete event simulation model is built as the schema in Figure 1, in accordance with actual ticket-booking processes. The model originates with a potential passenger's arrival and request for ticket(s) at the system. The potential passenger is mapped to the properties of a randomly drawn customer from our database, which is based on real customer booking records, to imitate the customer's behavior. If the potential passenger's request for a specific travel section (origin-destination pair, O-D pair) and number of tickets can be met, the booking is accepted. If not, the customer may possibly return to the system the next day for another attempt. The customer's choosing to make a further attempt depends on the customer's rebooking intention. After a booking, one of three possible follow-up actions may occur within a deadline: purchase, cancellation, or failure-to-pay. The customer's action depends on the probabilities of his or her past behavior. If the booking is cancelled, or if there is a failure-to-pay within the deadline, the ticket(s) will be released for subsequent possible booking. However, if the booking is paid for, the booking process is completed.

FIGURE 1.
Base model for ticket-booking processes



Among the aforementioned processes, four decision points exist at which a customer's personal characteristics, or behaviors, are considered. The relevant characteristics are "booking timing," "travel features," "rebooking intention," and "purchase features," as noted in Figure 1. The interactions between booking processes and personal actions not only impact the inventory of tickets, but also comprise the dynamics of the ticket booking system. PNRs were collected and managed, as listed in Table 1, to obtain these personal characteristics.

TABLE 1.
Contents and Specifications of Customer Characteristics

Personal Characteristics		Characteristic Specification Method
Booking timing	Customer segment	Customers categorized into several different segments by RFM analysis
	Customer arrival	Segments' inter-arrival times for each booking day tallied to build their arrival distributions
Travel features	Traveling section	O-D pair most frequently traveled by customer
	Number of tickets booked	Rounded average number of tickets booked each time by customer
Rebooking intention	Rebooking rate	Number of bookings for this train as percentage of total bookings (for all trains); this ratio displays train's importance to customer – the higher the ratio, the more likely that the customer will attempt to make bookings again; there are two maximum attempts to rebook in this study
Purchase features	Purchase rate	Number of purchases as percentage of total bookings
	Cancellation rate	Number of cancellations as percentage of total bookings
	Failure-to-pay rate	Number of failure-to-pays as percentage of total bookings

Ticket-Booking Strategies

The purpose of this study was to propose strategies to improve a ticket booking system's efficiency by helping high-value customers obtain the tickets they want or/and reducing troublemakers to incur cancellations and failure-to-pays. To meet this objective, we proposed one high-value customer-friendly strategy and two low-value customer abandonment strategies and evaluated their performances along with the base model.

1. High-value customer-friendly strategy: flexible booking limits (FBL) – The goal with this strategy is to facilitate high-value customer bookings by combining two or more available O-D pairs to turn into an O-D pair that the customer had failed to obtain initially because it had been fully booked. Normally, a train's seat allocation is fixed. The disadvantage of a fixed booking limit policy is that it can cause considerable inefficiency when demands are stochastic (Talluri and Ryzin 2004). Hence, when some O-D pairs are fully booked, others may still have vacant seats. High-value customers are reliable, loyal, and profitable for a company; helping them obtain bookings not only raises their satisfaction, but also increases ticket bookings' overall purchase rate.

2. Indirect abandonment strategy: overbooking (OB) – The objective with this strategy is to borrow booked tickets from low-value customers, who have a low purchase rate, and lend them to high-value customers. This method is similar to the airline industry's overbooking strategy. It still provides booking services to low-value customers initially, but these booked seats will be taken away if and once they are cancelled and transferred to overbooked high-value customers. It is expected that this strategy will increase the booking success rate of high-value customers, and lower the overall cancellation rate.

3. Direct abandonment strategy: rejecting low-value customers (RLC) – Although it is difficult to implement in real life, this study builds an extreme strategy to reject all bookings from low-value customers, to observe its impact. When a low-value customer wants to make a booking, the customer will be rejected. This strategy is expected to increase the overall purchase rate, and reduce cancellation and failure-to-pay rates.

4. Base model – The base model follows the booking processes illustrated in Figure 1 and is basically a first-come-first-served scenario. Whether or not a customer obtains tickets is based on both the order of arrival and the availability of seats in the desired O-D pair.

Simulation Results

Experimental Design

The Taiwan Railway Administration (TRA) is the largest railway operator in Taiwan. In its booking system, ticket fares are fixed during its 14-day booking period. A customer can book up to 6 tickets for a train. Customers who book in the system have to make their payments or cancel their bookings (free of charge) before the end of the next day or the booked tickets will be released. An analysis was performed to apply the extended RFM method; 332,584 customers with booking records on TRA's Western Main Line during the period of August 1–October 31, 2010, were analyzed, with their scores ranging from 6 to 30 points. Further, this study chose the customers who booked Train Number X (the identity of the train number is disguised for confidentiality reasons) during this period as subjects to extract their personal characteristics, as mentioned in Table 1, to use in the simulation model. During this period, there were 13,635 passengers who made 32,647 reservations for Train Number X, and in total they made 186,186 reservations from all 228 trains operated by the TRA. Among these passengers, 725 were graded 6–9 points and 766 were graded 29–30 points. As the number of target customers who are given favors or abandoned should not excessively distort TRA's daily operations, these two groups were defined as low-value and high-value customers, while the others were categorized as regular customers. The results in Table 2 exhibit the differences among the three customer segments, showing that low-value customers never pay for their booked tickets, and most tend to cancel their bookings; the high-value customers have a high purchase rate, and they spend and travel more than others.

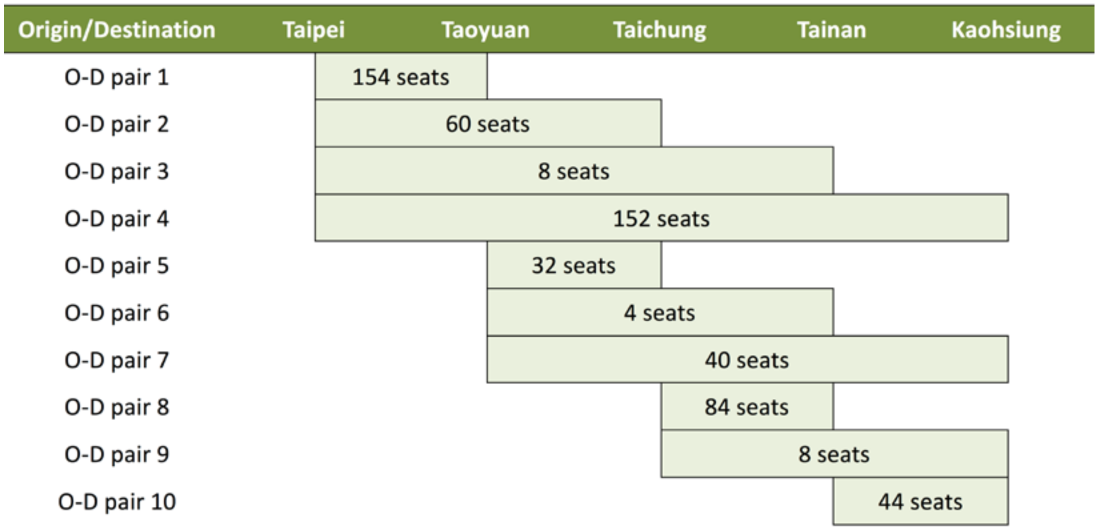
TABLE 2.
Averages of Variables for Three Customer Segments

Segment	Number of Customers	R (day)	F (times)	M ($)	TM (mi)	PR (%)	ASS (point)
High-value customer	776	21	16	17	1801	90%	4.76
Regular customer	12,134	41	14	10	695	51%	3.74
Low-value customer	725	75	2	0	0	0%	2.22
Total	13,635						

R = Recency; F = Frequency; M = Monetary; TM = Total Mileage; PR = Purchase Rate; ASS = Average Status Score

The original Train Number X had 18 stops, which gave 153 possible combinations (that is, C_2^{18}) for seat allocations. However, 5 stops were adopted to simplify the situation, as were 10 combinations (O-D pairs). Figure 2 illustrates seat allocations for the train.

FIGURE 2.
Seat allocations for all O-D pairs



Allocations rearranged according to train's original allocations; distance from Taipei to Kaohsiung is 231 miles.

Our discrete event simulation model was built using the SIMUL8 simulation package. SIMUL8 has the advantage of utilizing modularized blocks to facilitate model building and allows us to incorporate customer segmentation, individual customer behavior, and the intangible booking service process to examine different booking strategies' impacts. The aforementioned 13,635 customers were randomly chosen to reserve tickets according to their arrival patterns and booking characteristics. Four aspects of performances for each booking strategy were obtained via a 14-day booking period simulation, with 20 replications. These performances included segmental booking results, overall booking results, numbers of unsold tickets, and total revenues.

Segmental Booking Results

The results in Table 3 illustrate that the booking success rates of high-value customers with the first three strategies were all increased compared to the base model. The FBL strategy especially had the largest improvement (from 27.42% to 68.99%), and the success rates in the other two segments did not decrease. This advantage came from the reduction of booking failures by searching combinable tickets for high-value customers. The OB strategy had a smaller improvement (from 27.42% to 35.33%) and did not affect the other two segments' success rates. On the other hand, the RLC strategy, which blocks all bookings from low-value customers, also generated marginal improvements in the high-value and regular customer segments.

Additionally, the numbers of purchased tickets with the proposed three strategies were all increased, indicating that they can help increase ticket sales. One thing to note in Table 3 is that low-value customers have higher booking success rates in the FBL, OB, and Base strategies. It is because low-value customers tend to book tickets earlier during the booking period compared to regular and high-value customers in our database and, therefore, have higher chance to get reservations.

TABLE 3.
Booking Results by Segment

Strategy	Customer Segment	Able to Book			Failure to Book	Total	Booking Success Rate
		Cancellation	*Failure-to-Pay*	*Purchase*			
FBL	High	20	5	73	44	142	69%
	Regular	208	74	213	1,041	1536	32%
	Low	43	18	0	70	131	47%
	Total	271	97	286	1,155	1,809	36%
OB	High	10	3	37	91	141	35%
	Regular	205	75	210	1,046	1,536	32%
	Low	41	18	0	71	130	45%
	Total	256	96	247	1,208	1,807	33%
RLC	High	8	2	30	100	140	29%
	Regular	208	76	213	1,038	1,535	32%
	Low	0	0	0	176	176	0%
	Total	216	78	243	1,314	1,851	29%
Base	High	7	2	29	101	139	27%
	Regular	204	74	208	1,050	1,536	32%
	Low	41	18	0	73	132	45%
	Total	252	94	237	1,224	1,807	32%

Overall Booking Results

The overall booking success rates with FBL and OB strategies were higher than the rate in the base model, as noted in Table 3. This means that all customers can benefit from these two strategies helping high-value customers obtain tickets, and the TRA can simultaneously increase customer booking satisfaction.

Further, paired t-tests were used to compare the results of the Base model with other strategies to determine whether the differences are significant. As demonstrated in Table 4, the total number of booking successes (able-to-books) was significantly increased except for the RLC strategy. The reduction in the case of RLC occurred mainly because of the increase in booking rejections by low-value customers. If the possible consequences of successful bookings are considered, it can be noted that purchase rates with the first three strategies were significantly increased, and cancellation and failure-to-pay rates in the cases of FBL and RLC all decreased. This implies that overall efficiency improved, either because of boosting bookings from high-value customers or restraining bookings from low-value customers.

TABLE 4.
Overall Booking Results

Strategy	Able to Book			
	Cancellation	*Failure-to-Pay*	*Purchase*	*Total*
FBL	270* (41.4%*)	96$^{\Delta}$(14.7%*)	286* (43.9%*)	652* (100%)
OB	256 (42.8%$^{\Delta}$)	95 (15.9%)	247* (41.3%**)	598** (100%)
RLC	216* (40.4%*)	77* (14.4%*)	242** (45.2%*)	535* (100%)
Base	252 (43.2%)	94 (16.1%)	237 (40.7%)	583 (100%)

* *Significantly different from result of Base strategy; p<0.001.*
** *Significantly different from result of Base strategy; p<0.01.*
$^{\Delta}$ *Significantly different from result of Base strategy; p<0.1.*

Table 5 displays the averages of unsold tickets and corresponding mileages for the 10 travel O-D pairs at the end of the 14-day booking period. The unbalanced results of unsold tickets among these O-D pairs were due to the mismatch of seat allocation and real customer demand, which challenges all kinds of service providers. The FBL strategy was proposed because of this mismatch, to reduce the imbalance. The results in Table 5 confirm the effectiveness of FBL strategy; excess seats from some O-D pairs were added to enable the completion of bookings from high-value customers and thus, more tickets can be sold. The other two strategies do not aim to increase ticket selling. Therefore, these quantities of unsold tickets and mileages do not significantly differ from the base model.

TABLE 5.
Averages of Unsold Ticket and Mileage in Each O-D Pair

O-D Pair	1	2	3	4	5	6	7	8	9	10	Total	Unsold Mileage (mi)
FBL	114.3	1.8	0.7	6.4	1.2	0.3	1.1	38.3	0.7	8.1	173.0*	8,391*
OB	118.0	1.7	0.8	5.7	1.3	0.6	0.7	65.2	0.1	34.4	228.4	11,642
RLC	122.2	1.0	0.5	6.5	1.3	0.5	0.7	65.4	0.2	34.2	232.4**	11,779
Base	118.1	0.8	1.0	6.7	0.8	0.4	1.1	65.4	0.1	34.6	229.0	11,854

* *Significantly different from result of Base strategy; p<0.001.*
** *Significantly different from result of Base strategy; p<0.1.*

Total revenue for the above four strategies can be calculated from the prices and numbers of sold tickets. Their average revenues are $7,287, $6,892, $6,874, and $6,865, respectively. The results demonstrate that the FBL strategy again exhibited more improvement (6.1%), whereas OB and RLC strategies did not significantly differ from the base model.

Conclusions

From a business management perspective, as the best customers are more loyal and profitable, managers should always maintain a good relationship with them, even if it sometimes may be necessary to sacrifice low-value customers' benefits. However, the literature review reveals a gap in the railway industry's linkage between customer value analysis and a corresponsive CRM strategy. Concerning this inadequacy, this study provided an example of identifying customer profitability, implementing differentiated strategies for tiered customers, and demonstrating the effectiveness of the differentiated strategies. Through PNR analysis and comprehensive simulation experiments, the following important observations are made.

First, it can be observed that booking strategies responsive to high-value customers are effective. FBL strategy has the best potential to assist high-value customers and simultaneously improves operational performance. Its booking success rate with high-value customers is up 156% (from 27% to 69%, as shown in Table 3), overall booking success rate is up 13% (from 32% to 36%, as shown in Table 3), overall purchase rate is up 8% (from 40.7% to 43.9%, as shown in Table 4), number of unsold tickets is down by 24% (from 229 to 173 tickets, as shown in Table 5), and revenue is up 6% (from $6,865 to $7,287 dollars). Additionally, the OB strategy also has slight improvements in all aspects. From booking efficiency and cost-saving perspectives, as "it costs five times more to acquire a new customer than to retain an existing one" (Pfeifer 2005), a wise decision would be for railway managers to favor high-value customers.

Second, some managers may presume that a direct abandonment strategy to reject unprofitable customers is beneficial for their businesses, but that effect is not clearly supported by this study. The RLC strategy has minor improvements in high-value and regular customers' booking success rate, total purchase rate, and total revenue, but its total booking success rate, total number of successful bookings, and number of unsold tickets do not perform well. Although the RLC strategy provides more booking opportunities for regular and high-value customers, regular customers' greater quantity and lower purchase rate weaken this strategy's performance. This direct abandonment strategy does not improve booking efficiency, and risks inducing negative WOM and other costs (Mittal et al. 2008; Haenlein and Kaplan 2011); therefore, managers should consider educating and converting low-value customers to general customers rather than directly abandoning them.

Finally, the RFM analysis reveals that variations in customer booking behavior exist among different customer segments, and railway operators can benefit from allocating seat resources according to customer value. The model is especially applicable for air and railway transportation, which maintains booking data. Further, the concept of linking customer behavior and a company's operation strategy also can be employed in bus and metro transportation that does not own passenger identifications. For example, some transportation smart cards can be used to pay for parking fees, bike rentals, and store purchases, in addition to bus and metro fares. Cardholder travel data allows transport operators to know their customers' travel origins and destinations, when they travel, where they stop, and even what they purchase, and transport operators can arrange vehicle resources and advertising strategies accordingly. Along with the development of information technology, the applications of customer analytics to operation strategies will become more and more popular.

As with any research, this study has limitations. First, rebooking rates for rejected customers were estimations in this study because the actual rejected booking data were not recorded by the TRA. More detailed customer booking behavior could be explored were these data available. Second, the costs of customer rejection, cancellation, and failure-to-pays are difficult to quantify and, hence, were not considered. Future extensions can focus on the appraisal of these costs. Third, possible reactions to the customer-friendly and customer abandonment strategies are not considered, such as positive or negative WOM, or individual purchase rate increments.

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