Value Assessment of Airport Billboards Based on Passenger Big Data

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Abstract. As an important element of the airport ecosystem, airport billboards are playing a crucial role in publicizing the city image and facilitating humanistic airport construction. At the same time, airport billboards have great commercial value and is a popular channel for enterprises to prompt their products and to build their brand image. Currently, most airports in China adopt a simple fixed pricing mechanism for airport billboards. Specifically, for any type of billboard, the advertising price is mainly determined by considering historical prices and the total passenger flow of the entire airport during a whole year. However, this seemingly crude pricing mechanism only considers macro-level data of passenger flow and fails in reflecting the real value of billboards in different locations effectively, since the value of a particular billboard depends not only on its media form, but also on the number of passengers flowing through and whether these passengers are the target customers of the advertising content. Based on big data on airport layout, flight information, and passenger attributes, this paper proposes a time- and location-based value assessment model for airport billboards. Using sample data collected from the Beijing Capital International Airport, the assessment model is adopted to evaluate the value of two real billboards in Terminal T3. Application of this model can reflect the difference in the value of airport billboards located in different spots during various periods. Furthermore, this model provides a solid foundation for airport executives to develop differentiated/dynamic pricing and flexible advertisement scheduling strategies, thereby improving the overall efficiency.

Keywords: Airport billboards, value assessment, passenger big data, passenger portrait, advertisement pricing

1. Introduction

As a core hub of national transportation, civil aviation airports are playing an indispensable part in boosting local economy. Airports are commonly known as the windows and business cards of a city or a country. Since the airport is a special type of public infrastructure, airport management is subject to government regulation on the pricing of their primary airline business, so as to reflect the public interest nature of the service. As an important part of humanistic airport construction, advertisement media within an airport takes an irreplaceable role in building the visual order of airports, advocating public welfare, and providing guidance for passengers. Meanwhile, as a scarce resource with its unique advantages, billboards of various forms within an airport have great commercial value and their revenue provides strong financial support for the airport construction and operation. In fact, advertising revenue is an important source of the non-aeronautical earnings of airports. Taking the Beijing Capital International Airport as an example: the advertising revenue of this airport in 2019 reached 1.081 billion RMB, accounting for 16% of its total non-aeronautical revenue. During the COVID-19
pandemic, despite the sharp decline in the number of flights and total passenger flow, Terminals T2 and T3 of the Beijing Capital International Airport still generated a total advertising revenue of nearly 0.8 billion RMB in 2021, with the advertising revenue per-passenger reaching a new record of 24.5 RMB, as shown in Figure 1.

As an infrastructure with both public service and commercial functions, airport billboards are normally subject to the physical conditions of the airport, including the layout and the design. The yearly investment devoted to the construction and maintenance of advertising facilities is tremendous. Therefore, how to continuously improve the revenue of billboards is a topic of concern for airport executives. For a typical advertising media located in the airport, such as LED billboards, light boxes, and window films, major Chinese airports commonly adopt a "blanket fee + overage fee" pricing scheme. Under this pricing scheme, the selling price (i.e., blanket fee) of a particular advertising space mainly depends on the total passenger flow of the whole terminal in the previous year (called the "operating period"). If the passenger flow of the whole terminal announced by the airport for a given year does not reach the passenger flow during the operating period, then the airport will not charge any additional overage advertising fee. Otherwise, if the actual passenger flow exceeds that during the operating period, then advertisers need to pay a proportion of extra advertising fee. The COVID-19 pandemic had a far-reaching impact on the aviation industry. In the context of lockdown at home and frequent flight meltdowns, the passenger flow at China’s civil aviation airports have encountered a sharp decline in 2020 and 2021. For example, the Beijing Capital International Airport merely had a total passenger flow of 32.6 million in 2021, which was equivalent to only 32.6% of the passenger flow recorded in 2019. Faced with the reality that its actual passenger flow is far less than that during the operating period, over the past two years, the Beijing Capital International Airport introduced a policy of advertising cost reduction for advertisers. Meanwhile, due to the rapid development of new media advertising on mobile internet, airport billboards are also suffering from high vacancy rates (which were 45.2% and 30% in 2020 and 2021, respectively) and airports are facing difficulties in collecting advertisement receivables.

Similar to other outdoor advertising media, the value of airport billboards to advertisers lies in the exposures of the advertising content to its target customers. It has been widely recognized that various factors, including the bill-

![Figure 1](image-url) Beijing Capital International Airport: Advertising Revenue and Revenue per Passenger (2005-2021)
board form, size, location, surroundings, and passenger flow that is covered, all affect the actual value or effectiveness of the advertisement. The pricing scheme for billboards commonly adopted by most airports in China is majorly based on historical data, with appropriate adjustments made according to the actual passenger flow in a given year. Admittedly, this scheme is reasonable to a certain extent, because under this pricing scheme, the airport advertising revenue is positively correlated to the yearly passenger throughput; for example, the correlation coefficient between the gross advertising revenue and yearly passenger flow for the Beijing Capital International Airport during 2005-2021 is 0.834. However, this relatively crude advertising pricing scheme relies on the fact that airports usually have significantly stronger bargaining power relatively to the agencies and advertisers; and it has some obvious limitations. Specifically, this scheme is based primarily on the investment of advertising resources rather than on the actual advertising effectiveness. As shown in Figure 1, the advertising revenue per passenger exhibited a violent fluctuation during the past few years, implying significant risk for advertisers. Also, the airport passenger flow in different locations within an airport varies significantly, thus the relatively simple pricing scheme usually fails to reflect the difference in the real value of the same type of advertisement located in different areas of an airport. In addition, under the current sales mode of airport billboards, a billboard will continuously display the advertising content of a particular advertiser during the entire contracting period; much is yet to be discussed about the efficiency of this advertisement scheduling strategy.

With the increasing popularity and adoption of personalized advertising strategies based on recommendation algorithms, airport executives in China are also investigating the feasibility of applying differentiated pricing schemes and flexible advertisement scheduling strategies for airport billboards. Following the successful practices in other industries and scenarios (e.g., portal sites, electronic retailing, and social and entertainment platforms), through adopting flexible pricing and advertisement scheduling strategies to match the demand and supply sides of airport advertising, airports are expected to improve their efficiency in utilizing the scarce advertising spaces and therefore improve the overall performance. Also, the flexible pricing and advertisement scheduling strategies can help to reduce risks for advertisers. However, one of the premise conditions for an airport to optimize the pricing and scheduling decisions is the possibility to quantify the actual value of the different billboards.

Intuitively, the performance of each billboard in an airport during a certain time interval depends on various factors, such as the number of passengers passing through the billboard, the flow time of passage, and whether the passengers passing through the billboard are the target customers of the advertising content. Therefore, the real value/effectiveness of a billboard is closely related to the physical layout of an airport, the flight schedule of airlines, the traveling route that passengers may follow within the airport, and the attributes of these passengers. However, to the best of our knowledge, at the moment there does not exist any uniformly recognized standard/framework for evaluating the value of an advertising media in an airport. In this paper, we seek to propose a framework for assessing the value of airport billboards; in particular, our framework is based on the analysis of passenger big data. Application of our proposed assessment framework will: on the one hand, provide useful information for advertising agencies and/or advertisers in their decision making; and on the other hand, lay a necessary foundation for airport
executives to improve management through differentiated pricing and flexible advertisement scheduling strategies. Of course, the basic idea of our assessment framework also applies to other public transportation hubs, such as high-speed railway, subway, and coach stations.

2. Literature Review

As one of the main marketing approaches to promote products and to build brand image, advertising expenses usually accounts for a large portion of the operating costs of a company. However, are these advertising spent desirable at all? This question has always been an important consideration for managers when making advertising decisions, and has long been a hot research topic for scholars in the field of marketing management. The fundamental objective of advertising is to build brand awareness and to prompt purchase in the short term as well as in the long term (Bijmolt et al. 1998). By creating positive consumer attitudes, advertisement can trigger the emotional reactions of consumers and ultimately influence their purchase decisions (Goldsmith et al. 2002). Advertising effectiveness refers to the impact of advertisement on the purchasing behavior of the audience achieved through both emotional responses, such as cognition and attitudes, and environmental responses (Niaizi 2012). On this basis, the Cross-Media Optimization Study (XMOS) developed an advertising evaluation scheme that identified brand awareness, brand image, and purchase intention as important aspects in assessing advertising effectiveness (Briggs et al. 2005). Therefore, the value of advertising depends mainly on two dimensions, including the exposure of advertising content and the corresponding conversion rate (Olson 2009, Xu and Du 2014). In the mobile internet environment, through accurate advertisement placements based on visitor portraits and related big data analysis technologies, the exposure and conversion rates of advertisements can be tracked to a certain extent. However, accurate data on advertising exposure in traditional media, such as newspapers, TV, and outdoor advertisement, are relatively difficult to collect. Also, precisely tracking the advertising audience and measuring the actual conversion rate through these media are usually extremely difficult (if possible), which introduces great challenges in assessing the effectiveness of advertising.

Realization of advertising value is influenced by both objective and subjective factors. Objective factors mainly refers to indicators such as advertisement appearance, location, and exposure. Mitchell (1986) explored the role of visual and verbal messages in advertising. Manchanda et al. (2006) developed a model to examine the impact of online banner advertisements on the individual purchase timing behavior based on advertisement exposure and consumers’ purchase history. Fu and Chen (2012) analyzed the impact of appeal strategy, negative comments, and customer involvement on the effectiveness of blog advertising. Jessen and Rodway (2010) discussed the influence of the environment and surroundings of outdoor advertisements on the behavior of audience.

On the other hand, subjective criteria that influence advertising value majorly include indicators that are difficult to quantify precisely, such as consumer perception and cognition. Cox and Cox (1988) examined the effects of prior exposure and familiarity on the attitudes of consumers toward advertising. Batra and Stayman (1990) investigated the impact of emotions on the attitudes of print advertisement readers toward brands. Calder et al. (2009) provided an online media engagement-based approach to examine how the personal and social interactive engagements of consumers influence advertising effectiveness.
Hong and Zinkhan (1995) discussed the effect of the consistency between advertising claims and the customer self-concept claims on the efficiency of advertising.

Many studies have been designed to construct advertising value assessment systems. The extant methods for evaluating advertising value can be divided into two categories: transmission process based and marketing result based. The former category assesses the changes in perceptions, attitudes, and actions of the advertising audience at each stage of the transmission chain to evaluate and predict the effectiveness of advertising. For example, Ducoffe (1995) and Ducoffe (1996) proposed a conceptual model to assess the value of advertising in general media based on its impact on the perceived value of consumers. Xing et al. (2009) proposed an evaluation system based on digital video processing that captures the scene in front of an advertisement through face tracking technology and estimated the effectiveness of the advertisement in public areas according to the number of viewers and the viewing intervals and patterns. Scott et al. (2016) studied the effectiveness of tourism magazine advertisement through eye-tracking and self-reported recall methods. Lin and Fu (2018) proposed an online advertising design on the basis of means-ends chain theory and performed a similarity analysis to evaluate the effectiveness of advertising. Aziza (2019) constructed a system assessing the value of advertisements in terms entertainment, informativeness, customization, and irritation to discuss the effectiveness of YouTube advertisements.

Another type of advertisement value assessment method is mainly based on advertising and marketing results. This approach is highly regarded by advertisers. However, due to the difficulty in attribution and the limitations of technology, the result-based evaluation system received limited application in early years. By comprehensively considering the propagation process and results of advertisements, Xu et al. (2011) designed an evaluation scale consisting of six indicative factors, namely, attention, interest, information search, trustworthiness, purchase behavior, and information sharing, and constructed a Web 2.0-based advertising effectiveness assessment model. Mulchandani et al. (2010) and Tanveer et al. (2020) conducted time series analyses to assess the effectiveness of bank advertising by examining the impact of advertising expenses on bank interest income and operating income. Qin and Jiang (2019) summarized the use of intelligent technology in advertising value assessment. Ge and Wu (2021) combined technology and computation with online advertising decisions and applied big data statistical analysis methods to evaluate the effectiveness of precise advertisement placement.

To the best of our knowledge, only quite few studies have discussed the value of airport advertising media. Despite that airport advertising shares some similar attributes with other forms of advertisement (e.g., outdoor advertising), in the specific physical environment of airports, the data which are usually difficult to acquire and measure in traditional outdoor advertising can be partially obtained from some available sources. Starting from the distinguished characteristics of airport advertisement, our airport billboard value assessment framework based on passenger data analysis is an obvious supplement to previous studies on advertising value evaluation. The ideas and evaluation methods in this paper can also apply to other public transportation hubs and scenarios.

### 3. The Value Assessment Model

Consider a terminal at an airport. For a specific billboard located in a certain spot, we
aim at evaluating its value during a certain period. According to the exposure theory of advertising, the value of an advertisement (VoA) is defined as

$$VoA = \text{passenger flow} \times \text{conversion rate} \times \text{flow time}$$

where passenger flow, including both outbound and inbound passengers, corresponds to the "breadth" of the advertisement, conversion rate reflects the "depth" of the advertisement, and flow time of passengers before the billboard reflects the "intensity" of the advertisement.

To measure the value of advertisement, information about the physical layout of the terminal, flights and their scheduling, and passengers’ attributes and their behavior need to be taken into account.

3.1 Terminal Layout

To facilitate the description of the passenger flow through an airport terminal, we use the concept of network diagrams to model the physical layout of the terminal. Without loss of generality, we assume that each passenger has a well-defined starting and ending point when passing through the terminal. For an outbound passenger, the starting point often corresponds to the entrance of the terminal, whereas the ending point corresponds to the boarding gate where the flight is located. For an inbound passenger, the starting point corresponds to the gate of the corridor where the plane lands (the far aircraft stands can also be considered as a starting point), and the ending point corresponds to the exit of the terminal, such as the exit passageway, the underground cab and airport bus pick-up points, or entrances of the airport express. We use $M = \{1, 2, \cdots, m\}$ to denote the set of all possible starting points for outbound passengers to enter the terminal, and $N = \{1, 2, \cdots, n\}$ to denote possible ending points for outbound passengers, which refers to the set of all boarding gates, including both the corridor gates and the remote gates. Note that $n$ also corresponds to the number of feasible starting points for inbound passengers at the terminal, and $m$ also corresponds to the number of feasible nodes for inbound passengers leaving the terminal. In addition to the set of nodes $M$ and $N$, there also exist many other intermediate nodes, such as commercial areas and VIP lounges.

For any "origin-destination" pair (briefly "OD" pair) $i \rightarrow j$ of a outbound passenger, we have $i \in M, j \in N$. According to the airport layout, let $p_{ij}$ denote the number of feasible paths/routes that passengers could choose under normal circumstances. In a realistic scenario, the shortest path to the boarding gate after an outbound passenger arrives at the airport, checks in at the counter, and goes through security check is normally unique. However, some passengers, such as first-class, business-class, and platinum and gold frequent flyers, may decide to rest in the VIP lounge before boarding. Therefore, there exist multiple paths from the same origin to the same destination. For example, in Figure 2, after the security check (intermediate node $\odot 1$), if a passenger needs to proceed to boarding gate $\odot 2$, he/she typically has two travel routes. For any OD pair $j \rightarrow i$ of arriving passengers, $i \in M, j \in N$, the route from getting off the flight to the baggage claim area is often unique, but after leaving the baggage claim hall, the paths of passengers start to diverge, since different passengers may leave the airport through different transportation modes. We denote $q_{ij}$ as the number of feasible paths that arriving passengers could choose under normal conditions.

Path $i \rightarrow j$ of OD pair $L_k(i, j)$ may or may not pass through the billboard. For example, as shown in Figure 2, the path with a longer distance passes through the billboard, while the path with a shorter distance does not. For
ease of presentation, we define an "indicative function" $l_k(i, j)$, which equals 1 if $L_k(i, j)$ passes through the billboard, and 0 otherwise; note that $k = 1, 2, \cdots, p_{ij}$ for the departing routes, and $k = 1, 2, \cdots, q_{ij}$ for the arriving routes.

### 3.2 Flights

Consider all the departing and arriving flights during a time window $T$. Let the number of flights departing from gate $j$ be $d_j$, then $D_j = \{1, 2, \cdots, d_j\}$ represents the set of departing flights. We use $DF_k(j)$ to denote the $k$th flight departing from gate $j$, where $k = 1, 2, \cdots, d_j$; $j = 1, 2, \cdots, n$. We use $CD_k(j)$ to represent the number of seats on flight $DF_k(j)$, which depends on the type of aircraft scheduled for the flight. Note that a flight may not fully loaded; let $\eta_k(j)$ denote the load factor of flight $DF_k(j)$. Therefore, the actual number of passengers on the departing flight $DF_k(j)$ is $CD_k(j) \times \eta_k(j)$.

Let the number of flights arriving at gate $j$ be $a_j$, then $A_j = \{1, 2, \cdots, a_j\}$ represents the set of arriving flights. Let $AF_k(j)$ denote the $k$th flight arriving at gate $j$, where $k = 1, 2, \cdots, a_j$; $j = 1, 2, \cdots, n$. We use $CA_k(j)$ to denote the number of seats on flight $AF_k(j)$, which also depends on the type of aircraft used for the mission of the flight. Let $\delta_k(j)$ represent the load factor of flight $AF_k(j)$. Therefore, the actual number of passengers on the arriving flight $AF_k(j)$ is $CA_k(j) \times \delta_k(j)$.

### 3.3 Passengers

For each flight, except for the possible differences in the passengers' travel paths through the airport, only a portion of the passengers are the target customers of the advertiser. On the one hand, for passengers with OD pair $i \rightarrow j$, they are faced with $p_i$ feasible paths. Using the image information captured by cameras in the terminal, it is theoretically possible to map the route of each passenger through the airport. With some simple statistical calculation, we can obtain the percentage of passengers who choose a certain path $L_k(i, j)$, denoted by $\lambda_k(i, j)$, where $k = 1, 2, \cdots, p_{ij}$. Straightforwardly, we have $0 \leq \lambda_k(i, j) \leq 1$ and the following equation

$$\sum_{k=1}^{p_{ij}} \lambda_k(i, j) = 1$$

where $i = 1, 2, \cdots, m$ and $j = 1, 2, \cdots, n$ for the departing flights, and $i = 1, 2, \cdots, n$ and $j = 1, 2, \cdots, m$ for the arriving flights.

On the other hand, some preliminary data analysis by airlines and airports suggests that
passengers on a same flight tend to share some similar attributes. For example, passengers on flights from Beijing to Sanya during the Spring Festival are mostly leisure passengers flying to Sanya for the winter vacation, whereas passengers on flights from Beijing to Shenzhen are usually business travelers, especially during the COVID-19 pandemic. As an initiative to improve management, it’s common for airlines to conduct big-data analysis on passengers based on their ticket booking, cancellation, and no-show behavior. For example, a significant percentage of travelers from Beijing to Sanya are the target customers of Hainan real estate advertisements, but not necessarily the target customers of a certain local bank (except Beijing and Hainan). For the departing flight $DF_k(j)$ and the arriving flight $AF_k(j)$, let the portions of target customers of the advertisements be represented by $\alpha_k(j)$ and $\beta_k(j)$, respectively.

In addition to the billboard size, content, and passenger attributes, the flow time of a passenger passing through a billboard is also related to the congestion level of its location. Intuitively, when there is more congestion in front of a billboard, travelers are more likely to pay attention to the content of the advertisement. Let the average flow time for passengers on the departing flight $DF_k(j)$ be $T_k(j)$, and the average flow time for passengers on the arriving flight $AF_k(j)$ passing through the considered billboard be $\tau_k(j)$.

### 3.4 Advertising Value

According to the above descriptions regarding terminals, flights, and passengers, the value of the advertising billboard under consideration can be quantified as:

$$
VoA = \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{d_r} \sum_{l=1}^{p_j} \left[ CD_k(j) \times \eta_k(j) \times \lambda_l(i, j) \times I_l(i, j) \times \alpha_k(j) \times T_k(j) \right]
+ \sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=1}^{a_j} \sum_{l=1}^{q_i} \left[ CA_k(j) \times \delta_k(j) \times \lambda_l(j, i) \times I_l(j, i) \times \beta_k(j) \times \tau_k(j) \right]
$$

where the first term corresponds to the value contributed by departing flights, and the second term corresponds to the value contributed by arriving flights.

### 4. An Illustrative Application

In this section, we apply the above value assessment framework to evaluate two representative billboards located in Terminal T3 of the Beijing Capital International Airport. Specifically, we selected two wall-mounted light box billboards near the security check area for domestic departure on the third floor of T3C, as shown in Figure 3. These two light box billboards are basically the same size at 7.2 m × 2.9 m and 7.22 m × 2.84 m, respectively. For the time window under consideration, the two billboards are contracted with Yili and Alibaba, respectively. Given the content displayed on the two billboards, all passengers at the airport can be considered as the target customers of these two advertisements (this corresponds to $\alpha_k(j) = 1$). For illustrative purposes, the congestion level in front of these two billboards are supposed to be almost the same. Therefore, we assume that the average flow time passengers pass through the billboards are almost identical. In addition, given that the locations of billboards A and B are only passable by departing passengers, the advertising value contributed by the arriving passengers is almost negligible.

The layout of Terminal T3 (see Figure 3) shows that there are 13 boarding gates (i.e., C19-C31) that passengers need to pass through.
billboard A to reach and 6 boarding gates (i.e., C32-C37) that passengers need to pass through billboard B to reach. We randomly select three consecutive days, from June 6 to June 8, 2021 as the sample. The daily flight information of the 19 gates from C19 to C37, including the airline, aircraft type, flight scheduling, origin-destination, passenger capacity, and load factor, was collected at the Beijing Capital International Airport. Table 1 lists the descriptive statistics of the boarding gate and flight data. As was shown, the maximum number of flights per day for a single boarding gate is 7. The load factors of different flights varies significantly, with the lowest load factor corresponding to flight CA1315 from Beijing to Guangzhou (the aircraft type is Boeing 77W with a total capacity of 311 seats, while the actual number of passengers onboard is only 54).

Using the assessment framework proposed in Section 3, we calculate the total daily passenger flow of the two billboards, and report the major results in Table 2. The data reveals a clear difference in the value of the same type of billboards during different periods and in different locations. On the one hand, the passenger flow varies on the location of the billboards. According to the sample data, the average number of flights covering billboard A is 64 per day, whereas that covering billboard B is only 26.33 per day. It is possible that the difference in the aircraft types used for different destination cities will ultimately lead to a significant variance in the values of billboards A and B. Table 2 shows that the realized value of billboard A is 1.82, 2.28, and 1.40 times that of billboard B over the three selected days, respectively, and 1.796 times that of billboard B overall. On the other hand, the adjustment in flight scheduling may also lead to the significant difference in
Table 2 Value Comparison between Billboards A and B

| Billboard | # Boarding gates covered | Date        | # Flights | # Passenger flow covered | Total  |
|-----------|--------------------------|-------------|-----------|--------------------------|--------|
| A         | 6 (C23 to C37)           | June 6, 2021| 64        | 7302                     | 22241  |
|           |                          | June 7, 2021| 65        | 8220                     |        |
|           |                          | June 8, 2021| 53        | 6719                     |        |
| B         | 13 (C19 to C31)          | June 6, 2021| 28        | 3995                     | 12383  |
|           |                          | June 7, 2021| 22        | 3603                     |        |
|           |                          | June 8, 2021| 29        | 4785                     |        |

the value of the same billboard at different periods. Taking billboard A as an example, the number of flights covered in three days is basically the same (all between 63 and 65), while the total passenger flow covered varies greatly. Specifically, the passenger flow on June 7 and 8 was 1.126 and 0.920 times that on June 6, respectively. According to the average number of passengers per flight, the average advertising values of a single flight on June 7 and 8 are almost the same, with about 126 passengers per flight, which is significantly higher than 114 passengers per flight on June 6.

Table 2 validates the rationality and necessity of our proposed framework to assess the value of airport billboards. Given that billboards A and B cover only a portion of departing passengers, the advertising value contributed by arriving passengers is not considered in the above example. For billboards in other areas of the airport, such as the light boxes inside of the bridge of the boarding gate or near the check-in counter, both departing and arriving passengers may be covered. Following the above assessment framework, the proportion of advertising value contributed by departing (or arriving) passengers can also be measured in detail.

5. Concluding Remarks
Based on the distinguished characteristics of airport billboards, this paper proposes a time- and location-based framework to assess the value/effectiveness of these advertising media. For illustrative purposes, we tested the proposed framework in measuring the value of two wall-mounted light boxes located at Terminal T3 of the Beijing Capital International Airport. Of course, the measurement based on a small sample has its limitations. For instance, due to the lack of relevant data, we do not use information such as passenger profiles and passenger behavior when passing through the billboard. Despite of this, our results validates the rationality of the proposed time- and location-based advertising value evaluation framework.

Our airport billboard value assessment framework has many potential applications. First, the framework provides a methodology for airport executives to systematically measure the relative values of all advertising media in airports. For example, information about the correlative relationship among the values of different billboards and the value contribution from passengers on different flights to each billboard can provide useful insights for airport managers, since they help managers systematically and comprehensively understand the differences, sources, and evolution paths of airport billboard values. In addition, the assessing result may provide useful support in decisions such as the relocation of airport billboards.

Second, with the understanding of advertising media value in the time and spatial dimensions, airport executives can further explore the possibility of implementing differentiated pricing strategies for different billboards.
within various time windows. At the moment, major Chinese airports mainly adopt a fixed pricing scheme, and most advertisers purchase advertisements on a yearly or half-yearly basis. Given the time- and location-varying value of billboards, a more reasonable and profitable strategy is to quote a differentiate price for different billboards during different periods. In particular, advertisers are free to purchase their billboards based on their individual needs and preferences. Moreover, airport advertising managers can consider selling different billboards and different forms of advertising media in a package (or a bundle) to some advertisers, so as to improve the overall value of their advertising resources.

Finally, in addition to the above differentiated pricing mechanism, airport managers can adopt dynamic and personalized advertisement displaying strategies as well. At present, once an advertiser purchases a billboard, the billboard will continuously display the advertisement content of the advertiser during the contracting period. Considering the varying attributes of passengers passing through the billboard, airport executives can optimize the display of different advertisements in different media in various locations at different times of the day. For example, for billboards located inside the arrival corridor, the advertising content can be adjusted at any time by considering the portrait information of the passengers on the arriving flight, so as to optimize the overall exposure of the advertising contents to their respective target customers.

The above potential applications also bring up many topics worthy of further research. For example, based on the evaluation of billboard value, how can airport managers use a combination of data analysis, optimizing models, and simulation to guide the advertisement pricing and scheduling decisions so as to improve the overall revenue/performance? In particular, it is practically important to study the interactive decisions between the airport, advertising agencies, and advertisers from the perspective of supply chain management. Also, developing a coordinating contract for the advertising supply chain based on the advertisement value assessment approach can help achieve a win-win situation and can yield interesting managerial insights.

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