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ANALYSIS OF PASSENGER PREFERENCES REGARDING CHECK-IN SERVICES: IMPACT AND POSSIBILITIES FOR THE AIRPORT TERMINAL

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ABSTRACT

With the passengers increase over the last few years, the demands to support and improve the levels of efficiency in airport service have grown significantly. Among the innovations that are necessary in this scenario, the implementation of new technologies to streamline the boarding processes can be highlighted. In this context, this study aims to investigate the attributes of travel and individuals that influence web check-in choice compared to the traditional counter and kiosks. For this analysis, it was used Multinomial Regression Logistic from the data of the three busiest Brazilian airports in the period 2020–2022. Data suggest that female passengers, the passengers who travel more times a year and who that arrived closer to the flight time, are the most likely to use the web check-in tool in relation to the counter or kiosk. Passengers belonging to basic education, accompanied and who travel low frequently are more likely to use the counter. The present results can inform airport decision-making, optimize the existing infrastructure to improve passenger flow, and set up the correct social distancing restrictions when necessary.

Keywords: Airline choice, Check-in services, Airport, Technology

1. INTRODUCTION

According to the International Air Transport Association (IATA, 2020), the airport economy has suffered an expected loss of $84 billion in 2020 due to the COVID-19 pandemic, which led to a travel slump and airlines cutting capacity. This damage was mainly caused by the transmission route of the airport agglomeration and the closed aircraft that circulates the virus (Choi, 2021; IATA, 2020).

However, the airport's environment, operations, and staffing have been impacted by factors other than the COVID-19 pandemic outbreak. Trends such as sustainability, e-commerce, metaverse, and the rise of urban air mobility, among others, have increased the demand for new technologies (De' et al., 2020). Among these technologies that can increase the maturity level of the airport, the following stand out: Automated gates with facial recognition and biometric sensors to increase the number of physically contactless passengers and, as a result, reduce the spread of viruses and bacteria. Smartphone use for check-in and to adopt virtual queuing can eliminate long physical lines and lessen social proximity (Experience, 2022; Lykou et al., 2019; Rajapaksha, 2020). These benefits have resulted in a reduced check-in/check-out times and immigration processing times; automated and virtual environmental monitoring processes to control passenger flux; and the ability to execute e-commerce at several airport markets (Wittmer, 2011).

The check-in process is generally associated with the evaluation of the air ticket and passenger document connected with the issuance of the boarding pass and baggage tag (Kalakou et al., 2015). Throughout the history of the airline industry, this process was generally carried out by airline employees themselves. However, followed by the electronic ticket launched by United Airlines in the 1990s, online check-in has been growing each year, achieving 45% of use in 2022 (Kalakou et al., 2015; SITA, 2022). Among these online used methods, the web page and mobile app phones have a 5% increase in adoption for bag collection, booking, and boarding in 2022 (SITA, 2022). However, this increase was not sufficiently high due to the meeting of health documentation requirements associated with the COVID-19 pandemic which gave passengers less opportunity to become acquainted with new technologies (SITA, 2022).

All those issues brought about by the fast growth of technology have demanded a new concept of airport for the modern aviation industry. Furthermore, the exponentially increasing number of passengers each year necessitates a technological innovation forefront that incorporates industry 4.0 advances to improve the efficacy of airport attendance. Kalakou et al., (2015) identified agents at terminals that encumber the transport processes experienced, such as stress level, consumption time and passenger discomfort. Such factors could be mitigated using smartphones associated with check-in, luggage dispatch, electronic tags, security process, immigration facility, food payment, general information for assistance and agility onboarding (Rajapaksha, 2020).

Several areas for improvement are evident to uphold the airport's high technological standards. This study specifically investigates passengers' preferences and the tools available during the check-in stage, a critical component of air logistics transport. Factors such as age, gender, education level, frequency of travel, presence of travel companions, and flight type were analyzed to understand their influence on check-in method selection. Additionally, the study reviews recent research on passenger preferences in check-in methods and details its methodology, with a focus on data collection and statistical analyses, including regression techniques. Conducted at Brazil's busiest airports from 2020 to 2022, the research aims to uncover the drivers behind passengers' choices between web-based and traditional check-in methods. The findings underscore demographic and behavioral determinants that shape these preferences, offering valuable insights to enhance airport services and meet the evolving needs of passengers.

2. BIBLIOGRAPHIC REVIEW

According to Bezerra and Gomes (2016), the term "check-in" is associated with the general efficiency of the indicators offered in airport terminals, such as passengers' waiting times for passport reviews, ticket validation, baggage check, operational efficiency, and the attitudes of service employees. However, it is necessary to carefully analyze sociodemographic factors to deeply comprehend the term "choice" (Castillo-Manzano and López-Valpuesta, 2013). Age and education of the passengers, reason for making the journey, and airline travel company, among others, are aspects used to understand the flight characteristics that influence the passenger's check-in choice (Castillo-Manzano and López-Valpuesta, 2013).

Lu et al. (2011), using a face-to-face interview and web questionnaire, investigated the check-in service choices of American, Australian, Korean, and Taiwanese passengers. Based on a chi-squared test and 897 responses, it was identified that passenger nationalities are directly related to the passengers' choices of check-in services. In this study, it was demonstrated that Western passengers use self-check-in services more frequently than Eastern passengers do. It was also found that are more willing to use self-check-in services the business travelers, passengers that buy tickets online, groups minor than 4 people, passengers who had traveled more than six times, passengers carrying less baggage (or only have carry-on bags) and younger passengers (between 26 and 45 years).

Airports are increasingly focused on implementing digital technologies (DT) in their key sectors to enhance passenger satisfaction (Al-Sultan, 2017). For instance, Negri et al. (2019) discussed the potential use of biometric technology in check-in procedures. Using a binomial logit tool with data from 760 passengers across three Brazilian airports, they found that 82.94% were inclined to use this technology. Additionally, Baashirah and Elleithy (2019) implemented a smart counter using the IoT (Internet of Things) concept, equipped with RFID (Radio Frequency Identification) tags in luggage to contain all necessary passenger information, thus increasing check-in efficiency and automating self-service check-in counters.

Taufik and Hanafiah (2019) emphasized the importance of management strategies and protective measures in enhancing passenger experience with self-service kiosks. To evaluate the benefits provided by kiosk technologies, statistical methods for passenger profiling have been employed. Chonsalasin et al. (2021) used confirmatory factor analysis to measure airport quality based on the expectations of 1,037 passengers on Thai domestic airlines, reporting that check-in service significantly contributes to airport service quality. They identified key variables such as waiting time in check-in queues and passport inspection, check-in staff efficiency, and staff courtesy and availability. Bruno et al. (2019) proposed a decision support system based on a mathematical model to design optimal check-in policies and incorporate staff scheduling decisions. Their study at Naples International Airport with over 5,000 passengers found trade-off solutions between check-in staff costs and service levels, optimizing the number of operators, shift start times, and shift types (Bruno et al., 2019).

Halpern et al., (2021) realized a survey with 6.082 passengers at airports in Norway. Three distinct segments of passengers were presented based on their preferences for technologies in airport terminals. It was reported those who prefer traditional manual processes, automated technology-based processes and more customized technology-based processes. Al-Sultan (2017) presented a study focused on passenger accommodations during the check-in system at airport terminals. It was presented a model to minimize the operational cost incurred by the airline's service desk personnel which can maximize the level of service to the passenger. The study presents the relationship between the personnel costs and the average passenger waiting time in the queue, considering the number of passengers and the space between them.

Implementing smart airport tools and methods in check-in services offers several advantages. Rajapaksha (2020) highlighted the benefits of check-in through shared kiosks as a solution for terminals with limited space, finding that these tools can reduce costs for individual airlines. This finding is supported by Wittmer (2011), who cited various check-in methods such as online (web), cell phones, and kiosks, which limit human involvement, thereby minimizing errors, reducing costs,

and avoiding physical contact, thus reducing the spread of viruses or diseases. Ku and Chen (2013) demonstrated that self-check-in allows passengers more leisure time, improving the boarding and disembarkation processes and enhancing user satisfaction. These technological advantages are directly linked to customer service satisfaction, as shown by Farooq et al. (2018), who demonstrated that traveler satisfaction is related to airline service quality. Additionally, Malaquias and Júnior (2020) showed that parameters associated with socioeconomic and demographic contexts, as well as a consumer's ethnicity, influence online behavior. Regarding the preference for traditional check-in counters, Lalita and Murthy (2022) researched the problem of allocating check-in counters at airports, improving the passenger flow plan within existing restrictions. Kuo and Jou (2018) investigated the factors influencing passengers' willingness to pay for check-in services at the counter. Tyagi and Lodewijks (2022), in their study at Sydney Airport using t-tests and chi-square tests, revealed that passengers' choices for check-in tools are strongly associated with situational factors such as better signage to locate the service and less crowding or waiting time.

The literature reviewed focuses on sociodemographic factors and flight characteristics influencing passengers' check-in choices, particularly in relation to the adoption of automated self-service counter technology. Many of these studies employ mathematical models to optimize check-in policies concerning queue and service times, as well as passenger preferences for various check-in methods, which directly impact logistical processes. However, this study offers a novel perspective by analyzing the utilization of three check-in mechanisms considering the transformations necessitated by the COVID-19 pandemic, which imposed social distancing measures and spurred the adoption of new airport technologies. Using Multinomial Logistic Regression, this research presents an innovative examination of passenger preferences gleaned from data collected at Brazil's three busiest airports. These insights enable the formulation of safer decision-making strategies for airport management, potentially reducing costs associated with technological upgrades such as replacing kiosks with more efficient tools in the future.

3. METHODOLOGY

The first step after the literature review consisted of identifying the three busiest airports in 2021 year to obtain a representative sample. Data collection from the January 2020 to August 2022 period was obtained by the National Civil Aviation Agency of Brazil (ANAC, 2022). Descriptive statistics were used to obtain an overview of the user profile that deals with check-in tools. To understand the existing relationships between them, each group mentioned above was described in terms of number of travelers in the last year, advance time to arrive at the airport, education, travel companions, age, and type of flight. The last stage consisted of a detailed analysis of parameters effect evaluated on the choice of check-in tool using multinomial logistic regression analysis. Three groups of check-in services were considered in this study: web check-in (which includes checking in via the internet or an app), kiosk check-in (which refers to electronic self-service totems), and traditional counter check-in. The four mentioned steps are illustrated in Figure 1, and each step of the methodology is described in detail in the next sections.

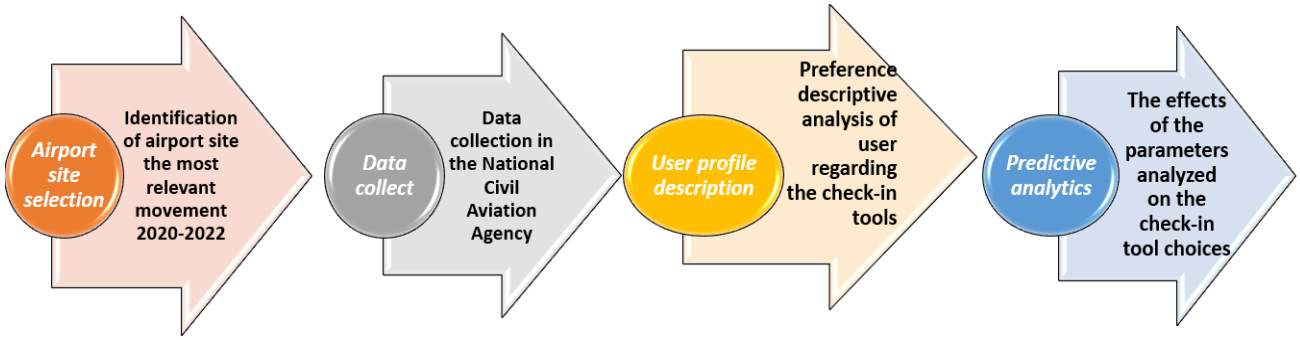


Figure 1: Research development stages. Source: developed by the author

3.1. Airport Selection

The data was collected from three major airports in Brazil based on their passenger movement in 2021: São Paulo/Guarulhos International Airport (SBGR; GRU), São Paulo/Congonhas Airport (SBSP; CGH), and Brasília International Airport (SBBR; BSB). In 2021, SBGR handled approximately 24 million passengers, with 84% on domestic flights and 16% on international flights, a significant decrease from 42 million in 2019 due to COVID-19 restrictions (ANAC, 2022). SBSP operated with around 9 million passengers exclusively on domestic flights, compared to 22 million in 2019 (ANAC, 2022). SBBR handled about 10 million passengers, with 99.1% on domestic flights and 0.9% on international flights, down from 17 million in 2019 (ANAC, 2022). All these airports experienced a substantial reduction in passenger traffic in 2021 compared to 2019 due to pandemic-related restrictions (ANAC, 2022).

3.2. Collected Data

The data set used in this study was provided by the National Civil Aviation Agency of Brazil (ANAC, 2022). Data were collected at the three selected airports, totaling 6,519 passengers interviewed between 2020 and 2022. Attributes associated with the interviewees' profiles included gender, age, formal education, number of travels in the last year, income, travel companions, and type of flight. According to Table 1, the largest share of respondents corresponds to Generation Y (born between 1982 and 1995) with 62.8%, followed by Generation Z (born between 1995 and 2020) with 16.7%, and Generation X (born between 1961 and 1981) with 18.6%. Regarding the number of travels in the last year, 28% of respondents traveled between 2 and 3 times. In terms of income, the predominant salary range was between 4 and 10 Brazilian minimum wages (~$260), totaling 27.1% of respondents. Although most participants are from international flights, the data analysis reveals that the sociodemographic characteristics between domestic and international passengers are quite similar, which mitigates the risk of bias. The average age of passengers is nearly the same between the groups (31.87 years for domestic flights and 32.05 years for international flights), indicating age consistency. Additionally, the gender distribution is balanced, with 52.66% male in domestic flights and 50.28% male in international flights. The education levels also show similarities, with 23.98% of domestic passengers and 26.89% of international passengers having only basic education, while the proportion of passengers with higher education is 47.75% and 50.85%, respectively.

Table 1: Profile of respondents by different arrival time categories at SBGR, SBSP and SBBR

Attributes	Category	Frequency	Percentage (%)
Gender	Male	3412	52.3
	Female	3107	47.7
Age	Generation Z	1086	16.7
	Generation Y	4094	62.8
	Generation X	1214	18.6
	More than 60	125	1.9
Education	Elementary school or High school	1589	24.4
	University education	3140	48.2
	Postgraduate	1790	27.5
Number of travels in the last year	First time	1710	26.2
	2 to 3	1826	28
	4 to 5	1062	16.3
	6 to 10	919	14.1
	More than 11	1002	15.4
Income (in Brazilian minimum wages)	0 to 1	110	1.7
	1 to 4	1316	20.2
	4 to 10	1768	27.1
	10 to 20	1216	18.7
	More than 20	687	10.5
Travel companions	Accompanied	2004	30.7
	Unattended	4515	69.3

Type of flight	International flight	5634	86.4
	Domestic flight	885	13.6

3.3 Data Analysis

According to Hosmer and Lemeshow (2000), Multinomial Logistic Regression (MNL) is interpreted as a similar binary logistic regression model. However, in this case, response variable can assume three or more possible categories based on probabilities and odds ratios. The odds ratio is an extracted value less or more than 0.00 reflecting a negative or positive relationship respectively among the analyzed parameters. To describe such type of dependent variable, the method needs to compare alternatives i., one by one, with the baseline category j.

As shown by Mcfadden (1974) in the case of baseline category logit, the log of ratio of probability is calculated as Eq. (1):

$$\log\left(\frac{P\,(category_i)}{P\,(category_i)}\right) = B_{i0} + B_{i1}x_1 + \ldots + B_{i1}x_1 + B_{ik}x_k \qquad (1)$$

Where Bi_0 is the constant of i alternative, x_k are k explanatory variables, and Bik is the parameter of alternative i related to x_k explanatory variables that can be binary, categorical, ordinal, or continuous (Mcfadden, 1974). These insights are invaluable for decision-making processes in airport management, enabling the development of tailored strategies to optimize operational efficiency and enhance passenger experience. In the context of airport operations, MNL can model the probabilities of passengers selecting different check-in methods based on predictor variables such as travel frequency, airport arrival time, and demographic attributes.

To verify the parameter effects of this study (number of travels in the last year, advance to arrive at the airport, education, travel companions, age, and type of flight) in relation to the check-in tool choice, a MNL regression model was used, having as variables the following outputs: web check-in, kiosk, and counter. The applicable model was conducted using the statistical software platform Statistical Package for the Social Science (SPSS) and the significance level (α) equivalent to 5% was considered.

4. RESULTS

Figure 2 shows the check-in evolution during the period of 2018 – 2022. It was used 6519 respondents from 2020-2022 and 8870 respondents from 2018 to 2019, data was provided by the National Civil Aviation Agency of Brazil. With the pandemic scenario, the aviation industry faced an unprecedented change to adapt to new safety requirements, requiring policies to encourage the use of technological tools. As shown in Figure 2, counter use in 2020 became less frequent (19.61%), while the option for web check-in grew significantly, reaching 67.21% of respondents. However, the data collected in 2022 suggests that the option for web check-in continues to increase while the option for the kiosk service has decreased over the years, reducing from 17.96% in 2018 to 8.02% in 2022.

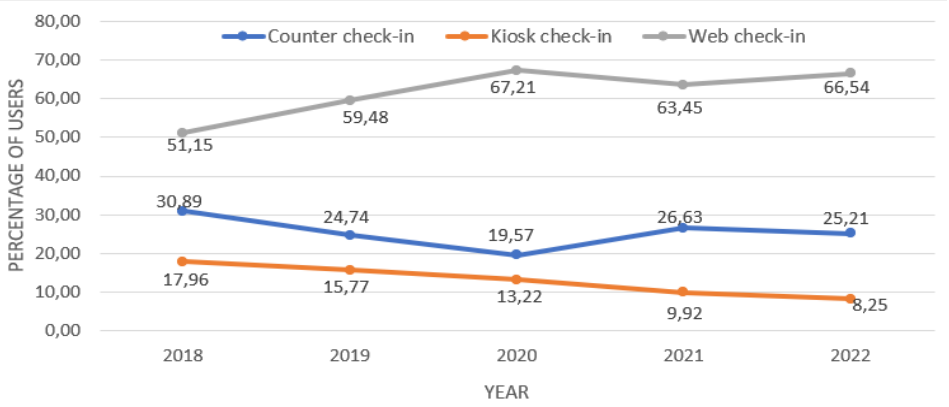


Figure 2: Check-in service choice evolution at SBGR, SBSP and SBBR airports from 2018 to 2022.

4.1 Web Check-in versus counter

Table 2 show the MNL regression results of the considered variables in this study and calculated effects between the counter choices versus the web check-in tool. According to Table 2, the Odds Ratios (OR) in association between web check-in and counter, infer that for each 30 minutes increase in advance to arrive at the airport ($p < 0.001$), the chance of the traveler use the counter increases by 23.2% in relation to the web check-in. Therefore, if the passengers arrive earlier to the airport, the probability to use counter tool is greater than web check-in use.

The highest OR values occurred for elementary or high School ($p < 0.001$) and passengers with over 65 years ($p = 0.002$). When compared to passengers with university education, passengers belonging to elementary school or high school have a 97% chance of choosing the counter in relation to web check-in, as showed by Table 2. When compared to an individual belonging to generation Z, passengers over 65 years have 104.7% more chance to choose the counter in relation to web check-in. Passengers accompanied ($p < 0.001$) have 34.1% more chance to choose the counter when compared with an unaccompanied user.

Table 2: Logistic regression: web check-in versus counter

Characteristic	**OR[1]**	**95% CI[1]**	**p-value**
Counter			
Number of travels in the last year	0.968	0.950 – 0.987	0.001
Advance to arrive at the airport	1.232	1.184 – 1.282	< 0.001
University education	-	-	-
Elementary school or High school	1.975	1.697 – 2.298	< 0.001
Postgraduate	0.936	0.798 – 1.097	0.414
Unattended	-	-	
Accompanied	1.341	1.170 – 1.537	< 0.001
Generation Z	-	-	
Generation Y	1.320	1.103– 1.580	0.002
Generation X	1.279	1.039 – 1,596	0.024
More than 65	2.047	1.333 – 3.234	0.002
International flight	-	-	
Domestic flight	0.336	0.284 – 0,401	< 0.001
Male	-	-	
Female	0.806	0.709 – 0.917	0.001
PseudoR2: 0,151			
Response: check-in services			
Model	Test		
1A Null	1A vs		
1B (Counter + kiosk)	1B	Df LR Stat: 20	Pr(Chi): $p < 0.001$

Domestic flights passengers have 66.4% more chance to choose the web check-in in relation to counter when compared with international flights passengers. It was also possible to observe that the female passengers present a chance reduction of 19.4% to opt the counter in relation to male passengers.

4.2 Web Check-in versus Kiosk

According to Table 3, for every 30 minutes in advance to arrive at the airport ($p < 0.001$), the user's chance to choose the kiosk increases by 33.8% in relation to the web check-in. Therefore, as the counter, with the advance boarding time increase, the more likely the user is to use the kiosk tool in relation to web check-in. The highest OR values occurred for individuals who frequent the elementary school or high school ($p = 0.001$) and passengers of domestic flights ($p < 0.001$). When compared to passengers with university education, passengers belonging to this level of education have 43.1% more chance to choose the kiosk in relation to the web check-in. It can also be concluded that female passengers present a reduction of 37.5% to choose the kiosk in relation male passengers. The age is not a significant parameter for check-in tools choice when

compared with the kiosk use. It is worth noting that passengers of domestic flights are 87.6% more likely to choose the kiosk in relation to web check-in when compared to passengers of international flights. On the other hand, people accompanied are less likely to go to the kiosk than to the web check-in, with a reduction of 34% ($p < 0.001$).

Note that female passengers, who travel more times a year and arrive closer to the flight time, are the most likely to use the web check-in tool in relation to the counter or kiosk. All those analyzed variables showed p- values significance less than 0.05.

The model is predicting more than the null model, since Pr(Chi) < 0.001, being less than 0.05. For the global analysis, the considered parameters prove to be significant predictors, since in all variables presents in the table 3 and table 4 the p-values were equal to or less than 0.015 in the likelihood ratio test. The absence of multicollinearity was assessed by calculating the VIF (variance inflation factor). As all VIF values were less than 5, all independent variables were included.

Table 3: Logistic regression: web check-in versus kiosk

Characteristic	**OR[1]**	**95% CI[1]**	**p-value**
Kiosk			
Number of travels in the last year	0.954	0.929 – 0.981	0.001
Advance to arrive at the airport	1.338	1,264 – 1,416	< 0,001
University education	-	-	-
Elementary school or High school	1.431	1.149 – 1.782	0.001
Postgraduate	0.802	0.783 – 1.075	0.067
Unattended	-	-	
Accompanied	0.660	0.530 – 1.821	< 0,001
Generation Z	-	-	
Generation Y	1.332	0.926 – 1.705	0.146
Generation X	1.288	0.936 – 1.563	0.143
More than 65	2.077	0.680 – 2.824	0.369
International flight	-	-	
Domestic flight	1.876	1.319 – 2.669	< 0,001
Male	-	-	
Female	0,625	0.517 – 0.757	0.000
PseudoR2: 0,151			
Response: check-in servicesModel			
1A Null Test			
1B (Counter + kiosk) 1A vs 1B	Df LR Stat: 20	Pr(Chi): p < 0.001	

The decreasing preference for kiosk services can be attributed to several factors. Notably, the exponential growth in smartphone adoption, as highlighted by Sabatová et al. (2016), has led to a fundamental shift towards mobile-based check-in procedures, reducing the preference for traditional kiosks or counter-based alternatives for airport boarding processes. However, strategic interventions, such as refining kiosk user interfaces and strategically placing kiosks adjacent to baggage carousels, as proposed by Chang and Yang (2008), offer promising ways to mitigate these challenges. These insights underscore the intricate interplay between technology trends, user preferences, and airport infrastructure, shaping the future trajectory of self-service technologies in the aviation landscape.

5. CONCLUSIONS

This study pointed to a significant relationship between check-in services choice and age, gender, education, number of trips in the last year, travel companions and type of flight. Passengers belonging to elementary school or high school have a greater chance to choose the counter in relation to web check-in when compared to passengers with university education. And

passengers over 65 years have a greater chance to opt the counter in relation to web check-in when compared to passengers belonging to generation Z. Passengers accompanied are more likely to choose the counter when compared with an unaccompanied user.

Another relevant topic pointed out in this research were that the female passengers, the passengers who travel more times a year and who arrive closer to the flight time are the most likely to use the web check-in tool in relation to the counter or kiosk. However, passengers belonging to basic education, accompanied and who travel with a low frequency are more likely using the counter. The results can be used for terminal sizing analysis and may contribute to future airport decision-making. This research can also aid airport operators to plan the check-in tools and increase the airport revenue. In addition, it can optimize the use of existing infrastructure about adverse scenarios restrictions.

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