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RESEARCH ARTICLE

Analyzing the Features of Passenger Drop-Off Behavior at Airport Curbsides: A Case Study From Guangxi Province, China

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ABSTRACT Vehicles often face congestion at airport curbsides because private vehicles, taxis, and ride-hailing vehicles compete for limited space while dropping off passengers. This competition may lead to blockages and long dwell times, thus worsening the congestion. To solve this issue, management strategies such as first-in-first-out queuing or fines for excessive dwell times have been suggested. However, there is a lack of reliable video data and analysis of drop-off behavior at airport curbsides. In this study, we empirically analyzed the key characteristics of passenger drop-off behavior at the Airport T2 terminal in Guangxi Province, China, which handles approximately 18 million passengers per year. First, we extracted the relevant features of both passengers and vehicles by deep learning algorithm, such as the direction of passenger movement, vehicle type, vehicle location, trunk state, and passenger drop-off time. Subsequently, we constructed new features, such as driver behavior and passenger behavioral complexity, based on the original features. We used least-squares regression and logistic regression to analyze the data. Our analysis reveals that the drop-off time of passengers primarily depends on the complexity of their behavior during the drop-off process. Additionally, we observed that specific features, such as driver behavior and vehicle type, could be employed to estimate passenger drop-off behavior. These findings have practical implications in providing valuable insights into the design and management of airport curbside areas and future strategies for connected vehicles.

INDEX TERMS Airport curbside, drop-off lane, deep learning, least squares regression, logistic regression.

I. INTRODUCTION

Special drop-off lanes are commonly designated for travelers at or near terminals such as airports and train stations [1], [2]. Typically, these special lanes are located on the inner side of the airport curbside, closest to the terminal building. Bypass lanes next to the inner lane are designated for vehicles that do not need to stop or bypass the drop-off area. Vehicles dropping off passengers typically transition from the bypass lanes to inner lane before passenger drop-off. After the passengers complete their actions, the vehicles start again, exit the inner lane, and reenter the bypass lane. However, in situations where some vehicles finish dropping off passengers earlier, while others are still in the process, they may be forced to wait or face challenges when entering the bypass lane. This can potentially impact the traffic flow. Previous research has

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shown that passenger behavior in vehicles affects traffic flow efficiency [3], [4].

However, there is a lack of reliable video data and analysis regarding drop-off behavior at airport curbsides. Therefore, it is important to extract relevant features of passenger drop-off behavior at airport curbsides and analyze the relationship between behavior and time. Further research is needed in this area to help analyze passenger behavior at airport curbsides. The drop-off area studied at the airport curbside is shown in Figure 1. The layout of the study area is shown in Figure 2. The perspective of the video data studied is shown in Figure 3.

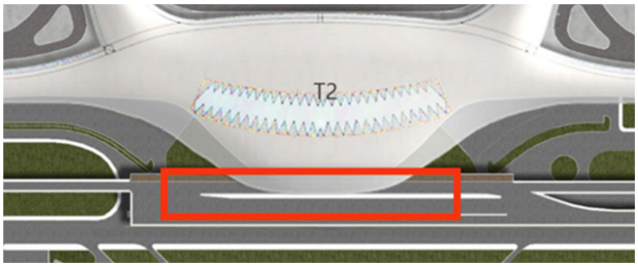

FIGURE 1. Airport curbside area which we research.

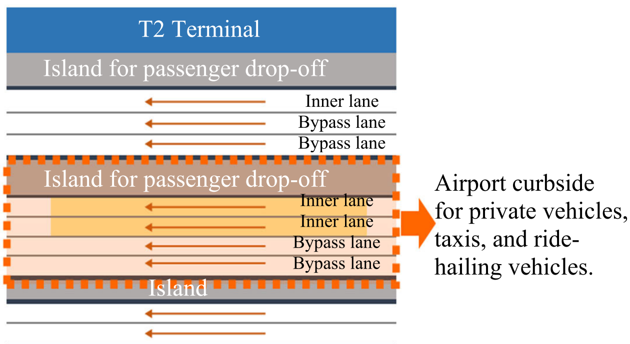

FIGURE 2. Airport curbside layout which we research.

FIGURE 3. A video perspective of the study area.

Passenger drop-off behavior has not been clearly defined. In general, this refers to activities in which passengers drop off. Passenger drop-off was defined in a previous study [5]. This ensures that passengers drop off in designated zones, but the time depends on the transportation mode. The passenger drop-off behaviors studied herein refer to the activity of passenger drop-off from taxis, private vehicles, or ride-hailing vehicles at the airport curbside, with the activity duration ranging from passenger drop-off to without passenger activity. In addition, we studied the internal factors influencing the different passenger drop-off modes.

Current research on traffic feature extraction mainly focuses on pedestrian or vehicle trajectories, and there is a lack of feature extraction for passenger drop-off behavior at airport curbsides [6], [7]. This study uses a method based on human-vehicle interaction logic to extract and analyze feature data.

We focus on Nanning Wuxu Airport in Guangxi Province for several key reasons. It is the primary civilian airport in Nanning, playing a crucial role in regional economic development and passenger mobility, particularly in its strategic connections with ASEAN nations. The airport has an extensive flight network, including direct routes to various cities, both domestic and international. It actively collaborates with international airlines to improve service quality and aviation capabilities. With Guangxi's civil aviation sector rapidly growing, the airport is continuously expanding and enhancing its operations. Thus, we chose this airport for our study.

A. RESEARCH MOTIVATION

At present, there are some studies that extract the features at the airport for research, but there is a lack of extraction algorithms for the drop-off behavior features of passengers on the curbside of the airport to study their intrinsic relationships [8], [9], [10], [11]. To understand the passengers' drop-off factors affecting drop-off time, we propose the following three questions:

Research question (RQ1): How to extract the feature of passengers drop-off at the airport curbside?

Research question (RQ2): How to analyze the passengers' drop-off factors affecting drop-off time?

Research question (RQ3): What are the influencing factors related to the passenger drop-off time?

By studying these questions in depth, we expect to provide a scientific method to explain the passengers' drop-off factors affecting drop-off time and thus provide a theoretical basis for optimizing overall airport operation.

B. RESEARCH CONTRIBUTION

This study investigated the passenger drop-off behavior of vehicles on airport curbsides at an airport terminal in China. A Case Study from Wu xu airport T2 terminal in Guangxi Province, China, which handles approximately 18 million passengers per year. This empirical study focuses on analyzing the essential characteristics of passenger drop-off behavior.

We collected and analyzed data on the relevant features of passengers and vehicles, such as the direction of passenger movement, vehicle type, vehicle location, trunk state, and passenger drop-off time. We used least squares regression to determine the influence features for drop-off time and found that behavioral complexity was linearly and positively correlated with drop-off time. It also identified three types of drop-off behavior for airport curbside passengers: quick, normal, and slow drop-off behaviors. Using logistic regression, we found that driver behavior, vehicle classification, and lane have an impact on the three types of behavior. Further analysis of all the influential features revealed that the interaction between passengers and accompanying personnel affects the drop-off time.

This study contributes to the research of airport curbside management in several ways. 1) It provides a novel method to collect and analyze passenger drop-off behavior data based on machine learning algorithms. 2) It reveals the relationship between relevant features and passenger drop-off times on airport curbsides, which can help optimize the design and operation of airport curbsides. 3) It extends the applicability of this study to similar scenarios, such as high-speed rail stations, which can benefit from the insights gained from this study.

II. RELATED WORK

A. APPLICATION OF ARTIFICIAL INTELLIGENCE IN TRAFFIC FEATURE EXTRACTION

1) EXTRACTING DATA FROM VIDEOS

In previous studies, traffic feature extraction technology has primarily focused on pedestrian and vehicle trajectories. The two methods are reviewed below. A method based on the You Only Look Once (YOLO)v3 algorithm to detect vehicles and employed Empirical Mode Decomposition (EEMD) to denoise trajectory data and extract meaningful information [6]. For improving pedestrian detection performance. some researchers integrated proportion-aware and scale-aware mechanisms into YOLOv3 to enhance detection accuracy in such scenarios [7]. They all used the YOLO detection algorithm but were limited to studying the trajectory characteristics of people and cars separately.

For airports, there are three methods are reviewed below. A novel method is proposed for detecting airport runways by using Synthetic Aperture Radar (SAR) images. The approach combines the region-based method and the Hough transform analysis stage, incorporating contextual information to identify suitable features [9]. Similarly, some researchers introduced a new method for airport detection and recognition using high-resolution wide-area remote sensing images [10]. Finally, a study on the use of Unmanned Aerial Vehicles (UAVs) and the YOLOv3 algorithm to detect atypical aviation obstacles and ensure passenger safety at airports [11]. At present, most feature extraction applications in airports focus on identifying environmental features and lack effective passenger behavior feature extraction methods.

2) EXTRACTING DATA FROM SMARTPHONE

Some researchers have discussed methods for detecting the orientation and movement direction of a smartphone user using sensors, such as Global Positioning System(GPS) and accelerometers, which are commonly used in indoor and outdoor navigation applications [13]. A method for recognizing pedestrian navigation activity using smartphone-based measurements, including sensor calibration, pedestrian modeling, and smartphone usage mode definition [14]. Some researchers evaluated the accuracy of smartphone-based driver monitoring systems and discussed practical considerations for data analysis [15]. Data collection from smartphone includes using Wireless Fidelity (Wi-Fi) tracking signals to extract waiting and actual service durations in indoor human queues [8], [16]. Some studies have extended this methodology to airport terminal applications. These studies highlight the potential of smartphones as useful tools for collecting data on various transportation-related activities. However, this data collection method is suitable for collecting large amounts of user data. However, it only collects passenger and vehicle data individually, and cannot obtain drop-off behavior data through the logic of passenger drop-off.

B. REVIEW OF BEHAVIORAL ANALYSIS RESEARCH

1) DEVELOPMENT OF REGRESSION MODELS

For research on regression models, the least-squares method was the earliest mathematical optimization regression algorithm used to study the regression relationship. Subsequently, machine learning regression models such as decision tree regression were developed [17], [18], [19]. Convolutional neural networks that can extract abstract features from matrices [20]. A backpropagation algorithm that made modern Convolutional Neural Network (CNN) regression models possible for regression research [21]. An Extreme Gradient Boosting (XGBoost) model based on gradient boosting trees [22]. Light Gradient Boosting Machine (LightBGM) which improves the regression speed while maintaining the same performance as previous models [23]. A fusion model combining CNN and LightBGM to build a regression model for the wind power generation relationship, which performed well [24]. Although neural network models have high predictive values, their interpretability is not as good as that of the traditional regression models.

2) TRAFFIC BEHAVIOR ANALYSIS

Existing research on traffic behavior can be divided into research on passenger behavior and vehicle behavior controlled by drivers. Huang et al. used a decision-tree-based model to analyze airport passenger transfer mode behavior [25]. Some researchers studied how the ratio of get-in to get-off passengers affect their behavior at subway stations [4]. Some researchers used statistical methods and Poisson and negative binomial regressions to analyze the impact of various factors on urban roadside parking maneuvering time [26]. Some researchers proposed the use of private car trajectory data to achieve fuzzy logic-based dwell behavior detection and dwell time inference [27]. Some proposed an airport curbside simulation model that calculates the optimal length of an airport curbside based on traffic characteristics, such as speed, dwell time, and parking demand [1]. For the study of passenger queuing behavior in airport terminals, Wi-Fi tracking signals have been employed to extract queuing data, with both Feedforward Neural Networks (FNN) and Long Short-Term Memory (LSTM) networks utilized for passenger behavior analysis and prediction [8]. However, research on the internal driving factors for passenger drop-off times at airport curbsides is lacking.

III. METHODOLOGY

A. FRAMEWORK FOR IDENTIFYING AND ANALYZING VEHICLE BEHAVIOR AT AIRPORT CURBSIDE

(RQ1): How to extract the feature of passenger drop-off at the airport curbside?

First, we use a feature extraction algorithm to extract data based on the interaction between vehicles and passengers at airport curbsides. The algorithm consists of eight steps: recording video data, detecting targets, tracking targets, coordinate transformation, get-in and get-off judgment, trunk-opening state judgment, and parking-obstruction judgment and data processing, as illustrated in Figure 4. We then generated and processed the raw data.

In step1, we recorded the video data in airport curbside. In step2 and step3, we used YOLO to detect and Byte track to track targets [28], [29]. we define set B^t as the collection of all recognized target results in a single frame of the video, and each target is represented as $O_{(1,2,\ldots,N)} = \{\text{id}, \text{cls}, x, y, x_{lt}, y_{lt}, x_{rb}, y_{rb}\}$, where id is the unique identifier of the target, cls is the classification label, (X, Y) represents the real-world coordinate position of the target at that time point, and $(x_{lt}, y_{lt}, x_{rb}, y_{rb})$ represents the coordinates of the top left and bottom right corners of the target region.

In step4, we used the findHomography algorithm to convert the actual coordinates of points in the real world and the perspective of the surveillance camera into a conversion matrix. This matrix is then used to determine the real coordinates of the recognized target. This is because the perspective coordinates of the surveillance camera are different from the actual coordinates of the objects being monitored. Using this conversion matrix, we obtained the real-world coordinates of the recognized targets.

In step5, we used the relationship between the vehicle and the passenger's position, as well as the logic of getting in or off the vehicle, to determine whether a passenger is getting in or off the vehicle. Initially, the task involves identifying the location of the open door, that is, whether it is positioned on the left or right side of the vehicle. The calculation formula is as follows (1)(2)

$$\left\{\begin{array}{l}\exists x_i \in O_i^t, \exists y_k \in O_k^t, \exists x_k \in O_k^t, \exists x_{ilt} \in O_i^t, \\ \exists y_{ilt} \in O_i^t, \exists y_{irb} \in O_i^t\end{array}\right\}$$

$$\text{op}_{\text{left}} = \begin{cases} 1, & (x_i < x_k) \wedge (x_k > x_{ilt}) \wedge (y_k < y_{irb}) \\ & \wedge (y_k > y_{ilt}) \\ 0, & \text{others} \end{cases} \tag{1}$$

In formula (1), set O_i^t represent the information about the vehicle, set O_k^t represent the information about the door, and the parameter op_{left} denotes the status of the left car door, with a value of 1 indicating an open door on the left side and 0 indicating no door is open on the left side.

$$\left\{\begin{array}{l}\exists x_i \in O_i^t, \exists y_k \in O_k^t, \exists x_k \in O_k^t, \exists x_{irb} \in O_i^t, \\ \exists y_{ilt} \in O_i^t, \exists y_{irb} \in O_i^t\end{array}\right\}$$

$$\text{op}_{\text{right}} = \begin{cases} 1, & (x_i > x_k) \wedge (x_k < x_{irb}) \wedge (y_k < y_{irb}) \\ & \wedge (y_k > y_{ilt}) \\ 0, & \text{others} \end{cases} \tag{2}$$

In formula (2), The parameter op_{right} signifies the state of the right car door, with a value of 1 denoting an open door on the right side and 0 indicating the absence of an open door on the right side.

Upon determining the direction of the open door, the subsequent step involves recognizing the get-in and get-off status of passengers. Initially, the focus was on identifying drop-off passengers. For individuals whose IDs have not been previously recorded in the external environment, recognition is based on their appearance in a position above the open door, already determined in the specified orientation. Conversely, for individuals whose IDs were detected outside the vehicle, their get-in status was determined by their disappearance for a continuous duration of 20 frames upon reaching a position above the open door, following the predetermined orientation. Equations (3), (4), (5), and (6) address the recognition of get-in and get-off passengers on the left and right sides, respectively.

$$\left\{\begin{array}{c}\exists y_j \in O_j^t, \exists y_k \in O_k^t, \exists x_j \in O_j^t, \exists y_{ilt} \in O_i^t, \exists x_{klt} \in O_k^t, \\ \exists y_{krb} \in O_k^t, \exists\, \text{id} \in O_j^t\end{array}\right\}$$

$$\text{oi}_{\text{left}} = \begin{cases} 1, & \left(y_j > \left(y_{ilt} + (y_{ilt} - y_k) * 0.1\right)\right) \\ & \wedge \left(y_j < y_k\right) \wedge \left(x_j > x_{klt}\right) \wedge \left(x_j < x_{krb}\right) \\ & \wedge (id \notin D_o) \wedge \left(id \notin D_{off}\right) \wedge \text{op}_{\text{left}} = 1 \\ \text{oi}''_{\text{left}}, & \left(y_j > \left(y_{ilt} + (y_{ilt} - y_k) * 0.1\right)\right) \\ & \wedge \left(y_j < y_k\right) \wedge \left(x_j < x_{klt}\right) \\ & \wedge \left(x_j < x_{krb}\right) \wedge (\text{id} \in D_o) \wedge \text{op}_{\text{left}} = 1 \\ 0, & \text{others} \end{cases} \tag{3}$$

$$\text{oi}''_{\text{left}} = \begin{cases} 0, & \text{others} \\ -1, & \text{id remains absent} \\ & \text{for 20 consecutive frames} \end{cases} \tag{4}$$

In formula (3), set O_j^t represent the information about the head, set D_O represent the ID of all the heads that appear, set D_{Off} contains the ID of all the heads that have already gotten off, and parameter oi_{left} denotes the get-in or get-off status on the left side of the vehicle. Specifically, a value of 1 signifies get-off status, 0 indicates normal status, and -1 represents get-in status.

$$
\mathrm{oi}_{\mathrm{right}} = \begin{cases} 1, & \left(y_j > \left(y_{ilt} + \left(y_{ilt} - y_k\right) * 0.1\right)\right) \\ & \wedge \left(x_j > x_{klt}\right) \wedge \left(y_j < y_k\right) \\ & \wedge \left(x_j < x_{krb}\right) \wedge \left(\mathrm{id} \notin D_O\right) \\ & \wedge \left(\mathrm{id} \notin D_{Off}\right) \wedge \mathrm{op}_{\mathrm{right}} = 1 \\ \mathrm{oi}''_{\mathrm{right}}, & \left(y_j > \left(y_{ilt} + \left(y_{ilt} - y_k\right) * 0.1\right)\right) \\ & \wedge \left(x_j < x_{klt}\right) \wedge \left(y_j < y_k\right) \\ & \wedge \left(x_j < x_{krb}\right) \\ & \wedge \left(\mathrm{id} \in D_O\right) \wedge \mathrm{op}_{\mathrm{right}} = 1 \\ \text{others} & \end{cases} \tag{5}
$$

$$
\mathrm{oi}''_{\mathrm{right}} = \begin{cases} 0, & \text{others} \\ -1, & \text{id remains absent} \\ & \text{for 20 consecutive frames} \end{cases} \tag{6}
$$

In formula (5), the parameter $\mathrm{oi}_{\mathrm{right}}$ denotes the get-in or get-off status on the right side of the vehicle. Specifically, a value of 1 signifies the get-off status, 0 represents the unchanged status, and -1 indicates the get-in status.

In step 6, we specifically labeled the characteristics of the trunk-opening state. This enables it to identify the state of the trunk being open and to match which car's trunk is open by using a method similar to step 5, based on whether the opened trunk is located at the rear position of the vehicle. The determination of the blocking state is similar to step 5, judging whether the outer vehicle is located at the upper-left position of the inner vehicle, which will block the inner vehicle from driving out of the curbside.

In step 7, we gathered all the information from the previous steps to obtain the raw data. In step 8, we apply the conversion algorithm to the feature data, which is derived from the relationship between the various features and transform the raw data into feature data. We also perform data cleaning in this step. Finally, processed data were obtained.

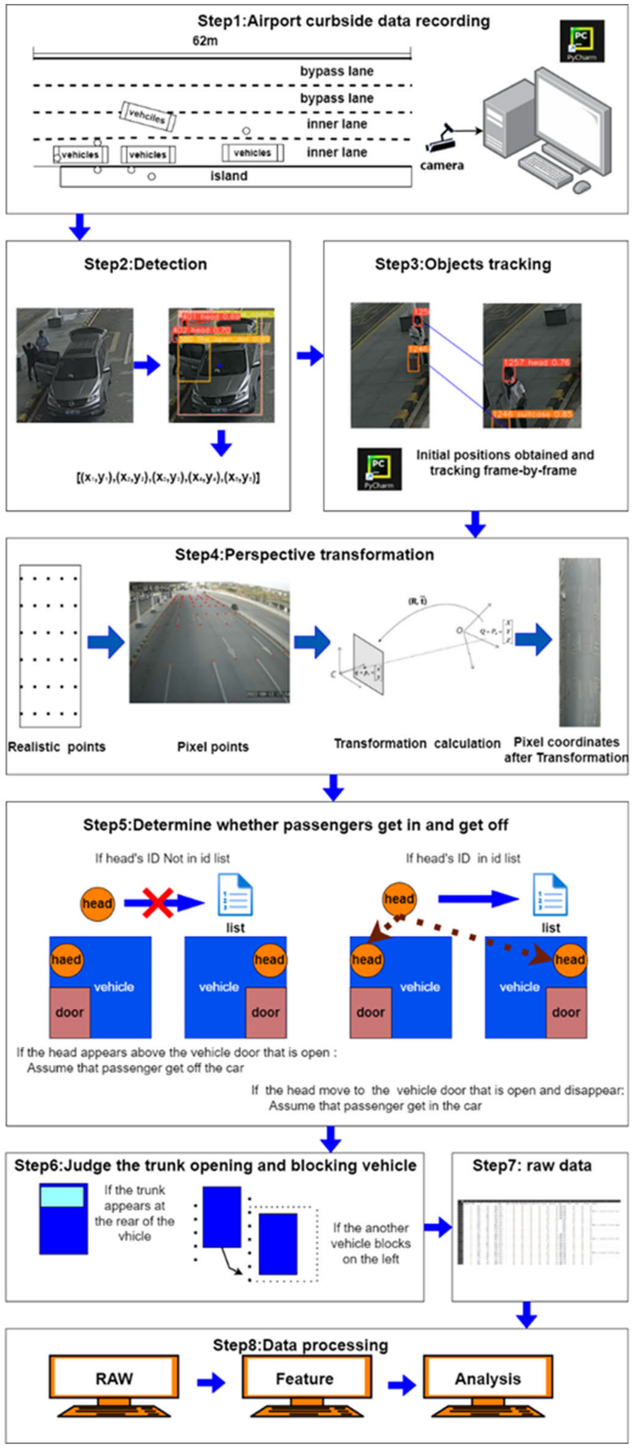

FIGURE 4. Process framework diagram for feature extraction algorithm.

B. ANALYSIS TOOLS

(RQ2): How to analyze the passengers' drop-off factors affecting drop-off time?

1) K-MEAN CLUSTERING ALGORITHM

Clustering is a technique used to partition data into groups based on their similarities. Clustering methods can produce different types of partitions with various scopes. One such method is the k-means clustering algorithm, which seeks to optimize partitioning by minimizing a loss function. The loss function can be defined as the sum of the squared deviations of each observation from its assigned cluster centroid as follows:

$$
J(c, \mu) = \sum_{i=1}^{M} \left\| x_i - \mu_{ci} \right\|^2 \tag{7}
$$

where x_i represents the ith sample, ci represents the cluster to which x_i belongs, and m is the total number of samples.

2) DUMMY VARIABLE

A dummy variable takes values of 0 and 1, where the values indicate the absence or presence of some categorical effect that may be expected to shift the outcome. In linear regression, categorical variables cannot be directly used as predictors, and they must be converted into dummy variables. Specifically, one category in each categorical variable is chosen as the reference category, and the other categories are encoded by one-hot encoding, where the value is 1 if the observation belongs to that category and 0 otherwise. As shown in Table 1.

TABLE 1. The transformation form of dummy variables.

	x_1	x_2	x_3
Category1	0	0	0
Category2	1	0	0
Category3	0	1	0
Category4	0	0	1

3) ORDINARY LEAST-SQUARES REGRESSION

Ordinary least squares regression was performed to estimate the relationship between the dependent variable (drop-off time) and independent variables. The results provided the statistical trends of the data and coefficients of each independent variable. In addition, a model was generated to estimate the passenger drop-off time. Ordinary least squares regression is a method for solving unknown parameters in linear regression models, which is based on minimizing the sum of squared errors between the actual values and the predicted values to obtain the optimal estimation model.

4) MULTICOLLINEARITY

Multicollinearity among the influencing factors of the study will cause the variance of the regression coefficients to increase and worsen the reliability and significance of parameter estimation. To prevent this situation, the VIF was introduced to measure the severity of multicollinearity and ensure the rationality of the regression results. VIF is the ratio of the variance of the regression coefficient to the variance when there is no collinearity, and is calculated as follows:

$$\mathrm{VIF} = \frac{1}{1 - R_i^2} \tag{8}$$

where R_i^2 is the coefficient of determination obtained by regressing the ith independent variable on the other independent variables. A common rule of thumb is that a VIF above 10 indicates a high degree of multi-collinearity.

5) LOGISTIC REGRESSION

Logistic regression is a method for analyzing the probability that the dependent variable is categorical data [30]. It can estimate the influence of the independent variable on the probability of the dependent variable (drop-off behavior). The basic principle of logistic regression is to convert the probability of the dependent variable into log odds and then use a linear model to fit the relationship between the log odds and the independent variable. The likelihood ratio test is a test method used to compare the fit of different models to the data, and it can be used to determine whether a certain independent variable has a significant effect on the dependent variable. Generally, an independent variable is considered to have a significant effect on the dependent variable if its p-value is less than 0.01.

IV. RESULTS

The experimental setup utilized an AMD Ryzen 9 5900HS CPU and an NVIDIA GeForce RTX 3060 Laptop GPU as computational devices. The data were obtained by monitoring the curbside area at Terminal 2 (T2) of Nanning Wuxu Airport in Guangxi. The video recordings had a resolution of $1,920 \times 1,080$ pixels. For this study, data were collected on September 12, 2022, between 7:00 and 18:30. To ensure clear and distinct features, vehicle information was collected within a range of 40-55 meters from the entrance of the airport curbside, from a monitoring perspective. Of the 7150 vehicles that entered the curbside during the specified period, 305 vehicles that dropped off passengers in this area were selected for analysis to study passenger drop-off behavior.

A. FEATURE IDENTIFICATION AND EXTRACTION

OpenPyxl, numpy, and pandas' functions were used in this study to filter and process tabular data. The original data shown in Table 2, consisting of frames with various targets and their tracking numbers, were analyzed and filtered to extract the behavioral states of each vehicle in the passenger drop-off state. The data were then divided into multiple datasets for each vehicle following the filtering criteria outlined in Tables 4 and 5. The behavior state transitions of each vehicle were quantified, and the data were integrated for further analysis. The data are presented in Table 3. Finally, the integrated data were analyzed.

B. LEAST-SQUARES REGRESSION

(RQ3): What are the influencing factors related to the passenger drop-off time?

According to the experiments presented in Tables 4 and 5, all information regarding vehicles parked for passenger drop-offs in the 40-55 m area of the airport curbside can be recorded. We used this information to establish a regression relationship for the passenger drop-off behavior.

First, we transform the categorical variables into dummy variables to meet the requirements of linear regression. Then, we normalize the remaining numerical variables and convert the dimensional expressions into dimensionless expressions, which facilitates the comparison of features with different units or scales.

After processing the data, we performed regression on these features and obtained the results, as shown in Table 6.

From the significance indicators in the table, only the p-value of the independent variable "Behavioral complexity" is less than 0.01, indicating that there is a significant relationship between "Behavioral complexity" and the dependent variable (drop-off time). According to the coefficients in the table, there is a positive correlation.

The VIF values of each feature in the table were lower than five, indicating that there was no multicollinearity problem, and the model was well constructed.

TABLE 2. One vehicle identification data.

CLS	ID	X	Y	LANE	RO	LO	RI	LI	N	S	OT	OD	ON	B
1	2	32	557	line1	0	0	0	0	6	4.52	0	0	0	1
1	2	33	557	line1	0	0	0	0	6	4.56	0	0	0	1
1	2	33	557	line1	0	0	0	0	6	4.6	0	0	0	1
1	2	33	557	line1	0	0	0	0	6	4.64	0	0	0	1
1	2	34	557	line2	0	0	0	0	6	4.68	0	0	0	1

CLS=Vehicle Classification, ID= Identification number assigned for tracking vehicles, LANE=Lane where the vehicle is located, RO= Passenger get-off on the right side, LO= Passenger get-off on the left side, RI= Passenger get-in on the right side, LI=Passenger get-in on the left side, N= Number of vehicles present on the airport curbside at that time, S= Time of occurrence, OT= Status of trunk opening, OD= Status of door opening, and B= Status of vehicle being obstructed.

TABLE 3. Summary data for multiple vehicles.

CLS	ID	RO	LO	RI	LI	ON	N	BT	AT	PT	PP	OT	L	DO	BC
1	78	1	1	0	1	1	10. 7	8	108. 1	99. 0	539	39. 8	3	1	30
1	531	1	1	0	0	2	8. 4	0	58. 0	47. 3	430	29. 1	1	0	20
1	883	1	0	0	0	1	9. 6	1. 4	34. 8	27. 0	422	15. 4	1	0	10
5	1217	1	0	0	0	2	3. 9	0	41. 3	32. 8	562	6. 0	1	0	10
1	1219	1	0	0	0	2	3. 8	0. 8	69. 6	60. 9	465	3. 0	1	0	10

CLS=Vehicle Classification, ID= Identification number assigned for tracking vehicles, L=Lane where the vehicle is located, RO= Passenger disembarks on the right side, LO= Passenger disembarks on the left side, RI= Passenger get-ins on the right side, LI=Passenger get-ins on the left side, N=Average number of vehicles present on the airport curbside throughout the entire process, ON= Number of passengers get-off from the vehicle, BT=Duration of time the vehicle is obstructed, AT= Time the vehicle spends traversing within the study area, PT= Duration of time the vehicle remains parked, PP=Position of the vehicle on the airport curbside, OT= Time elapsed from passenger disembarkation to the point when no passenger get-ins or get-offs, and the vehicle enters the ready-to-depart state, DO= Status indicating whether the driver get-off, BC= Behavioral complexity

To demonstrate the relationship between passenger drop-off behavior complexity and the corresponding drop-off time, a scatter plot cluster diagram (Figure 5) was created. In the plot, the size of the scatter points increases with increasing density.

C. ANALYSIS OF THE RELATIONSHIP BETWEEN PASSENGER DROP-OFF BEHAVIOR AND DROP-OFF TIME

In Figure 5, we use the k-means clustering algorithm, which was implemented using the Lloyd algorithm, to classify different drop-off behavior types [31]. To achieve more accurate clustering results, complexity values were multiplied by a certain factor.

The three types of drop-off behavior were classified as follows: "Quick drop-off behavior," "Normal drop-off behavior," and "Slow drop-off behavior."

Based on the analysis results, an increasing trend was observed between passenger drop-off behavior complexity and the corresponding drop-off time.

In the "quick drop-off behavior" category, the clustering range was relatively small, suggesting a close similarity between passenger drop-off behaviors. Video analysis revealed that passengers immediately carried fewer luggage items and left airport curbsides.

In the "Normal drop-off behavior" category, there was a positive correlation between passenger drop-off behavior complexity and drop-off time, although with some randomness. The video revealed that non-flight passengers saw off airline passengers and assisted them with their luggage or airline passengers organizing their luggage. The relatively higher complexity of these behaviors results in larger clustering dispersion. However, the overall trend remained consistent with the "Quick drop-off behavior" category.

The "Slow drop-off behavior" category displayed the highest clustering dispersion in Figure 5. Video analysis revealed that drop-off behavior within this category involved not only non-flight passengers seeing off airline passengers and assisting them with their luggage but also engaging in conversations with them. Despite the increased complexity of the behaviors within this category, the overall trend remained consistent with that of the other two behavior categories.

Furthermore, a pie chart (Figure 6) is presented to illustrate the proportion of the three behavior categories, and smooth trend lines are used to connect the scatter plot cluster centers of these categories (Figure 6). Analyzing these charts provided further insight into the characteristics and trends of the different behavior categories.

In conclusion, this study employed the k-means clustering method to investigate and categorize three types of drop-off behavior based on an analysis of passenger drop-off behavior complexity and drop-off time. The research findings indicated a positive correlation between passenger drop-off behavior complexity and time.

An analysis of the pie chart (Figure 6) depicting the proportion of the three types of drop-off behavior yielded the following findings: The first category, "Quick drop-off behavior", accounted for the largest proportion (57.7%). This indicates that most passengers tend to have a rapid drop-off process.

The second category, "Normal drop-off behavior" was followed by 34.4%. This suggests that approximately one-third of the airline passengers require a certain amount of time for

TABLE 4. Quantitative feature judgment criteria.

Category	Recognition Criteria
Left or right get-off the vehicles	When a passenger who has not appeared before appears above the opened door on the side where the door opens (either left or right), it is considered a get-off event.
Left or right get-in the vehicles	When a passenger who appears outside moves to the side where the door is open (left or right) and disappears continuously for 20 frames, it is considered a get-in event.
Number of airline passengers	Subtracting the get-in count from the get-off count on both sides of the vehicle to obtain the number of airline passengers.
Block time	The duration of time when a vehicle obstruction appears in the left front of the vehicle.
Drop-off time	Timing starts from the moment the doors or trunk open and ends when all doors and trunk of the vehicle are closed, indicating the completion of the passenger drop-off event.
Dwell time	Time for vehicles to stay at airport curbside
Experimental Area Vehicle Count	The count of vehicles within the monitoring and recognition range of 0-60 meters.
Parking Location	The coordinate position when the displacement is less than 10cm continuously for 20 frames.
Behavior Complexity	Sum of the number of times of passenger get-in or off

Left or right get-off vehicles= direction of passenger movement; eft or right get-in vehicles= direction of passenger movement; drop-off time= passenger drop-off time

TABLE 5. Categorical feature judgment criteria.

Recognition Type	Recognition Criteria
Driver behavior	Number of passengers in left-side get-off minus number of passengers in left-side get-in (To judge whether the driver has got off).
Vehicle Classification (class)	Classification of vehicle types based on the classifier.
Lane	The lane information of the parking vehicle is obtained based on the lane markings and the parking position data.

the drop-off process. They may have friends or relatives who see them off, leading to a longer drop-off duration.

The third category, "Slow drop-off behavior" had the lowest proportion (7.9%). This implies that a small percentage of airline passengers require extended drop-off time because they engage in complex activities with passengers who are seeing them off. This behavior may have a negative impact on the traffic conditions at airport curbsides. These three categories exhibited significant differences in passenger drop-off times, and during periods of high traffic volume, they may experience interference from one another.

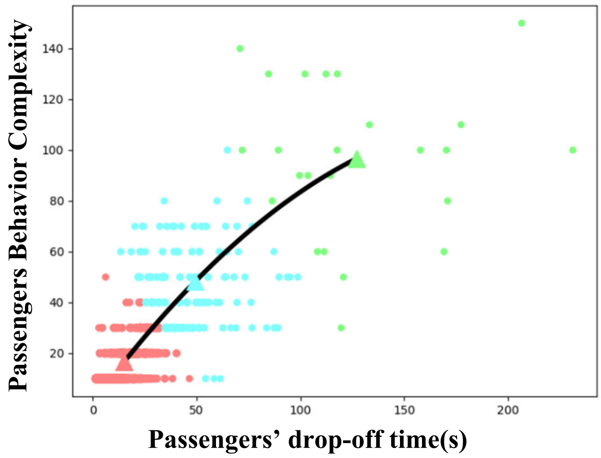

FIGURE 5. Scatter plot of passengers drop-off time and behavior complexity clustering.

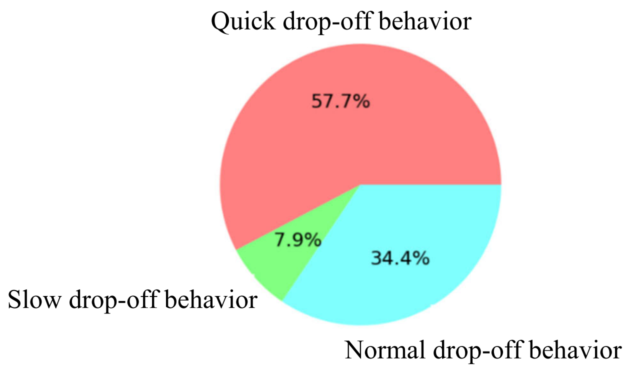

FIGURE 6. Proportion of each category.

D. RELATIONSHIP OF CATEGORICAL VARIABLE

1) LOGISTIC REGRESSION

We determined the relationship between behavior complexity and drop-off time through linear regression, but linear regression is not good at regressing categorical variables. Therefore, we used the three categories of drop-off behavior obtained through clustering as dependent variables and the categorical variables in the data as independent variables to perform logistic regression.

Because the original data had an imbalance in the number of instances for each category of categorical variables, we used oversampling to process the data and obtained the likelihood ratio test results, as shown in Table 7. The p-values of the three independent variables, driver behavior, class, and lane, were all less than 0.01, indicating that the relationship between these three independent variables and the dependent variable was significant.

We analyzed the relationship between categorical variables with significant effects and the dependent variable by plotting them, as shown in Figures 7 and 8.

2) THE RELATIONSHIP BETWEEN DRIVER BEHAVIOR, AND DROP-OFF BEHAVIOR

In Figure 7, when the X-axis value is "remained" refer to the driver remaining in vehicle and "off" is refer to the driver

TABLE 6. Linear regression results.

independent variable	unstandardized coefficient	standard error	standardized coefficient	t	P	VIF
Behavioral complexity	9093.624	819.392	0.68	11.098	0.000***	2.48
Lane2	-7.476	5.261	-0.057	-1.421	0.156	1.067
Lane3	-22.963	24.753	-0.037	-0.928	0.354	1.026
Driver exit	6.059	3.871	0.081	1.565	0.119	1.778
parking location	-79.836	4813.567	-0.001	-0.017	0.987	1.032
Vehicle Count	1445.822	1435.071	0.042	1.007	0.315	1.131
Block time	-80.99	142.861	-0.023	-0.567	0.571	1.067
Vehicle Classification (taxi)	1.838	5.587	0.013	0.329	0.742	1.026
Number of airline passengers	-110.968	969.494	-0.006	-0.114	0.909	1.625
Dependent variable: Drop-off time						

TABLE 7. Likelihood ratio test results for logistic regression.

Independent variables	Chi-square	df	P
Class	131.211	2	.000
Lane	64.416	4	.000
Driver behavior	1399.11	2	.000
Dependent variable: Drop-off behavior			

getting out of the vehicle, the following observations were made by analyzing the grid heatmap, which represents the relationship between driver behavior and passenger drop-off Behavior:

When the driver remained in the vehicle, it can be observed that most passengers belong to the category of "Quick drop-off behavior," while a few passengers fall into the category of "Normal drop-off behavior," and hardly any passengers fall into the category of "Slow drop-off behavior."

When the driver exits the vehicle, it can be observed that most passengers belong to the category of "Normal drop-off behavior", while a few passengers fall into the two categories of "Quick drop-off behavior" or "Slow drop-off behavior".

Video analysis revealed that when the driver exits the vehicle, there is a high probability that they will assist passengers with their luggage and engage in conversations with them. In most cases, these fall into the "normal drop-off behavior" category. However, there is quick drop-off behavior when there is little luggage and no conversation." When there is a lot of luggage and extensive conversation, it may exhibit "slow drop-off behavior."

When the driver remains in the vehicle, there is a high probability that there will be no significant amount of luggage and no prolonged interaction; therefore, only sudden drop-off behavior and "Quick drop-off behavior" and "Normal drop-off behavior" are likely to occur.

3) THE RELATIONSHIP BETWEEN VEHICLE CLASSIFICATION, LANE, AND PASSENGER DROP-OFF BEHAVIOR

Figure 8 shows the percentage of each drop-off behavior for classes and lanes. Table 8 shows the average drop-off time according to class and lane. The results indicated that the quick drop-off behavior for cars was 57% and that for taxis was 67%. The average drop-off time for cars was 36.1 s, and for taxis was 29.3 s This suggests that compared to cars, taxi passengers tend to exhibit quicker drop-off behavior.

Regarding lane, the feature where vehicles drop off passengers, it is generally preferred to park in lane 1, which is the closest to the pedestrian island. However, when lane 1 is congested, drivers may choose to park lanes 2 or 3. The quick drop-off behavior for lane 1 was 56%, for lane 2, 72%, and 100 % for lane 3. The average drop-off times for lane 1 was 36.9 s, for lane 2 was 23.6 s, and lane 3 was 4.6 s. These results indicate that the farther the lane is from the pedestrian island, the more likely it is to exhibit quick drop-off behavior. Video analysis revealed that, when vehicles are not in lane 1, parking in lanes 2 or 3 can cause obstructions near the pedestrian island and lead to conflicts with other vehicles. This can create invisible pressure that encourages passengers to choose a quick drop-off behavior.

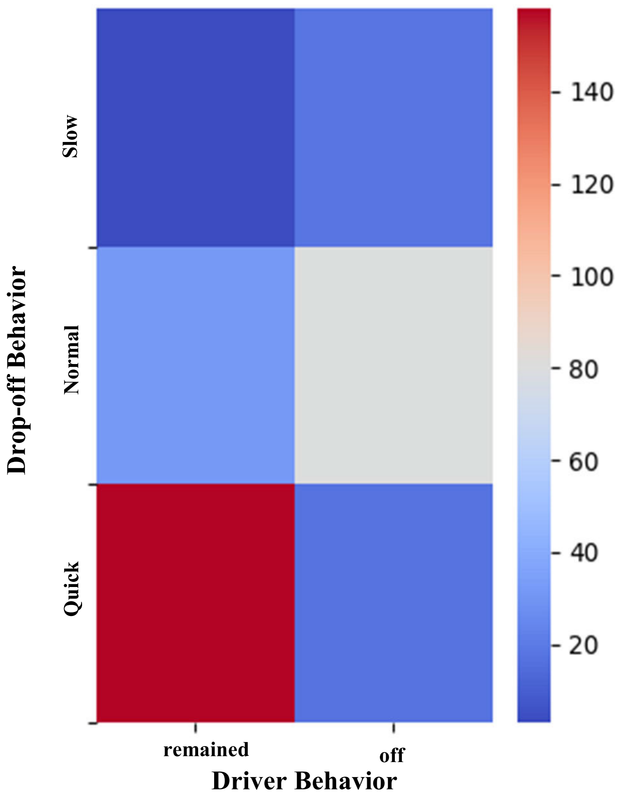

FIGURE 7. The impact of driver behavior with Drop-off behavior.

TABLE 8. Average drop-off time for class and lane.

Variables	lane			class	
Sub-variables	Lane1	Lane2	Lane3	car	taxi
Drop-off time	36.9	23.6	4.6	36.1	29.3

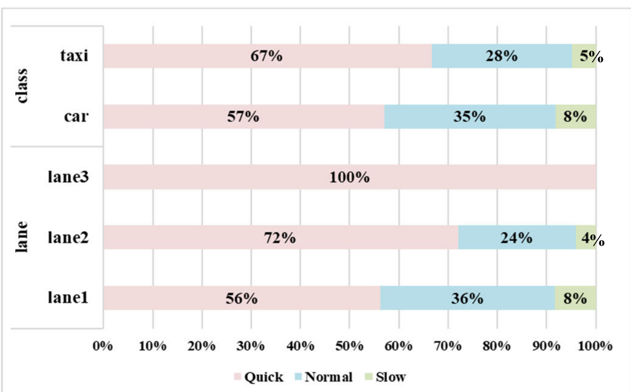

FIGURE 8. Distribution of drop-off behavior for class and lane.

V. DISCUSSION

This study provides a new theory for understanding passenger behavior at airport curbsides. Based on our research, it would be helpful to study how to manage traffic on airport curbsides.

A. INTRINSIC FACTOR

According to previous studies [3], [4], [26] passenger drop-off behavior and characteristics are related to the effects of drop-off time and traffic flow. Our experimental results verified the influence of the passenger drop-off behavior and time.

Based on the former results, three types of behavior are described, and the behavioral complexity of passenger drop-offs is positively correlated with drop-off time.

Taxi passengers usually belong to the category of ''Quick drop-off behavior.'' Taxi drivers and passengers are strangers; thus, airline passengers have minimal interaction requirements with drivers who transport them, and at most, request their assistance with luggage handling. The drop-off model for ride-hailing services was like that for taxi services.

However, the drop-off model of private vehicles is diversified, and the three categories are ''Quick drop-off behavior,'' ''Normal drop-off behavior,'' and ''Slow drop-off behavior.'' are all included. passengers who see airline passenger off may their friends or relatives. Some of them may experience long drop-off times owing to their activities such as conversing and packing luggage. When they end their activities, people who see airline passengers off will enter the vehicles. However, most passengers do not require long drop-off times. Only a few airline passengers exhibit the drop-off behavior of the category ''Slow drop-off behavior.''

In summary, the intrinsic factor that affects drop-off behavior and time is the relationship between airline passengers and people accompanying them. If they have a close relationship and show a reluctant attitude, they may have a long drop-off period. When airline passengers and people accompanying them do not show a reluctant attitude, they do not have a long drop-off time.

B. PROSPECTS FOR CURBSIDE MANAGEMENT STRATEGY

Many problems remain unsolved in airport curbsides. According to previous research [32], traffic can be managed by separating the different types of vehicles. Based on the above research, we know that there are three types of drop-off behavior and times. Therefore, our future focus will be on diversion management of these three types of vehicles.

First, a certain area can be designated for taxis and ride-hailing vehicles to park, so that these vehicles category of ''Quick drop-off behavior'' can be unaffected by vehicles with long passenger drop-off times.

Second, for private vehicles, the curbside area should be divided into two sections: a long-time drop-off area, and a normal-time drop-off area, each with different parking time limit rules. The long-term drop-off area can be visually distinguished using bright colors and clear signs to guide drivers who intend to park for an extended period. However, the normal-time drop-off area should have prominent signs that indicate the maximum time limit allowed for parking. Furthermore, it is important to establish a more convenient location for normal-time drop-off vehicles that are separated from the long-time drop-off area to prevent any disruption to the flow of vehicles.

Finally, future research should use machine learning algorithms to combine simulations to train an optimal management division area division scope strategy.

C. PROSPECTS FOR RESEARCH ON CONNECTED VEHICLES

Previous studies on connected vehicles have shown that they optimize their driving strategies by exchanging information and coordinating with each other [33], [34], [35]. This study reveals that the relationship between passengers inside vehicles affects their drop-off behavior and timing. Connected vehicles can estimate passenger relationships by exchanging information on vehicle types, such as ride-hailing or private vehicles. Thus, they can decide in advance to separate different types of passenger behaviors in different parking areas to avoid conflicts [36]. Furthermore, a natural language model can be trained using a large amount of data on vehicle passenger dialogue and the final drop-off behavior type of vehicles at the airport curbside. In this way, they can estimate the drop-off behavior type in advance through vehicle passenger dialogue and avoid potential spatial competition.

Conventional regression methods were used to analyze the interpretability of the features. If we need to predict the drop-off time in future scenarios, we can use neural network regression for the prediction. We propose a novel parallel CNN and LightGBM structure for regression in future scenarios that may require predicting the drop-off time. The parallel architecture effectively combines the advantages of the CNN in extracting abstract features and LightGBM in extracting concrete features. This enables connected vehicles to precisely predict the departure time of preceding vehicles, reducing delays caused by searching for positions.

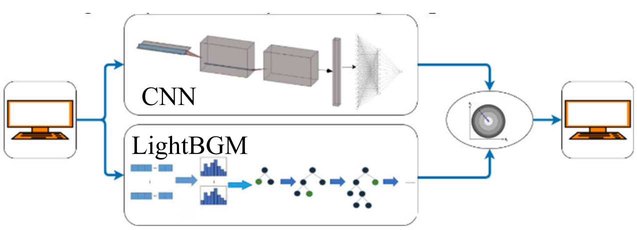

FIGURE 9. Fusion regression model.

D. SHORTCOMINGS

However, the current study has some limitations that require further investigation and improvement in the future.

It is possible that the passenger drop-off behavior results are affected by the weather. The proposed analysis was not performed under different weather conditions. The researcher will further expand the analysis to include rain conditions. Therefore, it was possible to obtain more detailed relationships.

E. IMPACT OF FINANCIAL INDUSTRY

The operational efficiency of an airport, while directly influencing its own economic viability, also has profound implications for the economic trajectory of the region in which it is situated [37], [38]. Especially given Nanning Wuxu airport's key role in China's collaborations with ASEAN. Enhanced airport efficiency can stimulate regional economic activities, including boosting tourism and attracting international businesses. This, in turn, creates opportunities for the financial industry, from increased demand for travel-related financial services to the attraction of foreign investments. As the airport's passenger flow is expected to rise, improving its efficiency is crucial for both its sustainability and to catalyze Nanning's economic momentum. We aim to provide actionable insights for Airport's management and shed light on potential growth areas for the financial industry in the region.

VI. CONCLUSION

Vehicles on airport curbsides often competition for limited space. Passenger drop-off behavior is an important factor that determines vehicle dwell time, so it influence traffic. Therefore, we collected data on the passenger drop-off behavior of vehicles on airport curbsides based on machine learning algorithms and used least squares and logical regression to analyze the data. To provide useful suggestions and information for future airport curbside management strategies and connected vehicle strategies for curbside entry.

We conducted an empirical study at the T2 terminal of Nanning Wuxu Airport in Guangxi, China. By collecting passenger and vehicle information, we extracted the relevant features of passengers and vehicles, such as the direction of passenger movement, vehicle type, vehicle location, trunk state, and passenger drop-off time. Using this information, we studied the relationship between relevant features and passenger drop-off times on airport curbsides.

This study used least squares and logistic regression to determine the influence features for drop-off time. We found that behavioral complexity was linearly and positively correlated with drop-off time. There are three types of drop-off behavior for airport curbside passengers: quick, normal, and slow drop-off behaviors. We then studied the behavioral characteristics of the three types of passengers and the relationship between airline passengers and accompanying personnel by analyzing driver behavior and vehicle classification. We found that the relationship between airline passengers and accompanying personnel is an intrinsic factor that affects drop-off behavior complexity. Moreover, it is possible to estimate passenger drop-off behavior based on the driver behavior, vehicle classification, and lanes. For future airport curbside management, traffic congestion can be reduced by separating these three types of vehicles which drop-off passenger. For Nanning region, which cooperates with ASEAN, our study can provide references for airport managers to cope with the future passenger growth and boost the regional financial industry development. Moreover, this study is not only applicable to airport curbsides, but also to similar scenarios, such as high-speed rail stations.

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(Wan Qian and Liu Qianqian contributed equally to this work.)

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