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Temporal Patterns Underlying Domestic Departure Passengers Behavior in the Airport

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ABSTRACT Air travelers' behavior is closely related to the operational performance of any airport terminal. Much of previous research has focused on how airport operators balance the number of facilities in a terminal and the Level of Service (LOS), while the behavior of passengers is less considered. Not much is known, however, about passenger's behavior during the entire departure process in an airport. In this study, we analyze empirical departure passenger's data to gain an insight into the regular patterns of their activities in an airport. We find that there exist two distinguished temporal patterns during two discretionary periods—*post check-in* and *pre-security check*, *post security check* and *pre-boarding*. The time that departure passengers spend in these two periods is well approximated by a double power-law distribution and an exponential truncated power-law distribution respectively. The two distinguished distributions suggest that there may be different mechanisms underlying passengers' behavior as indicated by previous studies on human mobility. We introduce a stochastic model that considers traveling experience and time pressure to capture the decision dynamics of human behavior. Simulation results suggest that traveling experience and time pressure dominate passenger's decisions before and after security respectively. Our findings contribute to a better understanding of human dynamics, and also offer the potential for optimizing and simulation of airport terminal operation.

INDEX TERMS Air transportation, human dynamics, airport passenger, data-driven approach.

I. INTRODUCTION

Air transport provided transportation service to more than 3.5 billion passenger segments in 2015, with an average of 5.5% growth rate since 2010 [1]. Although efforts from every aspect of air transport industry have been made to improve the safety, capacity, and efficiency of the air transportation system, ranging from the development of new types of aircraft to the deployment of most advanced automation tools in air traffic management system, there are still important challenges remaining. One of these great challenges is airport planning and management. The airport is a social-technological complex system involving various parties, including airport authority, airlines, air traffic control, security, immigration, customs, fire department, and passengers. The operation of the airport thus demands an effective planning and dynamic coordination of multiple processes [2].

With the aim of optimal utilization of system resources, while considering each stakeholder's interest, the concept of Collaborative Decision-Making (CDM) has been successfully applied to operations in many airports. Apart from those professionally trained operators involved in CDM, air travelers play a significant role in airport operations, since the airport is the interface where passengers are engaged in transportation operation. Comparing to the uncertain weather or technological systems, passenger's behavior is much more difficult to be predicted. Passengers' long-time

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stay in airport terminal may increase the airport's commercial revenue, while the late arrival of passengers may cause disruptions in the airline's network operations. The understanding of passenger's behavior needs to be inherent research.

The problems related to airport terminal operations have received a considerable amount of attention from airport operators and researchers around the world. Both analytical and simulation models have been developed to support airport terminal decision-making [3]–[5]. In an early work, Ashford *et al.* put forward the importance of understanding of passenger's behavior in design airport terminal [6]. The performance of processing passengers is critical to the level of service of the airport. Yuan and McCabe validated a computer model with service times and arrival rates at a check-in counter, a security checkpoint, and a boarding gate [7]. A review of the studies of airport passenger behaviors including both departing passengers and arrival passengers is presented in [3].

An enduring aim of research in airport passengers' behavior is to support airports and airlines providing better service to their customers by enhancing the level of service while minimizing cost [8]. It was recognized that check-in as perhaps the major point of congestion in the terminal. Given the nature of passenger's activity-processing in an airport, the most prevalent analytical approach is using queuing theory or queuing network [3], [9], [10]. The purpose of using queuing theory is to encapsulate the essential stochastic nature of passenger's behavior as well as of the operators. The service processes at Check-in, security check, and boarding can be modeled with a Poisson input or passenger arrivals process M, and a negative exponential service time distribution M, and a number of servers C ($C = 1$ for boarding). These models employ a first-come-first service queuing discipline.

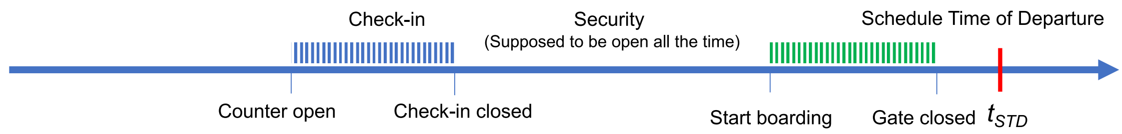
For instance, Stolletz proposed a stationary backlog carryover approach to approximate the performance measures of check-in counters [11]. But his work is restricted to models with homogeneous operators and homogeneous passengers.In [10], Wu *et al.* introduced a method that integrates a Bayesian Network model based on stochastic queuing theory to model passenger facilitation in airport. The central idea of the model is that the Bayesian network is used to capture the causal relationships between airport system factors, while Poisson and exponential distributions are used to model passenger movements from one subsystem to another. There are also discussions in improving performance by optimizing the utilization of check-in facilities. Hsu *et al.* investigated minimizing total waiting time and maximizing utilization facilities by dynamic allocation of check-in facilities and dynamic assignment of passengers [12]. Combining an evolutionary approach and simulation, Mota *et al.* proposed an approach to solve the optimization problems of check-in allocation [13]. Clearly, however, the queuing approach is fundamentally limited when it comes to accounting for time-dependent arrival and heterogeneous nature of passengers.

The security check process and boarding process are another two extensively investigated topics [14]–[16]. Li *et al.* demonstrated different network structures have different effects on the optimal queuing performance of security checkpoint [17]. At the frontiers of research in boarding, passenger boarding behavior is modeled as a one-dimensional, stochastic, and time/space discrete transition process, then a set of indicators for prediction of boarding time is proposed in [18]. These works have some limitations. For example, passenger's arrival patterns are needed in order to improve the accuracy of predictability in boarding time.

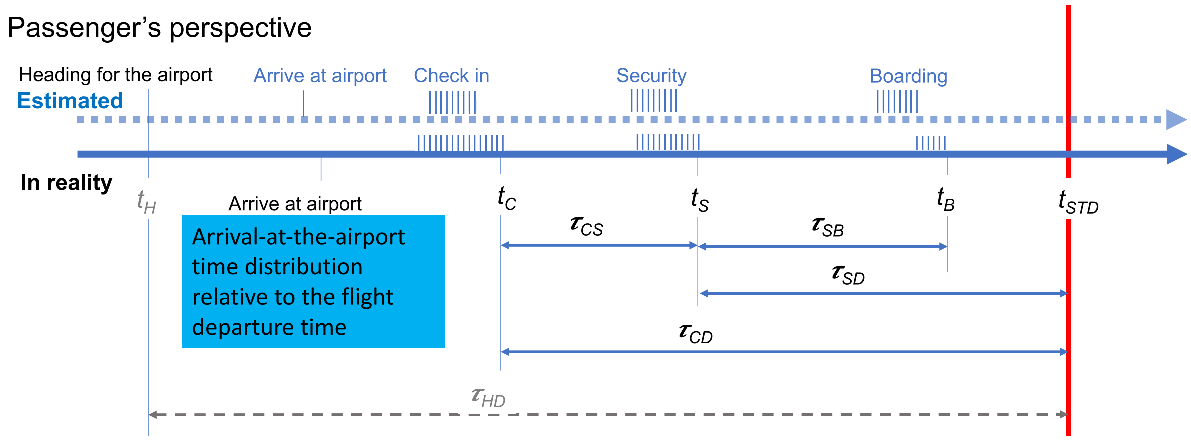
Alternative simulation approaches like agent-based modeling and logit modeling have been proposed. The development of the model that is capable of describing airport passengers' behavior has attracted increasing attention [19]–[23]. To predict air travelers' activity patterns in an airport, Liu *et al.* developed a nested logit model based on passengers' socio-demographical characteristics and travel-specific information (e.g. number of check-in baggage, flight time, etc.) [23]. Passengers' data was collected using a web-based survey, and a total of 359 passengers' data was analyzed. Departing passengers' activities were divided into three phases: *Before-check-in*, *Before-security*, and *Before-boarding*. Kierzkowski *et al.* developed a simulation model by dynamic management of check-in counters to obtain a uniformly distributed passenger arrival flow at security checkpoint [24]. Crucially, however, these work over the past couple of decades has focused almost exclusively on the analysis of airport operation while ignoring passenger's ability of adaption. Less is known about how passengers behave in the airport.

Advances in data science and information technology have further sharpened our understanding of human behavior. Research in human dynamics and human mobility has long sought to understand the underlying mechanisms that govern human traveling behavior [25]–[33]. Human dynamics studies have emphasized on the temporal patterns in various human activities, while human mobility have focused on the patterns of human movements. Contemporary research has further elaborated that urban mobility patterns with a resolution of 10 *min* and hundreds of meters can be generated from mobile phone data [34]. A question may arise in airport passengers whether we can understand and predict passengers' "mobility patterns" in the airport terminal.

This rapidly developing field in data science holds great promise for advancing research on passenger behavior in the airport terminal. Motivated by these overwhelming results in both fields, here we investigate 1 month's departure passenger's data to uncover the underlying patterns in passenger's temporal behavior. Our focus is specifically on domestic flight passengers due to data limitations. The paper is organized as follows: In Section II we depict passenger departing processes from two different points of view. Section III presents the information of the data investigated and a general description of the statistical testing method. Section IV and



(a) Operations of a flight from airline's perspective



(b) Passenger's perspective

FIGURE 1. The queuing process from two different perspectives. (a) Time-line of services provided to passenger by an airline/airport for a departure flight. (b) Time-line for a passenger to catch his/her flight. Red vertical lines indicate the schedule time of departure (STD) of the flight.

Section V show the patterns of passengers behavior and the model we developed. Discussions are given in Section VI.

II. TWO DIFFERENT PERSPECTIVES ON DEPARTURE PASSENGER FLOW

For many studies on airport terminal operations, there are important efforts for optimizing airline's and airport's resources including dynamic allocation check-in/security check facilities and staff. One of the objectives is to minimizing the total waiting time of passengers in each process, which is an important key performance indicator to measure the level of service [35]. Unfortunately, less attention has been given to understanding the departure process from a passenger's perspective. In Fig. 1, we show airline's and passengers' perspectives on the departure processes of a domestic flight.

A. AIRLINE/AIRPORT PERSPECTIVES

As illustrated in Fig. 1(a), three main types of service are provided by airlines and airport to departure passengers are check-in, security check, and boarding.

Check-in and boarding are typically provided by airlines. Given a departure flight, the airline first has to determine when and how many check-in counters shall be open and closed. Each airline has its own policy. Most airlines check-in counters open at least two hours before the scheduled time of departure of the flight, and close 60 minutes prior to departure. While the passenger boarding process has the potential to significantly influence the flight [18], [36], boarding gates open and close may depend on several factors, including the range of flight, the type of aircraft, etc.

The balance between the quality of service and the cost at the security checkpoints is an important issue that the airport should consider. A long time waiting and processing at security can result in passengers increasing complaints, which may cause loss of passenger flow departing from the airport.

B. PASSENGER's PERSPECTIVES

A passenger has his/her own plan on how to take a flight. In an individual passenger's perspective, he/she first estimates total time spent on traveling to the airport, queueing times at check-in, and security check before reaching the boarding gate as shown in the upper dot arrow line in Fig. 1. The time when begin to depart for the airport, t_H, depends on several factors, such as passenger's past experiences, airport, and airline. This will generate different patterns of time of arrival at the airport. If the passenger is familiar with the airport and airline, he/she can make a good estimation of traveling time to the airport. Otherwise, a passenger may ask a local when and how to arrive at the airport. Queuing time and processing time at check-in and security checkpoint are estimated as well to be able to arrive at the boarding gate before boarding gate closed (t_B).

Most of the previous studies on departure passengers are based on some assumptions. For example, the arrival patterns of passengers are described by the Poisson process, and the service times are following unit distributions or exponential distributions.

C. SELF-ADAPTATION OF OPERATORS AND PASSENGERS

The direct interactions between passengers and operators occur in three subsystems: check-in, security check, and boarding, which are typically modeled as queuing systems. As indicated in [37], queuing people should consider both strategies of operators and customers since the results of combining queues may counterproductive. Operators may adjust his/her service time based on the length of the queue. Sometimes, the quicker he/she serves, the more customers he/she gets. Passengers can choose a queue with minimum length or a queue that moves fast. The self-adaptation ability should be considered while building a simulation model.

III. DATA AND METHODS

A. DATA DESCRIPTION

Every time a passenger prints out his/her boarding pass, screening the boarding pass at a security check desk or at a boarding gate, a new record of the passenger will be automatically created. To study passenger's behavior, information from three separate databases is retrieved to form a comprehensive dataset in which a single record represents a single passenger. Each data record contains passenger's name, gender, ID, age, mobile phone number, flight number, scheduled departure time of the flight, check-in counter/machine, security check counter, and boarding gate, as well as the temporal information listed below. Passengers' names are replaced with surrogate keys for the purpose of retaining anonymity. Empty and noise data are first cleaned. We then drop passenger's national identity number and mobile phone number after using them to locate his/her city of residence.

The inter-activity time in our study is the time intervals between *check-in* and *security check*, and between *security check* and *boarding*. We calculate the following time intervals for every passenger. We define the following variables for a passenger i based the data and Fig. 1.

- t_C^i: time stamp when a passenger has completed check-in. It is recorded when the boarding pass is printed out;
- t_S^i: time stamp when a passenger has entered security checking queue, which is recorded when his/her boarding pass is scanned at security checkpoint;
- t_B^i: time stamp when a passenger has passed boarding gate by scanning boarding pass.
- t_D^i: scheduled time of departure of the flight that passenger i takes
- τ_{CS}^i: time interval between check-in and security checking, i.e. $\tau_{CS}^i = t_S^i - t_C^i$;
- τ_{SB}^i: time interval between security check and boarding, i.e. $\tau_{SB}^i = t_B^i - t_S^i$;
- τ_{SD}^i: time difference between scheduled time of departure and security checking, i.e. $\tau_{SD}^i = t_D^i - t_S^i$;
- τ_{CD}^i: time difference between scheduled time of departure and check-in, i.e. $\tau_{CD}^i = t_D^i - t_C^i$.

The original datasets were obtained from different automation systems which contain inaccurate records and inconsistent data. It is therefore very important to clean the data before any further analysis. Empty and noise data are fist cleaned, then the following rules are applied for further cleaning and preprocessing.

1) All the records with negative time intervals τ_{CS}^i, τ_{SB}^i, τ_{CD}^i and T_{SD}^i, are dropped.
2) The minimum of time intervals τ_{CS}^i and τ_{SB}^i is set to 2 minutes while considering the distances between check-in counters and security gate, and between security gates and boarding gates.
3) The maximum of time intervals is set to 6 hours according to the regulations of the airport and airlines.

TABLE 1. Information of the two datasets.

Dataset	D_1	D_2
The number of passengers	989,548	44,730,108
The number of departure flights	10,462	150,338
The number of check-in counters	150	160
The number of security gates	44	39
The number of boarding gates	75	65
Duration of passenger's data	1 month	1 year

In D_1 dataset, about 8.8% noise data was dropped after cleaning, leaving 989,548 records for investigation.

Two datasets, D_1 and D_2, were created from two Chinese hub airports. The statistical summary of the two datasets is given in Table 1. Due to data protection policy, we have only τ_{CS} and τ_{SB} in D_2.

Given the detailed information in D_1, both airport's operations and passenger's departure activities in the airport can be recovered from data. Fig. 2 gives a general summary of airport operations in the investigated 1 month period. Fig. 3 depicts temporal behaviors of 113 passengers of a flight which was scheduled to depart at *15:55:00* on *15 January, 2014*.

B. STATISTICAL MODELING AND TESTING

To estimate the parameters of probability distribution functions of empirical data, the Maximum Likelihood Estimation (MLE) method is used. To test the fitness of statistical functions, Kolmogorov-Smirnov tests (K-S test or KS test) are then performed. Detailed information on how to use MLE and K-S test in statistical modeling can be found in [38], [39]. All fitting results presented in the following sections have passed K-S tests.

IV. EMPIRICAL EVIDENCES

In contrast to human mobility, departure passenger's activities in the airport terminal are under temporal and spatial constraints. Due to the various operational regulations, each flight has its deadlines for passengers to be at Check-in counters, or boarding gates. Departure passengers have three discretionary time periods: pre-check-in, post check-in and pre-security, post-security and pre-boarding. The locations that passengers can be at are also limited, which normally include information desks, dining/drinking places, shops, and restrooms. Research into departure passengers activities during discretionary periods has mainly focused on the shopping behavior, other activities such as dining and relaxing, have not yet been explored [40], [41]. This paper focuses on the temporal patterns of departing passengers, leaving the spatial patterns into our further study.

A. POST CHECK-IN AND PRE-SECURITY

As shown in Fig. 3, there exist significant individual differences in temporal behavior among passengers. On a

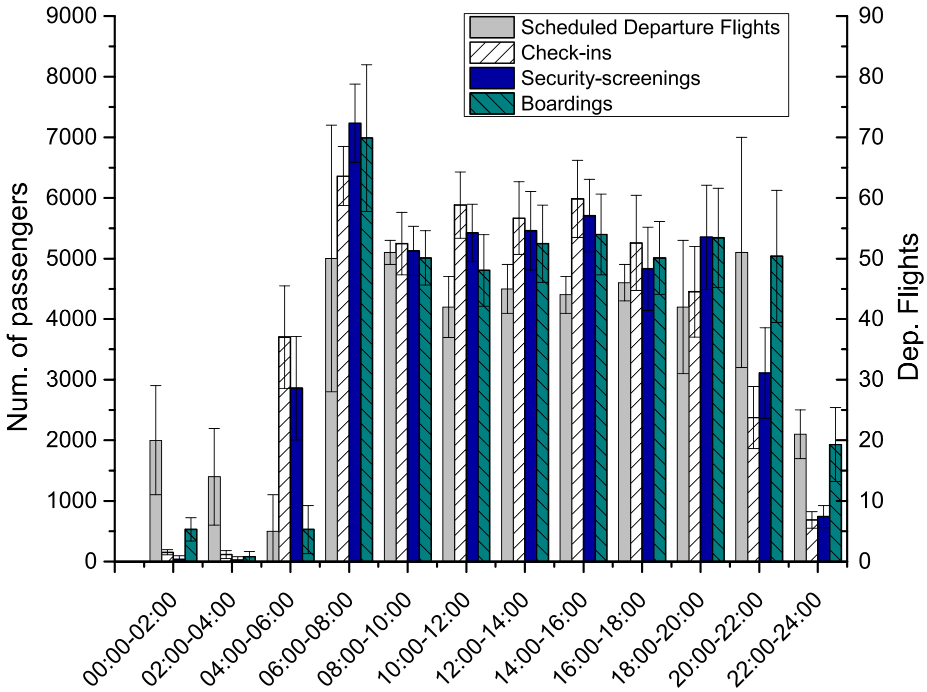


FIGURE 2. **Average flow of passengers and departure flights in very two hours. Error bars show the standard deviation of the two-hour flow.**

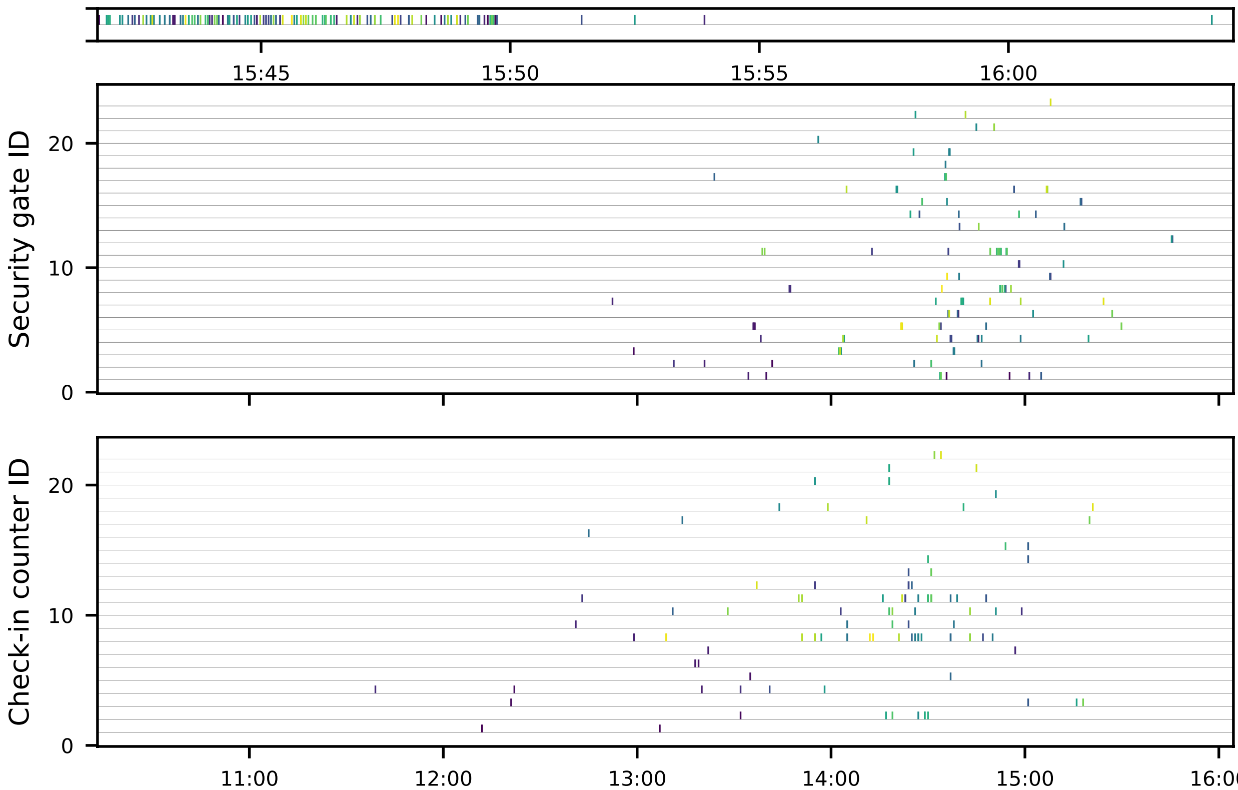


FIGURE 3. **Departure activities of a flight of passengers. The horizontal axis denotes time (in 1s) and each vertical line corresponds to an event (check-in, security check, or boarding). Each color of vertical line represent a passenger. Check-in counters, security check gate, and boarding gate are shown with horizontal lines in grey. The upper plot presents boarding activities at a boarding gate, while the middle and lower plots sharing the same x-axis show passengers' security check and check-in activities respectively. There are 22 check-in counters, 23 security gates.**

large scale, however, the bursty phenomena that emerged in departing passengers are quite similar to many other human activities. The distribution $P(\tau_{CS})$ of the inter-activity time τ_{CS}, the interval between check-in and security check,

TABLE 2. The example of departure passenger's data.

Passenger ID	Gender	Age	City	Check-in time*	Security time*	Boarding time*	STD of flight*
440694	Male	48	Shanghai	13:57:00	14:04:01	15:45:43	15:55:00
421161	Male	64	Nanjing	10:13:00	13:47:27	15:43:58	15:55:00
445177	Male	23	Guangzhou	15:21:00	15:24:20	15:42:49	15:55:00

* All time stamps are in the format of "DD/MM/YYYY hh:mm:ss" as shown in *Check-in time*. The date was not shown due to limited space.

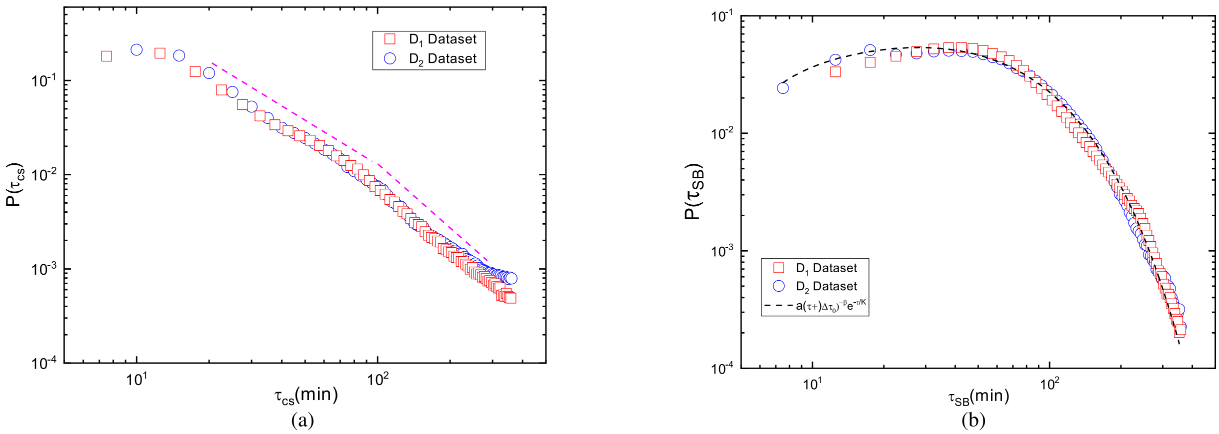


FIGURE 4. Temporal patterns of departure passengers in airport. (a) and (b) plot the distributions of time intervals of an individual passenger between check-in and security, and between security and boarding.

is double pwer-law rather than power-law (Fig. 4), which can be well described as:

$$P(\tau) = \begin{cases} a_1\tau^{-\alpha_1}, & 0 < \tau < \tau_{min} \\ a_2\tau^{-\alpha_2}, & \text{otherwise.} \end{cases} \quad (1)$$

The probability that a passenger goes to a security checkpoint in τ_{CS} minutes is approximated by double power-law. We can see that the scaling spans from 5 minutes to 5 hours. The majority of passengers ($\approx$ 80%) were at security checkpoints within 1 hour after completing check-in. However, there are still few passengers who did early check-in but spent more time before going to a security check.

Across all datasets, we find exponents $\alpha_1 = 1.654 \pm 0.003$, $\alpha_2 = 2.179 \pm 0.128$ ($a_1 = 3.902 \pm 0.017$, $a_2 = 45.658 \pm 1.169$). The temporal pattern observed here is different from those patterns reported in1 human dynamics studies which are typically characterized by a single power-law. It does however similar to collaborative human dynamics that have been recently uncovered in inter-update activities on Wikipedia articles [42]. Their model consists of three ingredients: (i) individual behavior of updating articles captured by Poissonian initiation; (ii) human interaction with power-law waiting time; and (iii)population growth. Most passengers after check-in go to a security checkpoint, without any collaborative activity with other individual passengers. Few passengers may spend time with families or friends before entering the terminal airside. Rather, passenger's individual decision-making rules may play a dominant role in this process.

B. POST SECURITY AND PRE-BOARDING

To explore the statistical properties of passenger's activities after security checking, we measured the time intervals between a passenger's security check time and boarding time, τ_{SB}. Surprisingly, we found that the distribution of intervals of all passengers can be well approximated by a truncated power-law:

$$P(\tau) = a(\tau + \Delta t_0)^{-\beta} exp(-\tau/K), \quad (2)$$

with $a = 0.021$, $\Delta t_0 = -5.141$, $K = 45.455$, and exponent $\beta = -0.504$.

Yet, we observe a markedly different pattern from the one before security, but it follows the patterns in human mobility [27]. Compared to pre-security discretionary period, passengers now may feel released since boarding is the only process remaining. The changes in passengers' modes can have a potential influence on their activity. The clearly distinguished distributions in check-in-to-security and security-to-boarding imply that there are different mechanisms underlying passenger's mobility.

C. PRIOR TO SCHEDULED TIME OF DEPARTURE (STD)

A third question is how long before the scheduled time of departure of the flight a passenger arrives at the airport. It is not possible to give a comprehensive description of arrival patterns of passengers in the context of the present data sets since there is no information on when the passenger entering the airport terminal. Instead of looking into the time of passenger's arrival, we investigate the time difference between

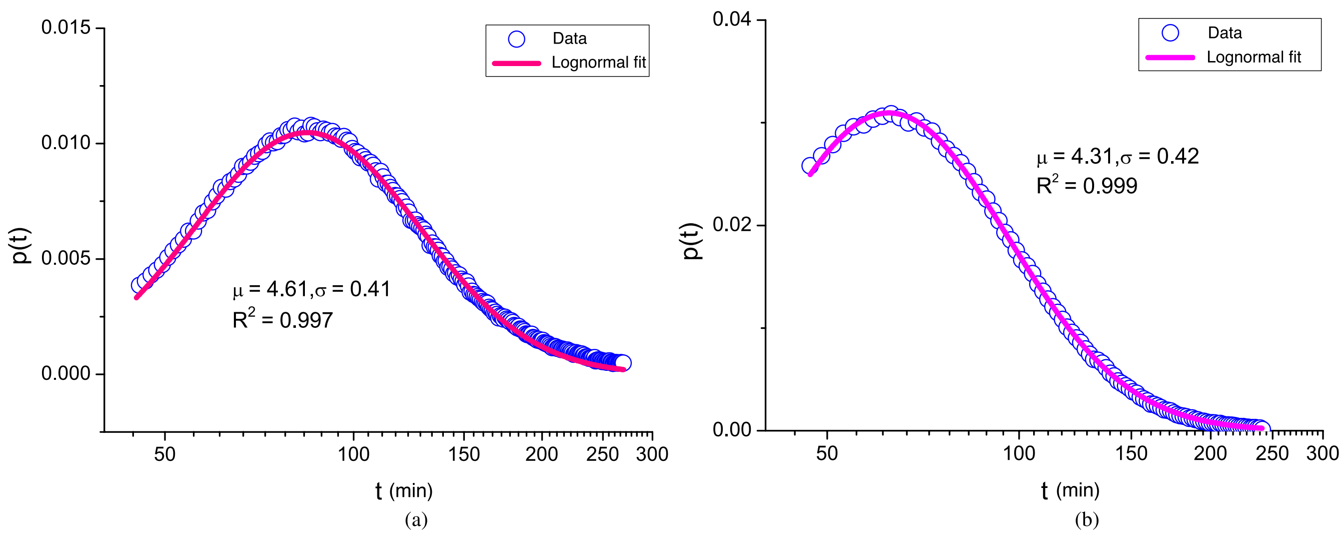


FIGURE 5. Distribution of arrival time at (a) check-in and (b) security prior to STD.

TABLE 3. Fitting results to empirical data.

Day	Check-in-to-Security (τ_{CS}) Double power-law		Security-to-Boarding (τ_{SB}) Truncated power-law				Check-in prior to STD(τ_{CD}) Lognormal	
	α_1	α_2	a	K	Δt_0	β	μ	σ
01/12	1.656	2.282	0.040	49.684	-6.843	-0.305	4.574	0.399
01/13	1.651	2.103	0.012	45.703	-4.529	-0.626	4.585	0.406
01/14	1.657	2.336	0.105	37.818	-7.496	-0.147	4.456	0.345
01/15	1.651	2.103	0.001	34.199	7.203	-1.312	4.622	0.410
01/16	1.655	2.240	0.023	39.821	-5.605	-0.536	4.588	0.396
01/17	1.651	2.103	0.023	37.278	-4.430	-0.557	4.616	0.413
01/18	1.653	2.182	0.0005	27.920	29.597	-2.640	4.710	0.401
01/19	1.657	2.359	0.036	42.381	-6.679	-0.392	4.539	0.403
01/20	1.657	2.359	0.046	69.272	-7.421	-0.153	4.580	0.413
01/21	1.653	2.182	0.001	37.716	6.256	-1.198	4.689	0.400
01/22	1.655	2.240	0.017	47.648	-4.833	-0.538	4.625	0.409
01/23	1.655	2.240	0.0004	32.478	22.051	-1.867	4.680	0.401
01/24	1.657	2.347	0.014	35.243	-3.458	-0.711	4.516	0.400
01/25	1.654	2.190	0.044	48.829	-7.222	-0.286	4.619	0.394
01/26	1.654	2.190	0.026	45.288	-6.232	-0.451	4.569	0.400
01/27	1.651	2.103	0.0005	27.473	19.163	-2.010	4.653	0.398
01/28	1.653	2.182	0.003	39.805	3.585	-1.017	4.682	0.413
01/29	1.652	2.146	0.003	38.123	1.993	-1.027	4.646	0.405
01/30	1.657	2.359	0.030	46.848	-5.790	-0.392	4.585	0.403
01/31	1.653	2.182	0.019	48.162	-5.123	-0.505	4.596	0.417
02/01	1.651	2.103	0.046	48.617	-7.172	-0.276	4.535	0.411
02/02	1.654	2.219	0.033	49.319	-6.885	-0.352	4.525	0.404
02/03	1.663	1.653	0.001	25.609	6.042	-1.631	4.536	0.378
02/04	1.652	2.146	0.001	40.750	11.661	-1.241	4.676	0.405
02/05	1.651	2.103	0.020	38.767	-5.321	-0.585	4.543	0.418
02/06	1.654	2.190	0.024	41.966	-5.696	-0.498	4.600	0.396
02/07	1.651	2.103	0.043	47.123	-7.288	-0.309	4.545	0.410
02/08	1.655	2.240	0.009	39.028	-2.538	-0.763	4.585	0.415
02/09	1.653	2.182	0.046	45.063	-6.739	-0.304	4.618	0.390
02/10	1.652	2.146	0.021	84.809	-6.375	-0.273	4.663	0.436
02/11	1.651	2.103	0.011	37.781	-2.067	-0.724	4.638	0.407
02/12	1.651	2.103	0.006	37.606	0.234	-0.870	4.591	0.409
Mean	1.654	2.179	0.022	42.754	-0.561	-0.766	4.600	0.403
Standard Deviation	0.003	0.128	0.022	11.260	9.452	0.592	0.059	0.015

check-in and STD (τ_{CD}), and between security and STD (τ_{SD}). As shown in Fig. 5, a third pattern emerges.

The distributions of τ_{CD} and τ_{SD} can be well approximated by lognormal distribution:

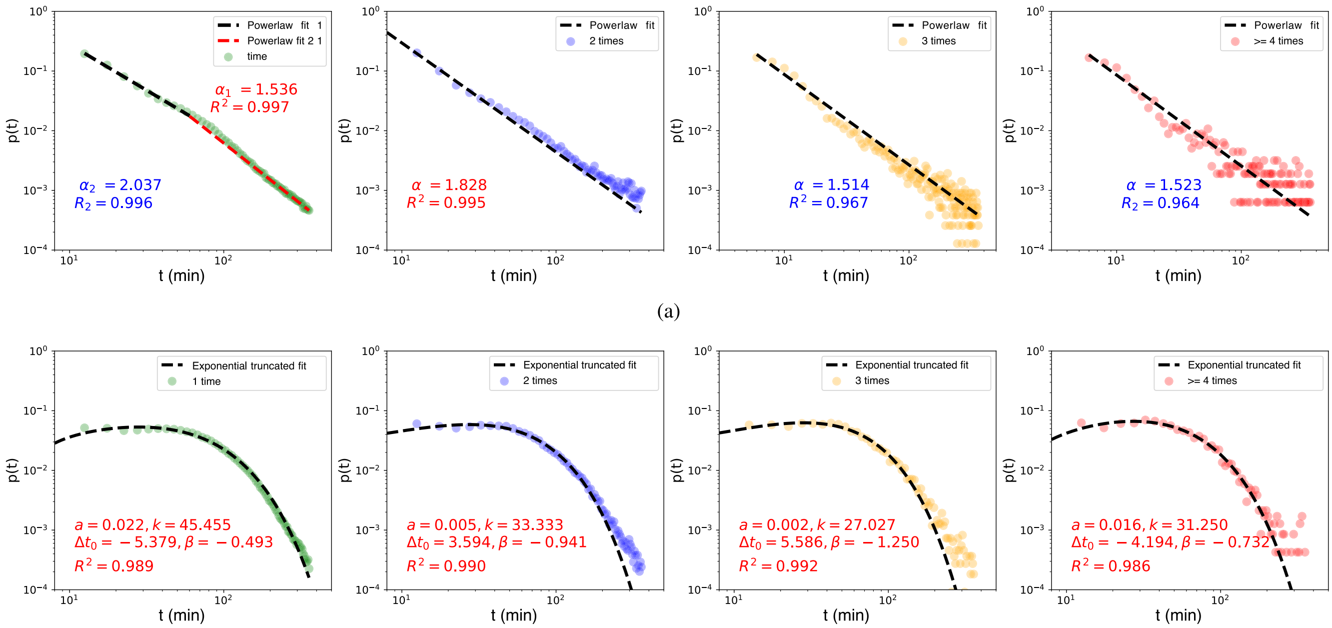
$$f(\tau;\mu,\sigma) = \frac{1}{\tau\sqrt{2\pi\sigma^2}} exp\left[-\frac{(\ln\tau-\mu)^2}{2\sigma^2}\right]. \qquad (3)$$

The R^2, known as the coefficient of determination, tells how well-observed outcomes are replicated by the statistical model. The R^2 in both figures indicate that the empirical data can be well captured by lognormal distributions

To minimize the effect of check-in processing time on the distribution of τ_{CD}, we generated a new data set by rounding check-in time stamp to its nearest 5 minutes. We do

TABLE 4. Factors examined in the determination of passenger's group.

Demographical factor	Distance between residence city and airport (km)	Flight departure time	Flight range (km)	Traveling experience (num. of records)
Age	$[0, 50)$	Morning	$[0, 1000)$	1 time (953,549)
Gender	$[50, 200)$	Afternoon	$[1000, 2000)$	2 times (53,278)
	$[200, \propto)$	Night	$[2000, 3000)$	3 times (6,258)
		Dining time	$[3000, \propto)$	$\geqslant$ 4 times (1,070)



(b)

FIGURE 6. Distributions of time intervals of (a) between Check-in and Security (τ_{CS}) and (b) between Security and Boarding (τ_{SB}) in passengers with different traveling experience.

not however observe any different patterns from the original check-in data. In fact, lognormal distributions have been widely reported in natural distributions and across the science [43], [44]. Specifically, human response times also follow such patterns [45]–[47]. It has been well explained by the decision-making process under diffusion models [48]–[50].

We tested the robustness of these parameters for a different day in data sets. These double power-law, truncated power law, and lognormal are found to be general across all the days in our data.

D. FACTORS THAT INFLUENCE PASSENGER's BEHAVIOR

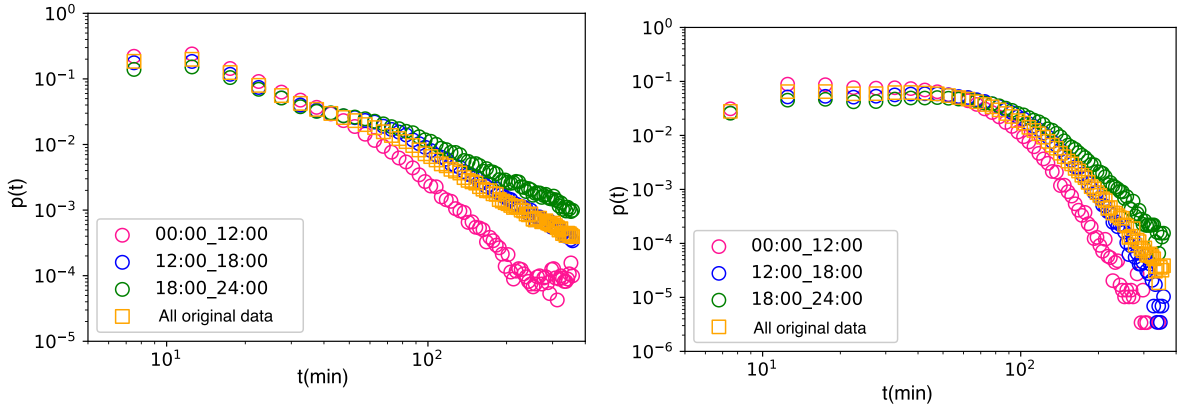
Here, certain aspects of passengers and flights are examined to investigate their effects on passengers' temporal behaviors. We group the data according to different factors that are listed in Table 4. For example, to examine whether passengers with different ages behave differently, we divide the data sets into four groups according to passenger's age:

- Group 1: (0, 20]
- Group 2: (20,40]
- Group 3: (40, 60]
- Group 4: (60, 80]

We did not observe a significant difference among groups. Similarly, gender, residence city, are also found to have in insignificant effect on passenger's temporal behavior. The traveling experience and flight scheduled time of departure may have an impact on passenger's behavior in the departure process.

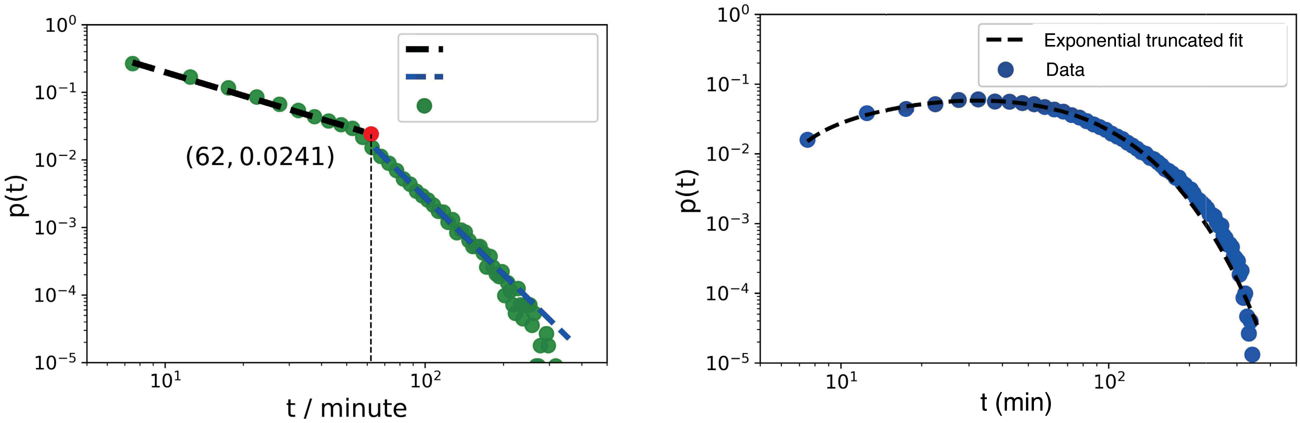
A regular traveling passenger has a good estimation of timing thus may have different temporal behavior compared to others. In our data set, we do have a certain amount of passengers who traveled more than 1 time in a month. The temporal patterns of passengers with different traveling experience are plotted in Fig. 6. One interesting finding is that the time intervals between check-in and security, τ_{CS}, of passengers who traveled more than 2 times are captured with a single power-law rather than double power-law. However, the patterns after security and before check-in are in agreement with previous observation. The difference between one-time flight passengers and experienced passengers (traveling more than twice) suggests that experienced passengers may adopt different strategies before security.

To examine whether the scheduled time of departure (STD) of the flight has an impact on passenger's behavior, we divide D1 into 12 subsets based on the STD of flights. We found three distinct patterns of distributions on tau_{CS} and tau_{SB} as shown in the Fig. 7. Compared to the afternoon and



(a) (b)

FIGURE 7. The effects of STD on passenger's behavior (a) between Check-in and Security and (b) between Security and Boarding.



(a) (b)

FIGURE 8. Simulation results.

TABLE 5. Model parameters for check-in and security check phase.

$\mu:\nu$	α_1	α_2	R_1^2	R_2^2	RSE
0.1:0.9	1.697	2.022	0.994	0.987	0.557
0.2:0.8	1.553	2.123	0.991	0.983	0.363
0.3:0.7	1.329	2.067	0.99	0.989	0.58
0.4:0.6	0.99	2.141	0.984	0.989	0.545
0.5:0.5	0.958	1.996	0.991	0.989	0.722
0.6:0.4	0.942	2.138	0.992	0.984	0.596
0.7:0.3	0.942	2.202	0.986	0.99	0.532
0.8:0.2	0.894	2.21	0.993	0.977	0.572
0.9:0.1	0.885	2.279	0.972	0.984	0.512

TABLE 6. Model parameters for security check and boarding phase.

$\mu:\nu$	α	Δt_0	K	β	R^2	RSE
0.1:0.9	0.001	0.051	13.402	-2.306	0.895	14.293
0.2:0.8	0.001	0.064	13.606	-2.15	0.987	15.813
0.3:0.7	0.001	0.063	14.81	-2.488	0.984	16.678
0.4:0.6	0.001	0.057	18.81	-2.024	0.994	11.136
0.5:0.5	0.001	0.056	14.422	-1.862	0.997	6.91
0.6:0.4	0.001	0.054	24.067	-1.816	0.997	6.599
0.7:0.3	0.001	0.053	31.417	-1.725	0.998	4.039
0.8:0.2	0.001	0.055	31.561	-1.837	0.999	4.073
0.9:0.1	0.004	0.049	33.275	-1.355	0.998	0.284

evening flights, passengers taking morning flights are more likely to go to security or boarding directly as indicated by the quick decay in the tail of the distributions.

V. MODEL AND SIMULATION RESULTS

To uncover the key mechanisms needed to reproduce passenger's temporal patterns, we propose the following model to capture the stochastic nature of departure passengers. We assume that (i) No passenger arrives at barding gate within 15 minutes prior to the STD; (ii) Traveling experience measured by the number of trips m_i and time pressure measured as the time difference between the STD of flight tf_i and current time t_i are the two important factors that influence passenger's behavior. The Bernoulli process is then implemented to simulate a passenger whether to perform the next mandatory activity directly. More specifically, the probability of a passenger i performing the next mandatory activity is given as

$$p_i = \mu \frac{1}{t_i - tf_i} + \nu \frac{1}{m_i}, \quad (4)$$

where μ and ν are the weights that also ensure $p_i \leq 1$. The probability of the passenger i go to non-mandatory activity is then given as $1 - p_i$. The time of a passenger spends between *Check-in* and *Security*, and between *Security* and *Boarding* are drawn from the following distributions, log-normal distribution (directly go to security), power-law distribution, two-Gaussian distribution (directly go to boarding), and log-normal distribution. These probability distributions are identified from the empirical data.

The model takes flight departure times as input. We optimize μ and ν to fit the simulated results to the empirical data. In the simulation, we first tuned parameters for check-in to security check phase. The μ and ν are tested from 0.1: 0.9 to 0.9: 0.1, with 0.1 increment. The same process was applied for the parameters tuning in security check to boarding phase. Simulate results are shown in the table 5 and table 6. Based on the sum of squared errors between the simulated data and the actual data, the optimized μ and ν for τ_{CS} and τ_{SB} are presented 0.2:0.8 and 0.9:0.1 respectively. The simulated data are plotted in Fig. 8. It can be seen that during check-in to the security check phase, the main factor that determines the passenger activity decision is passengers' traveling experience, while during security check to boarding, the main factor is the duration from finishing security check to flight departure time.

VI. CONCLUSIONS AND DISCUSSIONS

Overall, our analyses on departing passenger's data have unrevealed three general temporal patterns underlying their entire activities in the airport terminal. Importantly, we find two different types of temporal patterns in passengers before and after security, which indicate that they may adopt different strategies. Factors ranging from passenger's demographics and geographical residence to flight departure time distributions are examined. It is found that traveling experience and time pressure have a potential impact on passenger's behavior before and after security check.

There is growing interest in ''smart airport'' both in design and management. Our work here provides perhaps for the first time the analysis of departure passenger's activities in the entire departing process. A practical implication of our study is that it offers a unique perspective on departure flow from passengers rather than from operators. Our study further contributes to the suggestion that passengers could use different strategies after security. This would enable airport managers to implement new operational strategies to improve the performance of the airport. Although our analyses show that the statistical properties of passenger activities in airport terminal may constitute a useful starting point for the application of big data science in airport design and management, there are still some limitations. Our focus here is given on domestic departure passengers, it is unknown whether arrival passengers and international passengers have such general patterns. Note that passenger's behavior may be also affected by factors such as airport layout and the main function of the airport (for instance, the transfer hub airport, or the only international airport in the region). Indeed, this requires further work to validate the present study with empirical data collected at different airports. Useful extensions to the present work should be carried out. Another promising research direction would be to explore passenger's temporal-spatial behavior in airport terminal using passenger's mobile phone's location data.

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REFERENCES

[1] *Annual Review 2016*, Int. Air Transp. Assoc., Montreal, QC, Canada, 2016.

[2] R. D. Neufville, A. Odoni, P. Belobaba, and T. Reynolds, *Airport Systems: Planning, Design, and Management*, 2nd ed. New York, NY, USA: McGraw-Hill, 2013.

[3] V. Tošić, ''A review of airport passenger terminal operations analysis and modelling,'' *Transp. Res. A, Policy Pract.*, vol. 26, no. 1, pp. 3–26, Jan. 1992.

[4] W. Ma, T. Kleinschmidt, C. Fookes, and P. K. D. V. Yarlagadda, ''Check-in processing: Simulation of passengers with advanced traits,'' in *Proc. Winter Simul. Conf. (WSC)*, Dec. 2011, pp. 1783–1794.

[5] M. Schultz and H. Fricke, ''Managing passenger handling at airport terminal,'' in *Proc. 9th USA Eur. Air Traffic Manage. Res. Develop. Seminar (ATM)*, 2011, pp. 1–10.

[6] N. Ashford, N. Hawkins, M. O'Leary, D. Bennetts, and P. McGinity, ''Passenger behavior and design of airport terminals,'' *Transp. Res. Rec.*, vol. 588, pp. 18–26, Jan. 1976.

[7] L. S. Yuan and J. L. McCabe, ''Airport facility queuing model validation,'' U.S. Dept. Transp., Washington, DC, USA, Tech. Rep. FAA-AEM-77-4, 1976.

[8] Y. Park and S. B. Ahn, ''Optimal assignment for check-in counters based on passenger arrival behaviour at an airport,'' *Transp. Planning Technol.*, vol. 26, no. 5, pp. 397–416, Oct. 2003.

[9] M. Janic, ''Assessment and management of quality of service at an airport passenger terminal,'' *Transp. Planning Technol.*, vol. 26, no. 3, pp. 239–263, Jun. 2003.

[10] P. P.-Y. Wu, J. Pitchforth, and K. Mengersen, ''A hybrid queue-based Bayesian network framework for passenger facilitation modelling,'' *Transp. Res. C, Emerg. Technol.*, vol. 46, pp. 247–260, Sep. 2014.

[11] R. Stolletz, ''Analysis of passenger queues at airport terminals,'' *Res. Transp. Bus. Manage.*, vol. 1, no. 1, pp. 144–149, Aug. 2011.

[12] C.-I. Hsu, C.-C. Chao, and K.-Y. Shih, ''Dynamic allocation of check-in facilities and dynamic assignment of passengers at air terminals,'' *Comput. Ind. Eng.*, vol. 63, no. 2, pp. 410–417, Sep. 2012.

[13] M. M. Mota, ''Check-in allocation improvements through the use of a simulation–optimization approach,'' *Transp. Res. A, Policy Pract.*, vol. 77, pp. 320–335, Jul. 2015.

[14] D. Wilson, E. Roe, and S. So, ''Security checkpoint optimizer (SCO): An application for simulating the operations of airport security checkpoints,'' in *Proc. Winter Simul. Conf.*, Dec. 2006, pp. 529–535.

[15] D. M. Bullock, R. Haseman, J. S. Wasson, and R. Spitler, ''Automated measurement of wait times at airport security,'' *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2177, no. 1, pp. 60–68, Jan. 2010.

[16] D. L. Wilson, ''Use of modeling and simulation to support airport security,'' *IEEE Aerosp. Electron. Syst. Mag.*, vol. 20, no. 8, pp. 3–6, Aug. 2005.

[17] Y. Li, X. Gao, Z. Xu, and X. Zhou, ''Network-based queuing model for simulating passenger throughput at an airport security checkpoint,'' *J. Air Transp. Manage.*, vol. 66, pp. 13–24, Jan. 2018.

[18] M. Schultz, ''A metric for the real-time evaluation of the aircraft boarding progress,'' *Transp. Res. C, Emerg. Technol.*, vol. 86, pp. 467–487, Jan. 2018.

[19] S. Eilon and S. Mathewson, ''A simulation study for the design of an air terminal building,'' *IEEE Trans. Syst., Man, Cybern.*, vol. SMC-3, no. 4, pp. 308–317, Jul. 1973.

[20] M. R. Gatersleben and S. W. van der Weij, "Analysis and simulation of passenger flows in an airport terminal," in *Proc. 31st Conf. Winter Simulation, Simulation Bridge Future (WSC)*, 1999, pp. 1226–1231.
[21] P. F. I. Casas, J. Casanovas, and X. Ferran, "Passenger flow simulation in a hub airport: An application to the barcelona international airport," *Simul. Model. Pract. Theory*, vol. 44, pp. 78–94, May 2014.
[22] S. Kalakou and F. Moura, "Modelling passengers activity choice in airport terminal before the security checkpoint: The case of Portela airport in Lisbon," *Transp. Res. Procedia*, vol. 10, pp. 881–890, Jan. 2015.
[23] X. Liu, J. M. Usher, and L. Strawderman, "An analysis of activity scheduling behavior of airport travelers," *Comput. Ind. Eng.*, vol. 74, pp. 208–218, Aug. 2014.
[24] K. Artur and K. Tomasz, "A model of check-in system management to reduce the security checkpoint variability," *Simul. Model. Pract. Theory*, vol. 74, pp. 80–98, May 2017.
[25] A.-L. Barabási, "The origin of bursts and heavy tails in human dynamics," *Nature*, vol. 435, no. 7039, pp. 207–211, May 2005.
[26] D. Brockmann, L. Hufnagel, and T. Geisel, "The scaling laws of human travel," *Nature*, vol. 439, no. 7075, pp. 462–465, Jan. 2006.
[27] M. C. González, C. A. Hidalgo, and A.-L. Barabási, "Understanding individual human mobility patterns," *Nature*, vol. 453, no. 7196, pp. 779–782, Jun. 2008.
[28] N. E. Humphries, N. Queiroz, J. R. M. Dyer, N. G. Pade, M. K. Musyl, K. M. Schaefer, D. W. Fuller, J. M. Brunnschweiler, T. K. Doyle, J. D. R. Houghton, G. C. Hays, C. S. Jones, L. R. Noble, V. J. Wearmouth, E. J. Southall, and D. W. Sims, "Environmental context explains Lévy and Brownian movement patterns of marine predators," *Nature*, vol. 465, no. 7301, pp. 1066–1069, 2010.
[29] C. Song, Z. Qu, N. Blumm, and A.-L. Barabási, "Limits of predictability in human mobility," *Science*, vol. 327, no. 5968, pp. 1018–1021, Feb. 2010.
[30] C. Song, T. Koren, P. Wang, and A.-L. Barabási, "Modelling the scaling properties of human mobility," *Nature Phys.*, vol. 6, no. 10, pp. 818–823, Oct. 2010.
[31] X.-P. Han, Q. Hao, B.-H. Wang, and T. Zhou, "Origin of the scaling law in human mobility: Hierarchy of traffic systems," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 83, no. 3, Mar. 2011, Art. no. 036117.
[32] N. Scafetta, "Understanding the complexity of the Lévy-walk nature of human mobility with a multi-scale cost/benefit model," *Chaos, Interdiscipl. J. Nonlinear Sci.*, vol. 21, no. 4, pp. 043106–043110, 2011.
[33] F. Simini, M. C. González, A. Maritan, and A.-L. Barabási, "A universal model for mobility and migration patterns," *Nature*, vol. 484, no. 7392, pp. 96–100, Apr. 2012.
[34] S. Jiang, Y. Yang, S. Gupta, D. Veneziano, S. Athavale, and M. C. González, "The TimeGeo modeling framework for urban mobility without travel surveys," *Proc. Nat. Acad. Sci. USA*, vol. 113, no. 37, pp. E5370–E5378, Sep. 2016.
[35] A. R. Correia, S. C. Wirasinghe, and A. G. de Barros, "Overall level of service measures for airport passenger terminals," *Transp. Res. A, Policy Pract.*, vol. 42, no. 2, pp. 330–346, Feb. 2008.
[36] M. Schultz, "Dynamic change of aircraft seat condition for fast boarding," *Transp. Res. C, Emerg. Technol.*, vol. 85, pp. 131–147, Dec. 2017.
[37] M. H. Rothkopf and P. Rech, "Perspectives on queues: Combining queues is not always beneficial," *Oper. Res.*, vol. 35, no. 6, pp. 906–909, Dec. 1987.
[38] I. J. Myung, "Tutorial on maximum likelihood estimation," *J. Math. Psychol.*, vol. 47, no. 1, pp. 90–100, Feb. 2003.
[39] F. J. Massey, "The Kolmogorov–Smirnov test for goodness of fit," *J. Amer. Stat. Assoc.*, vol. 46, no. 253, pp. 68–78, Mar. 1951.
[40] S.-W. Perng, C.-C. Chow, and W.-C. Liao, "Analysis of shopping preference and satisfaction with airport retailing products," *J. Air Transp. Manage.*, vol. 16, no. 5, pp. 279–283, Sep. 2010.
[41] Y.-H. Lin and C.-F. Chen, "Passengers' shopping motivations and commercial activities at airports—The moderating effects of time pressure and impulse buying tendency," *Tourism Manage.*, vol. 36, pp. 426–434, Jun. 2013.
[42] Y. Zha, T. Zhou, and C. Zhou, "Unfolding large-scale online collaborative human dynamics," *Proc. Nat. Acad. Sci. USA*, vol. 113, no. 51, pp. 14627–14632, Dec. 2016.
[43] T. Grönholm and A. Annila, "Natural distribution," *Math. Biosci.*, vol. 210, no. 2, pp. 659–667, 2007.
[44] E. Limpert, A. W. Stahel, and M. Abbt, "Log-normal distributions across the sciences: Keys and clues," *BioScience*, vol. 51, no. 5, pp. 341–352, 2001.
[45] T. B. Sheridan, "Human response is lognormal; plan on waiting if you want reliability," *Ergonom. Des., Quart. Hum. Factors Appl.*, vol. 21, no. 1, pp. 4–6, Jan. 2013.
[46] W. J. van der Linden, "A lognormal model for response times on test items," *J. Educ. Behav. Statist.*, vol. 31, no. 2, pp. 181–204, Jun. 2006.
[47] R. Ulrich and J. Miller, "Information processing models generating lognormally distributed reaction times," *J. Math. Psychol.*, vol. 37, no. 4, pp. 513–525, Dec. 1993.
[48] R. Ratcliff and B. B. Murdock, "A theory of memory retrieval," *Psychol. Rev.*, vol. 85, pp. 59–108, Mar. 1978.
[49] R. Ratcliff and G. McKoon, "The diffusion decision model: Theory and data for two-choice decision tasks," *Neural Comput.*, vol. 20, no. 4, pp. 873–922, Apr. 2008.
[50] R. Ratcliff and H. P. A. Van Dongen, "Diffusion model for one-choice reaction-time tasks and the cognitive effects of sleep deprivation," *Proc. Nat. Acad. Sci. USA*, vol. 108, no. 27, pp. 11285–11290, Jul. 2011.

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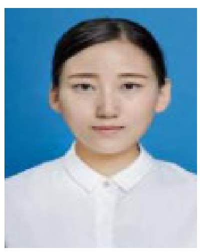

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