Abstract

Airport terminals are facilities that provide a variety of activities related to both the preparation of the passengers for their air trip (aeronautical) and their free time inside the terminal (non-aeronautical). In the last years, the number of non-aeronautical activities has substantially increased and significantly diversified both before and after the security checkpoint. The established role of non-aeronautical activities forces planners and managers to better understand passenger behavior. The potential of discrete choice models for the exploration of passenger behavior is analyzed in this paper. For the demonstration of the methodology, Lisbon Humberto Delgado International airport is used as a case study. Data is collected through a revealed and stated preference survey inside the terminal at the area before the security checkpoint. Activity-choice models are developed to identify the factors that affect the choices of the passengers over the area where they conduct non-aeronautical activities. Forecasts show that when increasing the percentage of passengers who conduct the check-in online and have planned their activities before arriving at the airport, the passengers´ preferences to conduct non-aeronautical activities only after the security checkpoint increase. This paper shows the contribution of developing discrete choice models in the better comprehension of passenger decisions over the activities they will perform in an airport terminal.

Key words: air passenger behaviour, air passenger activities, non-aeronautical activities, airport management

1. Introduction

As aviation demand and the role of passengers in airports´ operations are constantly changing, pressure is posed on the airports´ side to ensure that their capacity will accommodate efficiently both aircrafts and passengers. Passengers are viewed as direct airport customers attracting the interest of airport managers and moving away from the conservative and outdated view of being only airline customers (Graham, 2013). In addition to the general change in traffic volumes, the need to better understand passenger behavior is arising as the composition and preferences of the passenger population changes. Demand has been increasing but research shows that this is rather attributed to increases in travel frequencies than the actual increase in the number of people traveling (Alegre et al., 2009). This holds especially for business trips (Barros and Machado, 2010; Castillo-Manzano et al., 2011) and for modern tourism which is characterized by short and frequent stays spread throughout the year (Ferrer-Rosell et al., 2014; Salmasi et al., 2012). The effect of ageing population is another concern for the airport´s operations as it is estimated that by 2050, the population aged “60 *years and older will take more than 2 billion international trips, far more than the 593 million they took in 1999”* (Patterson, 2006) creating emerging needs for this passenger category.

In this aviation environment, airports provide a variety of activities related to both the preparation of the passengers for their air trip (aeronautical) and their free time inside the terminal (non-aeronautical). In the last 20 years, the number of non-aeronautical activities has substantially increased and significantly diversified both before and after the security checkpoint. The most common non-aeronautical facilities met at an airport terminal are: (a) Food and Beverage (F&B) and convenience retail (grab-and-go items) that cover passenger needs and (b) Duty Free/News/Gift and Specialty Retail that cover passenger wants. However, more specialized activities might be met at many airports such as casinos, cinemas, golf, spa, wellness centers among others. It is estimated that in 2018, the non-aeronautical revenues of these activities counted for around 40% of total airport revenues internationally (ACI, 2019). The composition of non-aeronautical revenues has been relatively stable during the last years with retail contributing the most (approximately 33%), then car-parking being the second biggest revenue source (approximately 23%) and car rental being third biggest contributor (approximately 8%) (Chen et al., 2020). The airport environment has an impact on these figures as well-designed and aesthetically pleasant environments tend to both improve the passenger experience and enhance airport revenues. An enjoyable passenger experience in the terminal has a positive impact on the shopping behavior of passengers and research has shown that “delighted” passengers spend 45% more than “disappointed” passengers on airport retail purchases ($20,55 versus $14,12) (J.D. Power and Associates Reports, 2010).

Airport passenger perceptions over the airport environment and the involved processes may vary. For example, different passenger tastes on technological innovationσ, at the check-in process for example, implies the provision of different processes for different passenger segments (Halpern et al., 2021). Better understanding of passenger behavior is required in order to improve airport operations and enhance the passenger experience and airport business opportunities. Although airport planning and management are traditionally approached as a top-down process, it is suggested that when it comes to passenger preferences and the space distribution of certain areas of the passenger building a bottom-up approach could be followed to explore passenger preferences to the services that are offered to them. The quantification of the different tastes of people, as a reflection of the human element, can materialize using Discrete Choice Models (DCM) (Ben-Akiva and Lerman, 1985). Discrete choice models can provide insights regarding the factors that form passenger activity choices while in an airport. Both airport planners and managers could better comprehend passenger behavior and make decisions on their processes. Relevant models could shed light on passengers´ activities upon arrival at the airport. In the airport sector there is the general belief that departing passengers underuse the areas before security because of the stress they undergo to fulfill on time all airport processes and avoid possible delays as soon as possible after arriving at the airport. Long distances in airports raise the level of anxiety for travelers, whose objective is to get straight to the departure gate (Crawford and Melewar, 2006). However, apart from some statistical analysis over space utilization (Livingstone, 2014), there is no study that analyzes which type of passengers use the areas before and after the security control. Hence, it could be interesting to analyze the kind of activities the passengers perform before the security checkpoint, the areas in the airport building where the passengers choose to perform non-aeronautical activities (only before the security checkpoint, only after, in both areas or nowhere) and what the passengers do after the security checkpoint and before boarding (this choice might concern either single choices or a set of activities). In this way, airport managers could identify the areas the passengers prefer to use, the kind of activities they choose and extract mobility patterns in airport building (origin-destination sets and route choices).

This paper deals with the issue of air passenger behavior before flight departure and the potential of modeling passenger behavior in the terminal in an attempt to explain and predict the choices of passengers to perform non-aeronautical activities before, after the security checkpoint, in both areas or nowhere. Lisbon airport is used as a case study and relevant data was collected through a survey conducted at the airport terminal. Logit models were estimated to reveal the factors that affect passenger choices and then, were used to forecast changes in passenger choices under different scenarios such as changes in the percentage of passengers who perform the check-in online and preplan the activities before arriving at the airport. The application of the models showed that changes in the check-in mode and the option of passengers to pre-plan their activities before arriving at the airport can affect their activity choices in the airport building. Although one airport was used as case study and the results concern the airport operations, activity offer and passenger behavior before the beginning of the COVID-19 pandemic, the suggested methodology and survey design could be applied to any type of airport. The presented work could contribute to better comprehend passenger activity choices within airport terminals and introduces a new application of discrete choice modeling in airport management so that operators understand passenger preferences over where to perform non-aeronautical activities.

The remainder of the paper is organized as follows: Section 2 present previous research of air passenger behavior and discusses the potential use of passenger behavior models in the airport planning process and operations. Section 3 briefly presents choice theory and the case study application. In Section 4 the models that explain passenger choices are presented. Section 5 discusses the implications derived from the models´ application and explains the contribution of the models in the airport´s planning and operation and finally, Section 6 summarizes the main points of the current work.

2. Previous research on passenger behavior in airport terminals

The air passenger experience comprises of various aeronautical and non-aeronautical activities performed within the airport terminal. Aeronautical activities are defined by the air transport environment and are met in all the kinds of airports. The range of non-aeronautical activities varies across airports and regions and highly depend on the passenger mix and airlines served by each airport. Non-aeronautical activities are crucial elements for airports because they stimulate the hedonic experience and excitement of shoppers or passengers (Ballantine, Jack and Parsons, 2010), especially when airports want to generate a high portion of their revenue from non-aeronautical means (Freathy and O'Connell, 2000; Graham, 2009). Airports have developed many non-aeronautical activities both before and after the security checkpoint where the passengers can spend their time. The typology of non-aeronautical activities depends on the size of the airport, the type of demand it serves and cultural aspects of its geographical location. Popovic et al. (2010) classified airport discretionary activities into those related to optional travel-related activities (such as currency exchange) and those related to non-travel activities (such as shopping) to extracted 4 activity patterns: group, concurrent and individual activities and activities related to the personal belongings of the passengers. Ma and Yarlagadda (2012) categorized non-aeronautical activities into ten groups according to the purpose they served (information service, cash service, major relief, basic relaxation, social connectivity, fast self-service, shops, tax return and religion-related service). At another study, eight activity groups were suggested by Kirk et al. (2012): processing, queuing activity, consumptive, walking, passive, entertainment, social and preparatory activities. In these studies, activity classification focused on clustering the non-aeronautical services.

Up to date, due to the increasing variety of non-aeronautical services and their role to airport revenues, previous studies have focused on the revenues that all these activities generate and a review of these streams is provided in Chen et al. (2020). The contribution of non-aeronautical revenues to the airport recovery from COVID-19 pandemic has also been highlighted by Choi (2021). A series of studies have attempted to analyze the relationship between passenger characteristics and airport revenues focusing on the identification of spending patterns. Graham (2009) claimed that the airport´s size favors non-aeronautical revenues due to the wide variety of the offered activities and the increased percentage of international travelers who have a propensity in spending more. However, Volkova (2009) concluded the opposite effect for international passengers and also found that short-stay parking influences positively airport revenues which increase after security mainly because of the bigger space devoted to retail and that retail revenue per square meter starts to grow after a certain level of retail area is provided. Carrying bags was an influential aspect on passenger purchase activities in the study of Kraal et al. (2009). Business travelers have traditionally been considered as more prone to retail purchases due to their inherent link to higher socioeconomic groups than the average passenger and due to the limited time they are assumed to have at their destination area (Freathy and O'Connell, 2000). Castillo-Manzano (2010) studied passenger shopping behavior in Spanish regional airports and found that the age, the frequency of flying, the trip purpose, the number of children traveling with, the number of people arriving with the passenger at the airport, the group size and being on transfer affected the level of purchases. Contradicting proofs exist regarding the purchasing tendency of passengers using low cost carriers (Castillo-Manzano, 2010; Francis et al., 2003; Gillen and Lall, 2004) and gendered preferences (Castillo-Manzano, 2010; Geuens et al., 2004). These insights on the relationship among passenger characteristics and purchasing behaviour could also provide insights for the exploration of the area in the airport building where these purchases occur.

Psychological factors have also been identified in the retail context to affect passenger behaviour especially in what time availability is concerned. The concept of the "*travel stress curve*" was introduced by Scholvinck (2000) to depict changes in the stress levels during the time prior flight departure. According to this stress curve, the period between "immigration" and "pre-flight security" is the least stressful period and according to passenger responses, it was more likely them to make purchases after passing through security control than before. Retail spending has also been found to be positively related to dwell time availability (Torres et al., 2005; Castillo-Manzano, 2010; Bohl, 2014; Choi, 2021). Torres et al. (2005) concluded that the level of passenger expenditures is proportional to the waiting time inside the airport and that when the time until boarding is more than 45 minutes, business travelers spend less than leisure travelers do. Another study conducted in Taiwan's Taoyuan International Airport (Lin and Chen, 2013) found that passenger shopping motivations had positive impacts on the commercial activities at the airport, and time pressure and impulse buying tendency affected shopping motivations and commercial activities related to luxury and travel products. Differences in activity behavior might be observed depending on whether passengers perform planned or impulsive shopping (Lu, 2014). This conclusion is timing as many airports nowadays provide information on the brands available in their areas and passengers can plan their activities easier than in the past. Finally, loyalty to airport shopping has also been analyzed and highlighted for the insights it can provide to important aspects of airport retail activities (Han et al., 2018). As it is observed apart from passenger characteristics, psychological aspects related to the passenger experience and behavioural aspects related to passengers´ habits and behaviour outside the airport environment may also affect their activity and purchasing choices before flight departure.

Despite the extended analysis on airport revenues, air passenger choice and activity modeling is a less explored field. Air travel choices have been studied by Beck et al. (2018) who analyzed the impact of security and distrust issues on the choice to travel by plane and the associated feeling of safety. After the air travel choice is made and the passenger is in the airport building further decisions are to be made. Hoogendoorn and Bovy (2004) developed an activity-based model, including route choices, in order to model passenger choices in Amsterdam Schiphol airport. Ma and Yarlagadda (2012) introduced in an agent-based model the conditional probabilities of performing each activity using Bayesian networks. Canca et al. (2013) integrated in a discrete-time, macroscopic attraction-based simulation model, the concepts of destination attraction, location and passenger route choices. A first approach to link activities, locations and passenger characteristics is met in the work of Liu et al. (2014) who analyzed passenger activity scheduling and developed a nested model for discretionary passenger activities based on the activity usage frequency and found that passengers´ age, frequency of travel, group size and gender have an influence on their decisions of where and what type of activity to perform. Specifically for the way that passengers manage their time within the airport, Liu et al. (2018) extracted passenger time distributions at the different areas of Chengdu Shuangliu International Airport in China and used them to make forecasts of the terminal space occupation during a day. Finally there are some previous studies that have modelled together the links among passenger characteristics, passenger behaviour, airport design and environment and found that these aspects can affect both the passenger´s intention to purchase (Suzianti and Lasarati, 2017; Han and Hyun, 2018), the type and time spent in an activity (Chung and Lu, 2020) and the choice of the retail area (Kalakou et al., 2015).

Such an integrated approach is also followed in the current work. Although a wide range of activities can be found in many airports, not all the passengers engage in the same type of activities. The use of these areas depends on many factors which have been poorly explored in the literature. Passenger preferences might differ according to passenger characteristics, psychological aspects, tip characteristics and the airport type. Aspects related to passenger characteristics, psychological aspects related to time availability, trip characteristics and terminal-related aspects will be analyzed in mathematical models. For the current study, the approach of Ma and Yarlagadda (2012) will be employed for the identification of non-aeronautical activities in Lisbon airport and the activities of the passengers. Regarding the passenger characteristics that have been found in the literature to affect the level of purchases, the trip purpose (Castillo-Manzano, 2010; Freathy and O'Connell, 2000), the frequency of flying (Castillo-Manzano, 2010), the number of people arriving with the passenger at the airport (Castillo-Manzano, 2010), age and the group size (Castillo-Manzano, 2010) will be assessed for their impact on the location where activities are performed in the terminal. In what concerns psychological aspects, previous knowledge on their impact on activity engagement will be employed (Torres et al., 2005; Castillo-Manzano, 2010; Bohl, 2014, Lu, 2014) for the analysis of the location of these activities in the airport terminal.

3. Methodology and case study

Airport terminals, as all other transport systems, are primarily oriented to serve people´s movements and correspond to the needs, desires and activities of all passenger types. This entails an inherent need for planners and managers to thoroughly understand people´s behavior to the extent that this is possible. Usually, the human aspect is difficult to be captured in the transport planning process, but it significantly affects, and often defines, the performance of any transport environment. To mitigate the impact of the unpredictable nature of passengers in the planning process, mathematical methods can be used to capture aspects of personal mobility choices. For example, quantified results of the different tastes of people, as a reflection of the human element, can be achieved using discrete choice models (Ben-Akiva and Lerman, 1985) which explain the individual preferences of the decision makers over a set of defined choices. In transportation, airport and mode choice have been the most typical choice models. In aviation, discrete choice models have been used to study the choice of the passengers over airports (Loo, 2008; Marcucci and Gatta, 2011; Jung and Yoo, 2016) or airlines (Barrett, 2004; Chen and Chao, 2015). An extensive review of the airport choice models and the influential factors is given in Luca (2012). The mode choice to access the airport is another issue that has been studied using discrete choice-models (Psaraki and Abacoumkin, 2002; Tam et al., 2008, Zaidan and Abudildeh, 2018; Birolini et al., 2019 among others.) Differences in choices have also been addressed for elder air passengers (Chang, 2013) and airport employees (Tsamboulas et al., 2012) while this method has been employed to analyze preferences in airport parking choices (Qin et al., 2017). In this paper, discrete choice modeling theory is employed to analyze passenger behavior in the airport context in order to understand more thoroughly passenger choices in the airport terminal. Airports can then test various scenarios and estimate the effect of the changes in their passenger population depending on their business model.

3.1. Discrete choice modeling

Discrete-choice-models are based on random utility theory and are used to explain a decision maker's choice over a collectively finite and exhaustive set of mutually exclusive alternatives. The concept of utility expresses the benefits that the decision maker gains from the choice of the specific alternative. It is assumed that an individual first collects information (attributes) over each alternative i of a choice set ($C_n = \{1,2,3,\ldots,n;\ n \in N\}$), then the individual assigns a perceived utility value or attractiveness (V_{jn}) to each of them and then makes a rational decision over the alternative that maximizes the utility. The utility of the decision maker, V_{jn}, is formed by the collective impact of the individual´s characteristics, the attributes of the different alternatives and interactions of these factors on the decision maker´s perception. Hence, V_{jn} is the function of a number of explanatory variables that explain the choice of the decision-maker. The attractiveness of each alternative might vary across the individuals or across the alternatives. Although the decision maker is assumed to collect perfect information before making a choice, external observers who study the choices of the decision-makers do not have full knowledge of the aspects that determined the final choice of the decision-maker. Hence, the deterministic utility of an alternative *i* for an individual *n* is expressed as the sum of the deterministic utility and a random component *ε* that captures the errors in the model coming from several possible sources: unobserved alternative attributes, unobserved individual characteristics, measurement errors or proxy variables (Masky, 1977 as cited in Ben-Akiva & Lerman, 1985):

$$U_{in} = V_{in} + \varepsilon_{in}$$

The deterministic term of the function, V_{in} in its simplest form is considered to be linear in its parameters and is given by the product:

$$V_{in} = \sum_{k} \beta_{K*} x_{ink}$$

where x is a vector of the k variables used in the modeling process, be it attributes of the alternatives, characteristics of the decision-maker or interactions of any of these, and β are the parameters which represent the effects (or interaction effects) of the variables to be estimated by the model. The probability (P_{in}) of a decision-maker *n* to choose an alternative *i* over a set of alternatives C_n is given by the formula:

$$P_{i|Cn} = \frac{e^{\mu V_{in}}}{\sum_j^n e^{\mu V_{jn}}} \text{, for all } i \in C_n$$

where μ is a scale parameter (a parameter of the error distribution).

3.2. Case study application

Lisbon Humberto Delgado airport in Portugal is used as a case study. Before the security control area, passengers can visit beverage, retail and a lounge area, or wait at benches located at different parts of the building. A survey was run at the area of the airport and the collected data provided information over five sections related to the passengers´ time management before flying, passengers´ personal information, air trip information, passengers´ activities (both aeronautical and non-aeronautical) and wayfinding aspects of the building (Figure 1). Passengers were asked to reply to the survey questions at random spots at the area before the security control. To capture information on the path followed in the building and the performed activities, the passengers were shown a map of the airport and they indicated the areas they used and the time spent in each of them. In total 429 valid responses were collected concerning trips that used the airport as origin. Some statistics on the sample are presented in Table 1. After the data was processed, the sample´s composition was validated and characterized as representative by the representatives of the same airport. The collected information was employed to develop models that would explain and predict passengers´ preferences to perform non-aeronautical activities either only before the security checkpoint, only after the security checkpoint, in both areas or nowhere. It is intended to understand which the drivers of passengers´ decisions in the airport building are and assess how they will behave when the airport environment, the passenger experience or the passenger composition changes. Biogeme software (Bierlaire, 2003) was employed for the modeling process.

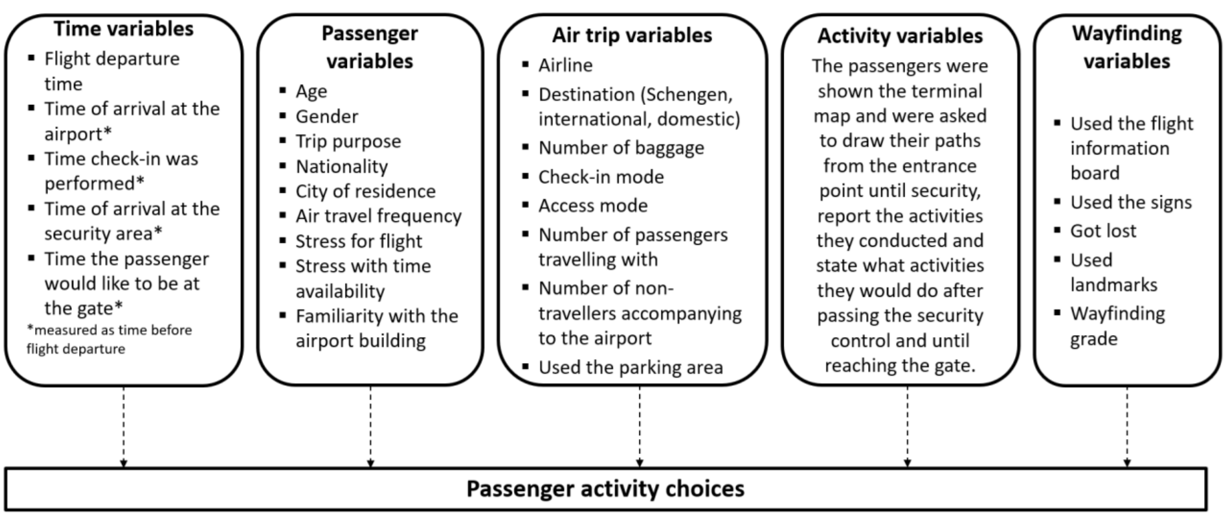

Figure 1. Information collected through a passenger survey at the airport

Figure 2 illustrates the concept behind the suggested modelling approach. Several paths may be followed by passengers within an airport terminal according to the number and type of activities they perform. As an example, it is indicated that in the space between the airport´s entrance and the security control area, passengers may follow different paths according to the activities they will perform. Passengers can either go directly to the security control without doing any other activity related to either aeronautical (eg. check-in) or non-aeronautical (eg. beverage area) tasks (blue path), do a discretionary activity before security such as the use of retail areas (yellow path) or after using the passenger and baggage check-in area and then go to security (orange path), visit a Food & Beverage area before conducting the check-in and then go to security area (pink path), just do the check-in and then go directly to the security zone (brown path) or perform activities both before and after the check-in area before passing the security control (black line). Some indicative spots where the passenger survey took place are also indicated in Figure 2 as “x” points (F&B area, check-in and security waiting lines and random spots).

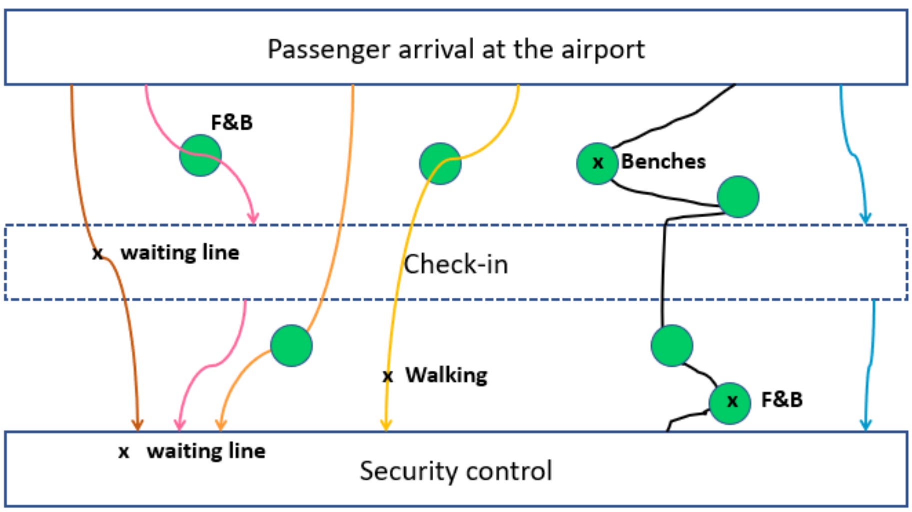

Figure 2. Example of passenger flow types and spots of data collection

Passenger characteristics	
Gender male	65%
Portuguese nationality	43%
Reside in Lisbon area	26%
First time to use this airport	27%
Be familiar with this airport	58%
Feel stress to lose the flight	12%
Feel fear to fly	11%
Air trip-related characteristics	
Personal trip purpose	20%
Business trip purpose	40%
Tourism trip purpose	40%
Travel with baggage	24%
Travel within Schengen area	66%

Travel alone	43%
Arrive alone at the airport	66%
Pre-planned the activities	53%
Check-in online	38%
Check-in at a counter	51%
Check-in at a machine	11%
Travel with baggage to check-in	64%
Morning departure	30%
Time-related aspects	
Check-in 90 minutes before departure	76%
Check-in 60 minutes before departure	15%
Check-in less than 60 minutes before departure	9%
Pass the security control 90 minutes before departure	69%
Pass the security control 60 minutes before departure	22%
Pass the security control less than 60 minutes before departure	9%
Behaviour and activities in the building	
Perform activities only before security control	27%
Perform activities only after security control	28%
Perform activities both before and after security control	33%
Perform no activities in the airport building	12%
Check the gate and go back to retail area	40%
Go directly to board after security	58%
Wayfinding	
Got confused moving in the airport	14%
Got lost in the airport	3%
Used the wayfinding signs	77%
Used spots in space as landmarks to move around	20%

Table 1. Sample statistics

4. Estimation and application of activity location model

For the parameter´s estimation of the model, 10 random samples of the dataset were extracted consisting of 80% of the dataset. The model´s specification was consecutively tested until reaching similar results in the parameters´ significance and a conclusion on the final specification according to the a priori assumptions. The choice set consisted of four alternatives: perform activities only before (“before”), only after (“after”) the security checkpoint, in both areas (“both”) or nowhere (“none”). Alternative structures were first tested considering that the alternatives “before”, “after” and “both” formed different nests. However, as they were not robust and the model was collapsing into a logit model, something that was also verified by the test of the assumption of independence of irrelevant alternatives (Hausman and McFadden, 1984), the four alternatives were studied individually. The alternative of using only the space before security for non-aeronautical activities was used as a reference for the analysis of the characteristics that affect passenger choices and the exploration of heterogeneity of preferences in population, as the variables included in the model do not vary across the alternatives and their impact on choices needs to be assessed comparatively. This alternative was chosen as it is considered that the space before security affects the after-security behaviour of the passengers since they remain in the terminal for a limited time period. The rest of the utilities were formed as follows according to the a priori assumptions on the variables that will affect the utility functions:

$$V_{afterSecurityCheckpoint} = ASC_{after}$$
$$+ \beta_{CI\_arriveAfter} * doCheckIn * arriveBeforeCheckInOpens$$
$$+ \beta_{travel\_Frequency} * travel\_Infrequently$$
$$+ \beta_{personal} * personalTripPurpose$$
$$+ \beta_{CI\_SS} * SelfServiceCheckIn$$
$$+ \beta_{AT\_AfterNone} * \frac{\text{arrival time}}{100}$$
$$+ \beta_{arrive\_Alone} * ArriveAlone$$
$$+ \beta_{planned\_Act} * PlannedActivitiesBefore$$
$$+ \beta_{sec\_30min} * PassSecurityLate$$
$$+ \beta_{sec\_60min} * PassSecurityEarly$$
$$V_{both} = ASC_{both}$$
$$+ \beta_{CI\_tourism} * doCheckIn * tourismPurpose$$
$$+ \beta_{AT\_Both} * \frac{\text{arrival time}}{100}$$
$$+ \beta_{arriveEarly\_AT} * arriveBeforeCheckInOpens * \frac{\text{arrival time}}{100}$$
$$+ \beta_{morning\_group} * morningFlight * paxGroup$$
$$+ \beta_{sec\_30min} * PassSecurityLate$$
$$V_{none} = ASC_{none}$$
$$+ \beta_{CI\_SS} * SelfServiceCheckIn$$
$$+ \beta_{AT\_AfterNone} * \frac{\text{arrival time}}{100}$$
$$+ \beta_{age} * young$$
$$+ \beta_{planned\_Act} * PlannedActivities$$
$$+ \beta_{resid\_metro} * LisbonResident * metro$$
$$+ \beta_{sec\_30min} * PassSecurityLate$$
$$+ \beta_{sec\_60min} * PassSecurityEarly$$

At first a model with only time-related variables was tested. However, the log-likelihood ratio test failed to reject the hypothesis that it was better than a model that includes passenger and trip characteristics and hence, below the final model with all types of variables is presented. The interactions between variables also added value to the model´s ability to explain passenger choices (eg. living in Lisbon and accessing the airport by metro). The results of the estimation are presented in Table 2. The signs of the calibrated parameters coincide with the a priori assumptions and are discussed below:

- ✓ V_{after}: The utility of performing activities only after the security is assumed to be negatively affected by the arrival of the passengers before the opening of the check-in and the use of the check-in at a counter (variable code: “doCheckIn*arriveBeforeCIOpens”) indicating a risk-averse behaviour in what concerns the passenger experience. The utility of performing activities only after security as opposed to only before decreases for passengers who travel less than 4 times per year (variable code: “travel_Infrequently”) revealing a behaviour met mostly in the past, tending to disappear, as passengers become more familiar with air travelling and airport processes. Travelling for personal reasons (variable code: “personal”) decreases this utility revealing a preference for fast and simple process. Also planning to pass through the security control 30 minutes before flight departure (variable code: “PassSecLate”) indicates a preference towards minimization of the time spent at the closed space of the airport before departure; opposed to the after security area, the area before security still allows the passengers to have access to outdoor space. On the contrary, it is assumed that the utility of this alternative increases for passengers who arrive alone (variable code: “ArriveAlone”), have planned their activities before arriving at the airport (variable code: “PlannedAct”) and intend to pass through the security checkpoint 60 minutes before flight departure (variable code: “PassSecEarly”). These variables reveal a more independent and risk-free passenger experience.

- ✓ $\underline{V_{both}}$: It is seen that that the utility of the passengers who spend time in discretionary areas both before and after the security checkpoint increases for the passengers who perform the check-in inside the airport and travel for tourism (variable code: “doCheckIn * tourism”) as in this case passengers demonstrate willingness for a more relaxed experience. The value of this utility also increases for passengers who travel in group and in a flight that departs before 2pm (variable code: “morningFlight * paxGroup”). Passengers tend to arrive earlier at the airport when they have morning flights, probably due to the uncertainty related to traffic conditions or the stress of losing a flight (de Neufville and Odoni, 2004) and this also restricts their options to cover their personal needs increasing the chance of using all the space of the airport to cover them. Finally, the impact of the intention of the passengers to pass through the security checkpoint 30 minutes before flight departure (“PassSecLate”) as expected is negative due to the limited time availability and probably passengers would dedicate time only to aeronautical activities after security.
- ✓ $\underline{V_{none}}$: The utility of the passengers who did not perform any activity was confirmed to be positively affected by the use of Self-Service channels for the check-in (variable code: “SS_CI”), the anticipated planning of the passenger´s activities at the airport (variable code: “PlannedAct”), being young (variable code: “young”), living in the Lisbon area and arriving at the airport by metro (variable code: “residency * metro”), and passing though the security checkpoint 60 minutes before the flight departure (variable code: “PassSecEarly”) indicating a tendency to simplified and stressfree experience. Young passengers are also more likely to do nothing assuming they afford limited budget. Negative effects were found for the time spent inside the airport (variable code: “arrival time”) and the late arrival at the security checkpoint (variable code: “PassSecLate”).

Other specifications were tested but were not statistically significant. Passengers travelling for personal reasons usually arrive at the airport accompanied by non-passengers (relatives or friends) but it was not possible to test the impact of the accompanied passengers on the utilities as an interaction with the trip purpose as there was not enough variability in the data. Non-linear specifications for the continuous variables “travel frequency” and “age”, the time spent at the activities, baggage and trip purpose, travelling alone, travelling directly to the final destination, arrival mode, destination type and being familiar with the airport were also tested but did not contribute to the explanation of choices.

The 10 validation samples consisting of 20% of the dataset were used for the model´s validation. On average 60% of the observations were attributed a choice probability of 50%.

Parameter	Variable description	Parameter	Impact

name		Value	
Alternative "After"			
ASC_after		-0,227	
$\beta_{CI\_arriveAfter}$	1 if the passenger performs the check-in at the airport and arrives after the opening of the check-in	-0,783 *	Negative
$\beta_{travel\_InFrequently}$	1 if the passenger travels less than 4 times per year	-0,672 ***	Negative
$\beta_{personal}$	1 if the passenger travels for personal purposes	-1,89 ***	Negative
$\beta_{AT\_AfterNone}$	the time (min) before departure the passenger arrives at the airport	-0,843 ***	Negative
β_{sec_30min}	1 if the passenger plans to pass through the security checkpoint 30 min before flight departure	-1,08 ***	Negative
$\beta_{CI\_tourism}$	1 if the passenger performs the check-in at the airport and travels for tourism	0,667 ***	Positive
β_{arrive_Alone}	1 if the passenger arrives at the airport alone	1,26 ***	Positive
$\beta_{planned\_Act}$	1 if the passenger has planned the activities before arriving at the airport	0,704 ***	Positive
β_{CI_SS}	1 if the passenger performs the check-in through a self-service option	0,461 **	Positive
β_{sec_60min}	1 if the passenger plans to pass through the security checkpoint 60 min before flight departure	1,21 ***	Positive
Alternative "Both"			
ASC_both		-0,598 **	
$\beta_{arriveEarly\_AT}$	the time (min) available in terminal from the check-in opening to flight departure	-0,381 **	Negative
β_{sec_30min}	1 if the passenger plans to pass through the security checkpoint 30 min before flight departure	-1,08 ***	Negative
β_{AT_Both}	the time (min) before departure the passenger arrives at the airport	0,665 ***	Positive
$\beta_{morning\_group}$	if the passenger travels in the morning, the number of passengers he travels with	0,0671 ***	Positive
Alternative "None"			
ASC_none		-1,07 **	
β_{age}	1 if the passenger is younger than 25	1,57 ***	Positive
$\beta_{planned\_Act}$	1 if the passenger has planned her activities before arriving at the airport	0,704 ***	Positive
β_{resid_metro}	1 if the passenger is a resident of the Lisbon area and arrives at the airport by metro	2,78 ***	Positive
β_{CI_SS}	1 if the passenger performs the check-in through a self-service option	0,461 **	Positive
β_{sec_60min}	1 if the passenger plans to pass through the security checkpoint 60 min before flight departure	1,21 ***	Positive

Number of observations	358
Estimated parameters	18
Null log-likelihood ($\mathcal{L}$ (0))	-496,293

Log Likelihood ($\mathcal{L}$(β´))	-396,407
Likelihood ratio test	199,773
ρ^2	0,201
Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%	

Table 2.Estimation results for the activity-location model

To detect the effect of very early arrivals in the estimation dataset, additional models were estimated excluding passengers who had arrived earlier than 400min (Model 2_400, 3% of calibration dataset), 300min (Model_3_300, 6% of calibration dataset) and 240 min (Model_4_240, 10% of calibration dataset) before flight departure (Table 2). It was observed that the signs and the significance levels of the variables used in the previous model remain the same but slightly change values. After excluding the variables related to the arrival time from the utility “Both” and the “Self-service check-in mode” variable, the results stabilize in models 3 and 4. Only the impact of the arrival time in the utilities of the alternatives “after” and “none” changes by one unit. Changes are also estimated in the values of the alternative specific constants.

Parameter name	Model_1_all	Model_2_400	Model_3_300	Model_4_240
ASC_after	-0,227	0,881	0,780	0,679
ASC_both	-0,598**	0,291	0,137	0,160
ASC_none	-1,07 **	0,048	-0,024	-0,145
$\beta_{CI\_arriveAfter}$	-0,783 *	-1,04 ***	-1,10 ***	-1,10***
$\beta_{CI\_tourism}$	0,667 ***	0,592 **	0,541 **	0,445**
$\beta_{arriveEarly\_AT}$	-0,381	-0,187	---	---
$\beta_{travel\_Frequency}$	-0,672 ***	-0,765 *	-0,732 ***	-0,817***
$\beta_{personal}$	-1,89 ***	-1,88 ***	-1,85 ***	1,85***
β_{CI_SS}	0,461 **	---	---	---
$\beta_{AT\_AfterNone}$	-0,843 ***	-1,65 ***	-1,62 ***	-1,50**
β_{AT_Both}	0,665 ***	---	---	---
β_{age}	1,57 ***	1,46 ***	1,49 ***	1,47***
β_{arrive_Alone}	1,26 ***	1,43 ***	1,47 ***	1,48***
$\beta_{morning\_group}$	0,0671 ***	0,06 ***	0,067 ***	0,069***
$\beta_{planned\_Act}$	0,704 ***	0,816 ***	0,785 ***	0,780***
β_{resid_metro}	2,78 ***	3,05 ***	3,11 ***	3,11***
β_{sec_30min}	-1,08 ***	-1,26 ***	-1,22 ***	-1,18***
β_{sec_60min}	1,21 ***	1,44 ***	1,44 ***	1,41***
Number of observations	358	346	337	321
Estimated parameters	18	16	15	15
Null log-likelihood ($\mathcal{L}$ (0))	-496,293	-479,658	- 467,181	-445,000
Log Likelihood ($\mathcal{L}$(β´))	-396,407	-379,658	-372,777	-359,615
Likelihood ratio test	199,773	199,521	188,808	170,770
ρ^2	0,201	0,208	0,202	0,192
Adjusted ρ^2	0,165	0,175	0,170	0,158
Akaike Information Criterio	828,814	791,316	775,554	749,23
Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%				

Table 3. Estimation results with reduced datasets

Regarding the conditional use of the dataset employed for calibration of the model, it was concluded that no significant changes were observed in the model when excluding some observations of very early arrivals. This result allows us to consider that the allocation of passenger activity choices over terminal space is not sensitive to early arrivals and the observations were kept in the original dataset.

The estimated model (Table 2) was used to forecast changes in the probabilities of the studied alternatives when the characteristics of the passenger population change. First, as airport technologies are changing and passenger engagement may vary (Halpern, 2021), scenarios in which the percentage of passengers performing the check-in online changes is explored because the availability of the channels to conduct the check-in online is constantly rising. Hence, 10 different datasets were created by randomly choosing the passengers who switch from counter check-in to online check-in. The results are depicted in Figure 3. The purpose was to test the effect of an increase in the share of online check-in from 38% ("current") to 70% ("SS_CI_70"), first, and 100% ("SS_CI_100") of the total number of passengers. Originally, the shares of the alternatives "after", "both" and "none" were 28%, 33% and 12%. When the proportion of passengers who perform the check-in online was assumed to be 70% the shares of the alternatives "after", "both" and "none" changed to 31%, 31% and 13%. When all the passengers opted for the online option, the shares of the alternatives "after", "both" and "none" changed to 32%, 30% and 14% respectively indicating that there is a propensity for conducting activities only after the security checkpoint or nowhere when the passenger completes the passenger check-in through an online channel.

Pre-planning activities before arriving at the airport is another concomitant of modern lifestyle stemming from the increasing use of smartphones and smartphone applications and the familiarity of users with online services. Hence, next it was considered that the share of passengers who pre-plan their activities will increase in the future. In this case, considering mutual effects of checking-in online and pre-planning the activities before arriving at the airport for all the passengers, the shares of the alternatives are formed as follows: 36% conduct activities only after security, 21% only before, 27% in both areas and 16% nowhere. The insights of Figure 3 can be exploited from airport managers in order to optimize the use of airport space. In addition, the quantification of the preferences of the passengers to use different areas of the airport terminal can be used for the estimation of the value of each area of the airport terminal which is currently decided based on the percentage of passengers passing through the space (IATA, 2004).

From the planning and operational perspective, the future operations in the terminal if passenger arrival patterns change radically should be explored as well as the behavior of the passengers who arrive very early at the airport. At the next step of this research, more detailed analysis of these activities can give us insights on the relationship between arrival time, number of activities and purchases performed at each area of the airport terminal.

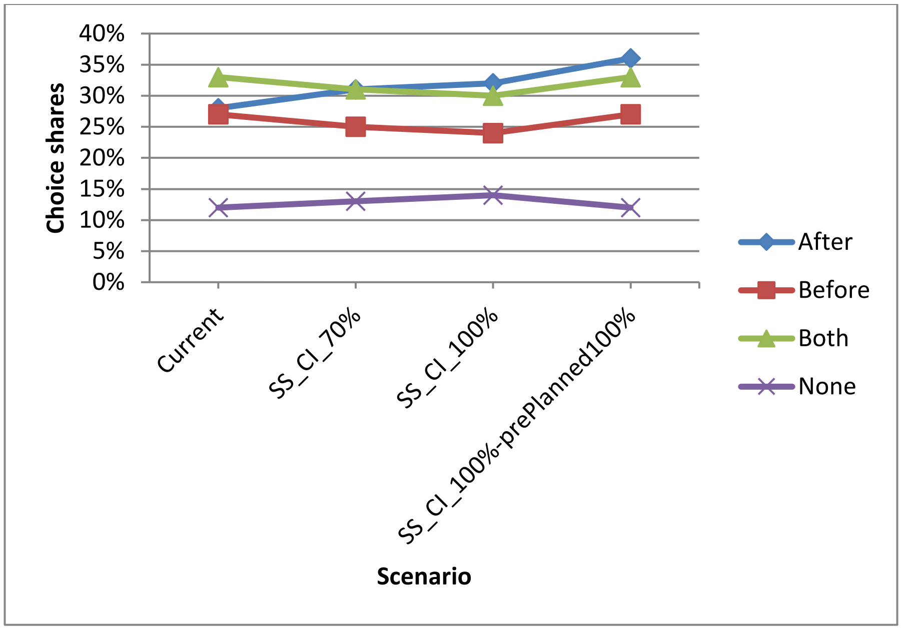

Figure 3. Activity forecasts for model for passenger activity-location choices

5. Conclusion

The service of the airport affects passengers' behavior as in all markets. In this paper, passenger behaviour in Lisbon Humberto Delgado airport was modelled by estimating the probability of a passenger conducting non-aeronautical activities before or after the security checkpoint, in both areas or in none of them. The developed models explore how the Lisbon airport environment affects passengers' choices, and the variables that can explain these choices are identified. It was shown that aspects such as travel frequency, travelling for business, performing the check-in online and having planned the activities before arriving at the airport influence passengers´ choice of performing or not discretionary activities before security. Opting for using a self-service check-in, having pre-planned the activities before arriving at the airport and arriving alone were aspects that favoured the engagement to non-aeronautical activities only after the security checkpoint. Performing the check-in at the airport while travelling for tourism and flying in the morning with other passengers favoured the choice of conducting activities in both areas while passengers who chose to perform no activities used a self-service check-in channel, were young, had pre-planned their activities and were residents who arrived by metro. When increasing the proportion of the passengers who perform the check-in online and pre-plan their activities before arriving at the airport it was found that the share of the passengers performing activities in each area presents slight changes indicating that passenger online options and information availability can have an impact on activity choices.

More in-depth perception and decomposition of passenger choices would introduce new elements in airport planning and enhance airport revenues. The applied methodology represents an initiative to understand behavior. It can be used in airport planning, operations and commercialization strategies. Airport managers could employ such models to better manage passenger flows inside a terminal either at an operational (daily), tactical (seasonally) or strategic (over the years) level. An example of daily use is the consideration of the differences in the number of international and domestic passengers served during a day. Typically, due to the time difference of origins and destinations, international flights depart either early in the morning or late at night. As the consuming behavior of international and domestic passengers differs, the airport managers might want to exploit this chance and flexibly use retail areas with dual offer types that change during the day, eg. differentiate product supply in the morning/night according to the needs of international and domestic passengers respectively. In the same vein, product differentiation may correspond to seasonal needs (winter/summer). As an example of a strategic-level decision, airport managers could decide the relocation of the customs control which separates the flows of international passengers to domestic and Schengen passengers as part of a reconfiguration plan.

Prudent airport planners could benefit from the combination of analytical configuration methods and discrete choice models in conjunction with marketing analysis as well. In terms of planning policy and flexibility, this step adds value to the evaluation process of the usage of the airport areas and allows conclusions on the value of each area, extracted from passenger utilization patterns. Depending on the evolution and the market plans of an airport, an airport could use discrete choice models to prioritize or justify investments in the airport building. In addition, this process can assist forecasting management by invoking small, costless interventions in initial forecasts of the airport system. Strategic decisions foresee the operation of the airport in a long-term; by using these models, soft interventions can be estimated in shorter period until reaching the final forecasted system. At the next step, data that could corroborate the validity of such models is data pertinent to financial factors such as money spent per passenger, rent ranges of the non-aeronautical areas, income of passengers and ticket price among others. This would allow a more complicated but complete and comprehensive planning process.

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