Brochado, A., Veríssimo, J. M. C. & Lupu, C. (2024). Airport experience assessment based on Skytrax online ratings and importance-performance analysis: A segmentation approach. *Journal of Marketing Analytics.* https://doi.org/10.1057/s41270-024-00326-x [classificação - SCOPUS =Q1, JCR=Q12, **ABS=ABS1**]

Importance-performance analysis of online airport ratings: a segmentation approach

Abstract

This study assessed airport service quality by conducting importance-performance analysis (IPA) of user-generated content and examining the usefulness of a priori segmentation in the airport industry. The data were drawn from 35,138 Web reviews of airports worldwide shared online via the Skytrax website. Importance ratings were derived using the indirect method based on an artificial neural network. The results reveal that the most important attributes are staff and queuing time. The findings also include that service quality attributes' importance and priority areas needing improvement vary according to traveler type, airport experience category, and region of origin. This study produced valuable insights into how airports can use IPA to leverage their passengers' online reviews in order to enhance service quality and address customer heterogeneity.

Keywords: service quality, Skytrax, importance-performance analysis (IPA), artificial neural network (ANN), airport, market segmentation

1. Introduction

The airport industry has had to change rapidly in response to travelers' accelerating demands and an increasingly competitive business environment (Hong *et al*., 2020). Airport service quality has been found to be a significant performance indicator for airport operations and management (Yeh and Kuo, 2003; Merkert and Assaf, 2015) in this constantly changing industry. Satisfied passengers contribute to competitive advantages (Fodness and Murray, 2007; Tsai *et al*., 2011), share positive word of mouth, increase intention to reuse airports, boost non-aeronautical revenues, improve airports' reputation, and potentially influence travel plans to related destinations (Bezerra and Gomes, 2020; Barakat *et al*., 2021; Chatterjee *et al*., 2023). Despite the importance of passengers' perceptions of airport service quality, the literature on this topic is still in the early stages of development (Wattanacharoensil *et al*., 2016) compared with airline service quality research (Brochado *et al*., 2019). Various authors have thus called for more studies on passenger-airport interactions (Bezerra and Gomes, 2020).

Similar to service quality research in other industries, past studies have focused on identifying airports' significant service quality attributes or measuring perceived quality from the passengers' perspective mainly. The results have been based on surveys and statistical methods such as regression and structural equation modeling (Fodness and Murray, 2007; Bezerra and Gomes, 2016; Allen *et al*., 2020). While survey data are widely used, they cost more money and time to collect and present various limitations, including lower response rates and respondent fatigue (Robertson *et al*., 2023).

More recently, researchers have made use of the wide availability of user-generated content shared by consumers in social media platforms, thereby generating a new type of dataset for service quality studies (Brochado *et al*., 2019). This alternative approach to gathering passengers' feedback offers multiple advantages over traditional surveys as reviews are spontaneously shared by users, perceived as trustworthy, are publicly available, and minimize cost and time restrictions.

In airport contexts, Martín-Domingo *et al*. (2019) and Barakat *et al*. (2021) used Twitter data, while Gitto and Mancuso (2017), Wattanacharoensil *et al*. (2017), and Arasli *et al*. (2023) collected user-generated content from the Skytrax platform. Previous studies using airport Web-generated contents have been mainly limited to analyzing narratives posted online, namely, unstructured text data. These investigations have been able to identify the main dimensions of service experiences based on consumers' voice, although researchers have been unable to examine the relative importance of these determinants of satisfaction (e.g., Aakash *et al*., 2021).

The new data's potential can be further unlocked by developing innovative data analysis approaches that focus on service quality (Arasli *et al*., 2023). The present study applied an innovative method of assessing airport service quality that used passengers' ratings of both overall service and service attributes shared in the Skytrax platform after their airport experiences. This methodology can be utilized in other sectors in which online ratings are available for these two service-related features.

This research sought to demonstrate that ratings of airport service quality (i.e., overall service and attributes) provide opportunities to evaluate not only passengers' perceptions but also the importance of specific service quality characteristics. The latter was achieved by using an importance-performance analysis (IPA) framework. IPA is a widely used method (Martilla and James, 1977) of assessing service quality in diverse sectors (Mikulić and Prebežac, 2008). However, only a few studies (e.g., Jiang and Zhang, 2016; Tseng, 2020; Allen *et al*., 2021) have prioritized airport service quality attributes using IPA, and all these investigations have relied on survey data. IPA provides guidelines for company resource allocation by comparing the importance and performance of product attributes using four-quadrant maps. These visual representations facilitate the prioritization of features via importance and performance scores based on travelers' voice.

Customer segmentation is a crucial marketing strategy, but the literature shows that few researchers have focused on whether the relationships between service quality attributes and overall quality assessments vary across market segments (Brochado and Rita, 2018; Awad *et al*., 2019). Prior studies have already tested for perceived quality variations that reflect different types of consumers. Research on airport service quality has revealed that variables such as passenger nationality, trip purpose, and earliness of arrival at airports can effectively be used to segment customers and thus allow airports to define a better positioning for each group (Bellizzi *et al*., 2018).

The current investigation addressed these gaps by applying an a priori segmentation approach. In service quality research, each attribute dimension might produce varied outcomes such as overall service quality (Brochado and Rita, 2018).

The study assessed each airport service quality attributes' importance and priority to enable improvements based on IPA (i.e., high importance and perceived low performance) and passenger characteristics voluntarily shared on the Skytrax website.

This research thus evaluated airport service quality worldwide based on ratings travelers have shared online. The first objective was to evaluate service quality in airports around the globe based on an IPA framework and passengers' ratings posted online. The second was to measure and compare IPA maps generated according to the characteristics reviewers freely imparted in the Skytrax platform: traveler type, region of origin, and airport type. To this end, four research questions were addressed:

1. What are the most important airport service quality attributes according to online ratings?
2. Do the most important airport attributes vary according to passengers' profile?
3. Which service quality areas should be given priority based on IPA?
4. Do these high-priority service quality areas vary according to passengers' characteristics?

The remainder of this paper is structured as follows. The next section discusses the existing literature on airport service quality, user-generated contents' use in airport service quality studies, prioritization of service attributes using IPA, and market segmentation in service quality studies. The third section describes the methodology applied to collect and process the data. The fourth section then presents the respondents' perceived service quality and the importance they give to each airport service quality attribute for both the overall sample and each market segment. The paper ends with conclusions comprising the results, theoretical and managerial implications, limitations, and avenues for future research.

2. Literature Review

2.1 Airport Sector Service Quality

Airport services can be divided into two categories—aeronautical and non-aeronautical (Marques and Brochado, 2008)—for which Gitto and Mancuso (2017) developed separate lexicons. Aeronautical services are related to the provision, maintenance, and operation of the infrastructure required for aircraft to take off and land and the provision and maintenance of the equipment and information technologies needed to handle passengers' baggage and check-in process. Non-aeronautical services include car parking, commercial airport activities (e.g., catering and commerce), Wi-Fi services, business lounges, rental units, and advertising (Gitto and Mancuso, 2017).

Airports are transition points that transfer air passengers from ground- to air-based modes of transport and thus are an important component of overall travel experiences (Allen *et al*., 2020). These facilities offer passengers tangible and intangible amenities that define airport servicescapes (Fodness and Murray, 2007). Similar to other service contexts, airports' service quality is necessarily a multidimensional construct (Prentice and Kadan, 2019; Allen *et al*., 2020).

Various studies have focused on identifying important airport service quality dimensions mainly based on survey data and structural equation modeling. However, researchers have not yet reached a consensus on which dimensions and attributes should be included in assessments (Barakat *et al*., 2021).

For example, Fodness and Murray (2007) developed a multidimension model to assess airport service expectations based on a survey of travelers, focusing on function (i.e., effectiveness and efficiency), interaction, and diversion (i.e., productivity, décor, and maintenance). Bezerra and Gomes (2016), in turn, proposed an airport service quality model that included the dimensions of check-in, security, convenience, mobility, ambience, and basic facilities. Awad *et al*. (2019) further developed a scale to measure airport service quality at Dubai International Airport by assessing check-in procedures, the terminal, employees' confidence and empathy, facilities' availability, and overall mobility. Allen *et al*. (2020) additionally confirmed that overall airport service quality in an Italian airport is mainly connected to services' accessibility (i.e., road signposting, flight information, terminal signposting, Infopoints, security staff, and information availability), control operations (i.e., waiting time at check-in, baggage and passenger control, and personal security), and terminal environment (i.e., terminal and toilets' cleanliness and air conditioning).

The airport industry has also developed measures for service quality self-assessment. Among the most prominent tools is Airport Service Quality, which was issued by the Airports Council International to their members, and Skytrax's World Airport Awards and corresponding survey (see www.worldairportawards.com) (Tuchen *et al*., 2020; Barakat *et al*., 2021). Skytrax's airport rankings and awards attract international interest, and airports use their results for promotional purposes (Pérezgonzález and Gilbey, 2011). Notably, these surveys' micro data are still unavailable to the public (Martin-Domingo *et al*., 2019)

2.2 Airport Service Quality Based on Web Reviews

Airport managers currently must measure, analyze, and extract relevant information regarding passengers' perceptions of airport service quality. Recent studies have highlighted the advantages of using user-generated content (Brochado *et al*., 2019) in service quality research, replacing (Wattanacharoensil *et al*., 2017) or complementing (Awad *et al*., 2019) traditional airport survey methods. Researchers have used either text reviews from the Skytrax platform (Merkert and Assaf, 2015; Gitto and Mancuso, 2017; Wattanacharoensil *et al*., 2017; Homaid and Moulitsas, 2022; Arasli *et al*., 2023), Twitter data (Martín-Domingo *et al*., 2019; Barakat *et al*., 2021), or multiple sources, including Skytrax and Tripadvisor (Abouseada *et al*., 2023). The cited studies have extracted the main dimensions embedded in review texts using qualitative, content, and semantic analysis.

Awad *et al*. (2019) gathered data from interviews and Skytrax reviews of Dubai International Airport to develop a survey measuring service quality. The most prominent themes in online reviews are the availability of facilities such as seating, restaurants and bathrooms, as well as walking distance throughout the terminal and staff behavior. In addition, Merkert and Assaf (2015) studied airports' operational and management efficiency using data envelopment analysis. The cited authors concluded that airport service quality data gathered from Skytrax passenger reviews should be considered valuable feedback in conjunction with the volume of passengers and cargo and airport profitability.

Wattanacharoensil *et al*. (2017) analyzed passenger narratives about 15 international airports shared in Skytrax (number = 762). The cited scholars explored passengers' airport experiences in three dimensions—processes (i.e., primary airport activities), phenomena (i.e., aesthetic and hedonic aspects), and outcomes (i.e., cognitive and affective elements)—using content analysis facilitated by NVivo software. Gitto and Mancuso (2017), in turn, analyzed passengers' feedback on five of the largest international European airports posted on the Skytrax platform. The cited researchers' findings include that passengers concentrate on evaluating a small number of services. The most referred to aviation services are check-in, baggage claim and security control procedures, while non-aviation service narratives concentrate on food and beverage and shopping areas (i.e., stores and duty free).

In addition, Barakat *et al*. (2021) used neural network architectures, that is, convolutional and long-short term memory neural networks, to investigate airport service quality. The data were gathered from Twitter texts on London Heathrow and London Gatwick Airports (i.e., English Tweets) and King Khalid and Doha Hamad International Airports (i.e., Arabic Tweets). Barakat *et al*.'s (2021) study isolated 23 airport attributes, which were organized into 7 dimensions: access, check-in and passport, finding the way, facilities, airport arrivals environment, people, and waiting time. The dimensions were also clustered according to their positive, negative, and neutral content (i.e., sentiment analysis).

Martín-Domingo *et al*. (2019) collected Twitter data from London Heathrow Airport's Twitter account and applied sentiment analysis to identify the main airport service quality attributes. The cited research revealed 23 attributes grouped into the following dimensions: access, check-in, passport, wayfinding, facilities, airport environment, arrivals, people, and waiting time. Martín-Domingo *et al*. (2019) report that the two most frequently mentioned attributes are ground transport and waiting time and that the areas needing improvement are waiting time, parking, passport arrival, staff, and passport control. Homaid and Moulitsas (2022) further analyzed air travelers' sentiments using five different algorithms, namely, XGBoost (i.e., most accurate results), a logistic regression algorithm, a support vector machine, random forest, and naïve Bayes.

Arasli *et al*. (2023) additionally analyzed the narratives shared online (number = 704) for the top five largest Scandinavian airports, with the help of Leximancer software, and identified nine themes in the narratives about travelers' experiences. The themes were staff, immigration, gate, shops, terminal, lounge, luggage, screen, and restaurants. Finally, Abouseada *et al*. (2023) conducted content analysis based on text mining procedures of 400 passengers' reviews of Cairo International Airport.

2.3 Prioritizing Airport Service Quality Attributes: IPA

IPA facilitates a clearer understanding of service quality and the formulation of improvement strategies (Martilla and James, 1977). This technique relies on the customer's voice to identify which airport service attributes need to be bettered (Jiang and Zhang, 2016). IPA's prioritization logic involves comparing the performance and importance of each service quality attribute in order to highlight which services most need improvement.

IPA generates basic maps that place attributes' importance along the vertical axis and their performance along the horizontal axis (Tsai *et al*., 2011; Allen *et al*., 2021). Each dimension is divided into two levels—high and low—thereby forming four quadrants (see Figure 1). Quadrant I is labelled "Keep up the good work" because this area contains attributes of high importance with high performance. Quadrant II is given the title "Concentrate here" as it includes extremely important attributes associated with low performance. Quadrant III is termed "Low priority" because its attributes exhibit low performance, but they are of low importance. Quadrant IV is entitled "Possible overkill" since its attributes are associated with high performance but given low importance.

Insert Figure 1 near here

A few previous studies have prioritized airport service quality attributes using an IPA framework. This research has targeted varied regions and applied different methodologies with regard to research contexts, attributes used to create maps, and approaches to defining each attribute's importance. Regarding the airports under analysis, studies have focused on Croatia (Mikulić and Prebežac, 2008), Australia (Jiang and Zhang, 2016), Taiwan (Tsai *et al*., 2011; Tseng, 2020), and Italy (Allen *et al*., 2020; Allen *et al*., 2021).

All the cited researchers gathered data with passenger surveys to create IPA maps. Performance ratings were directly obtained from the survey data. Attributes' importance ratings were derived by applying both a direct approach based on self-reported ratings (e.g., Jiang and Zhang, 2016; Tseng, 2020) and an indirect approach using statistics (Mikulić and Prebežac, 2008), structural equation modeling (Allen *et al*., 2020; Allen *et al*., 2021), and multi-criteria techniques (Tsai *et al*., 2011).

Mikulić and Prebežac (2008) used impact range-performance analysis to derive importance ratings from data on both satisfied (i.e., reward indices) and unsatisfied (i.e., penalty scores) passengers. Tsai *et al*. (2011) further extended traditional IPA by combining the analytical criteria method with an IPA framework. In addition, Tseng (2020) conducted diagnostic analyses of airport service attributes that combined the Kano model of quality service categories with IPA. The priority assigned to attributes with regard to improvement interventions has been quite variable in the above studies (see Table 1).

Insert Table I near here

2.4 Market Segmentation

Market segmentation is an important concept in the travel and tourism literature (Crawford-Welsch, 1990; Marques and Reis, 2015). Brochado and Rita (2018) argue that assuming homogeneity when estimating a holistic model of each service quality dimension's impact on perceived overall service quality can result in misinterpretations of data. The cited authors thus recommend that model parameters be estimated for each market segment.

Passengers' behavior during and after airport experiences can vary according to traveler type, trip purpose, and other context-related aspects (Fodness and Murray, 2007). For instance, Bellizzi *et al*. (2018) confirmed that different attributes' influence on overall airport service quality differs by passenger nationality (i.e., domestic or other), trip purpose (i.e., leisure or other), and earliness of arrival at the airport (i.e., less than 2 hours or more than 2 hours). Jiang and Zhang (2016) concluded that perceptions and expectations of airport service quality are affected by gender, age, and nationality. Punel *et al*.'s (2019) research also verified that service expectations vary according to passengers' region of origin and first or business and economy class tickets. Chatterjee *et al*.'s (2023) study revealed that the relative importance of different airport-lounge services varies according to the passengers' culture.

Investigations focused on airports have, therefore, found that service quality perceptions affect passengers' satisfaction (Mikulić and Prebežac, 2008; Bezerra and Gomes, 2015). As mentioned previously, airport services include multiple dimensions and attributes that have different impacts on travelers' satisfaction (Barakat *et al*., 2021). Awad *et al*. (2019) specifically detected variations in perceived satisfaction according to nationality. Prior studies of airport service quality have used mainly either survey data or unstructured text reviews from social media platforms. The present research, therefore, sought to add to the literature on this topic by conducting an IPA of airports worldwide using data from Web reviews. This study also responded to calls for more market segmentation studies (Awad *et al*., 2019).

3. Methodology

This section describes the methodology applied to create IPA maps and define market segments by traveler type based on passengers' online ratings of airports. The data were collected from the Skytrax website (see https://skytrax.com), which publishes independent reviews of airport experiences written by passengers.

3.1 Data Collection and Sample Profile

The data were drawn from 35,138 Web reviews of 298 airports worldwide shared online by air travelers from 2010 to 2022. The texts were collected directly from the Skytrax website. The sample included all online reviews for airports with at least 20 reviews.

The information gathered included quantitative ratings voluntarily shared online, namely, the passengers' evaluation of overall airport service quality on a 10-point scale and of airport service quality attributes on a 5-point scale. The attributes were queuing time, terminal cleanliness, terminal seating, terminal signs, food and beverages, airport shopping areas, Wi-Fi connectivity, and airport staff. The reviewers shared if they would recommend the relevant airport (i.e., yes or no). Passengers also added their country of origin, traveler type, and airport experience category.

The number of travelers whose reviews included their region of origin comprise 34,269, traveler type 21,906, and airport experience category 21,928. Passengers were from 167 different countries around the world: Europe (55.3%), North America (21.8%), Asia (12.3%), Oceania (8.8%), Africa (1.1%), and South America (0.7%). The 10 most represented countries in the sample (i.e., adding up to 75% of the reviews) are the United Kingdom, the United States, Australia, Canada, Germany, the Netherlands, Ireland, India, France, and Singapore. Around 19.5% of the reviewers were business travelers, while those on leisure trips traveled as a couple (29.8%), solo (29.0%), or with family (21.7%). Airport experience categories (number = 21,928) were both arrival and departure (38.8%), departure only (35.9%), transit (13.0%), and arrival only (12.3%).

3.2 IPA Mapping

The majority of previous research's IPA map dimensions have been based on surveys (e.g., Mohsin *et al*. [2019] for hotels) asking customers to rate each attribute's perceived quality and importance. However, the present study followed Bi *et al*.'s (2019) suggestion that online reviews can be used to identify IPA maps' dimensions. Performance was measured using the ratings passengers gave their overall airport experience. With regard to attributes' rating, the literature provides examples of both the direct approach based on self-reported ratings (e.g., Mohsin *et al*., 2019) and indirect approach using statistical or artificial intelligence-based methods (e.g., Bi *et al*., 2019). Indirect ratings have the advantage of being less influenced by overall performance scores than direct ratings are (Deng *et al*., 2008; Bi *et al*., 2019).

The current research applied an indirect approach based on an artificial neural network (ANN) (Deng *et al*., 2008), which is a subset of machine learning techniques. ANNs can be understood as a simplified model of the human mind. This representation comprises neurons in which the knowledge stored in the weighted links between neurons (i.e., synaptic weights) is obtained via learning processes or neural network training. One of the main ANN outputs is the importance scores of service attributes (Kalinić *et al*., 2021), which can be used to create IPA maps.

More specifically, the ANN approach was selected instead of other statistics-based methods because it can more easily deal with non-normal data, nonlinearity, heteroscedasticity, and missing data. Thus, ANNs can be used to model complex relationships and patterns in data (Mikulić *et al*., 2012; Bi *et al*., 2019). These networks' strength is their ability to offer good results despite the presence of multicollinearity, which frequently appears among service attributes and which can produce misleading interpretations of regression coefficients (Yau and Tang, 2018). Previous studies have further confirmed that ANNs outperform statistical methods and other machine learning approaches in terms of predicting satisfaction levels (Yau and Tang, 2018). Recent research has also highlighted ANNs' ability to rank the degree of influence predictors have on dependent variables (see Kalinić *et al*. [2021] for an overview).

Neural network architecture comprises three hierarchical layers: input, hidden, and output. Each layer encompasses a set of processing neurons interconnected by weighted communication links (i.e., synaptic weights). (Tsaur *et al*., 2002). ANNs are structured as one node in the output layer and/or responses to stimuli (i.e., overall satisfaction ratings) and eight nodes in the input layer and/or stimuli input (i.e., service quality attribute ratings). The present study, more specifically, used a multilayer perceptron, namely, a supervised method with a feedforward architecture (Hecht-

Nielsen, 1990). In the network training process (i.e., knowledge acquisition), synaptic weights are adjusted to minimize estimation error (i.e., the difference between the known and predicted output).

For each ANN, 70% of the sample is used to calibrate the model (i.e., model testing) and 30% to evaluate the calibrated model's validity (i.e., validation). The model's overall performance is assessed using goodness-of-fit indices (i.e., root mean square error) and the coefficient of determination (R^2) (Tsaur *et al*., 2002). The current ANN was constructed by setting the number of hidden layers (1) and hidden neurons (5), as well as the activation functions in the hidden (i.e., hyperbolic tangent) and output layers (i.e., identity). The rule of thumb used to calculate the number of hidden neurons (Kalinić *et al*., 2021) was *cINT* (number of input neurons/2) +1, in which *INT* is the integer-part function. The present study collected a large sample, so online training with a gradient descent algorithm was used (Kalinić *et al*., 2021).

The present ANN was used to calculate the relative and normalized importance of each input. The indirect measures obtained were understood to be determinants as they represent service quality attributes' importance in terms of explaining variations in overall service quality assessments (Mikulić *et al*., 2012). A sensitivity analysis of the importance ratings was also performed using a 10-fold procedure (Kalinić *et al*., 2021).

As mentioned previously, IPA maps are split into four quadrants by crosshairs. Martilla and James (1977, p. 79) note that IPA's value "lies in identifying relative, rather than absolute levels of importance and performance." Thus, the crosshair's placement can be determined by applying either a scale-centered method (i.e., mid-point scale dividing each dimension) or a data-centered method (i.e., mean values of performance and importance dividing the map (Martilla and James, 1977). The current research employed a data-centered approach because it has greater discriminant power when the data are skewed (Jian-Wu *et al*., 2019; Mohsin *et al*., 2019).

4. Results

The current research's IPA maps were based on air travelers' online ratings of different airport attributes. Direct performance ratings (i.e., arithmetic mean) and indirect importance ratings were calculated with the ANN.

4.1 Direct Performance Ratings

4.1.1 Overall Sample

The average overall rating is 3.83 (standard deviation = 2.89). Seventy-four percent of the passengers rated their experience between 1 and 5 and the remaining 26% between 6 and 10. The service quality attribute that received the highest rating was terminal cleanliness (3.13), followed by terminal signs (2.79), airport shopping (2.67), and Wi-Fi connectivity (2.57). The attributes with the lowest ratings are airport staff (2.27), terminal seating (2.44), food and beverages (2.44), and queuing time (2.47). The hypothesis of normality was rejected for all the variables included in the research model. Overall, the airport ratings shared on Skytrax were skewed toward negative responses. This distribution is similar to the data collected by Punel *et al*. (2019) for airlines. Passengers are evidently more likely to share a complaint than to give positive feedback (Punel *et al*., 2019).

4.1.2 Ratings by Passenger Profile

Leisure travelers give higher overall satisfaction ratings to airports than business travelers do (Kruskal-Wallis *H* test [*H*] = 20.90; $p < 0.00$). The same result holds true for all eight service quality attributes. In addition, travelers who post an online review of an airport they have arrived at and departed from report a higher overall satisfaction ($H = 494.86$; $p < 0.00$), as well as being more satisfied with 7 of the 8 attributes. The exception is airport shopping, with which passengers in transit are the most satisfied. Although the latter passengers registered the second highest overall satisfaction, they gave the lowest ratings for terminal signs.

The sample's overall satisfaction rating varies according to passengers' region of origin ($H = 332.26$; $p < 0.00$). Travelers from South America and Asia register the highest overall satisfaction ratings, while those from Asia and North America give the lowest scores (see Table II).

Insert Table II near here

4.2 Importance of Service Quality Attributes Based on ANN

4.2.1 Indirect Importance Based on ANN

The small difference in the R^2 between the training (78%) and testing (76%) samples suggests that the network has internal model validity. The ANN analysis revealed that the most important airport service quality attribute is airport staff (normalized importance = 100%), followed by queuing time (74.0%), terminal signs (62.0%), terminal seating (51.0%), food and beverages (49%), and terminal cleanliness (41.0%). The least important attributes are airport shopping (30.0%) and Wi-Fi connectivity (20.30%). The ANN results validate Hypothesis 1, that is, aviation services (e.g., airport staff, queuing time, terminal seating, and terminal signs) are more important than non-aviation services (e.g., food and beverages, airport shopping, and Wi-Fi connectivity).

4.2.2 Indirect Importance Based on ANN Sensitivity Analysis

The relative influence and importance of each airport service quality attribute was calculated by following a 10-fold cross-validation procedure, with a training dataset representing 90% of the sample and a testing dataset consisting of the remaining 10%. Each of the 10 solutions' average importance was ranked using the solution produced for the sample partition (i.e., 70% and 30% testing samples). To check the results' robustness, a second ANN was run in which recommendations (i.e., yes or no) comprised the output layer. The importance scores revealed no significant change in the outcomes.

Insert Table III near here

4.2.3 Indirect Importance Ratings based on ANN by Traveler Type

The findings show that passengers' perception of the most important attribute varies according to traveler type, namely, airport staff for leisure travelers and queuing time for business travelers (see Table IV). Food and beverage are more important for business travelers than for leisure travelers.

Insert Table IV near here

Regarding specific airport experience categories, airport staff is the most important attribute for the arrival and departure and transit groups, whereas queuing time is the most important for the arrival only and departure only groups. Food and beverages are more important to the departure only group and airport shopping to the transit group than these attributes are to the other airport experience groups.

Concerning region of origin, airport staff is the most important attribute for 5 out of the 6 regions considered. The exception is passengers from Africa, to whom airport cleanliness is the most important attribute according to the ANN importance ratings. The second most important attribute also varies according to the reviewers' region, that is, queuing time for passengers from Europe, Oceania, and South America versus terminal signs for those from Asia and Oceania and food and beverage for reviewers from Africa. The ANN results by traveler type also confirm Hypothesis 1 by verifying that passengers' airport experience category, traveler type, and region of origin are useful market segmentation variables in terms of airport service quality attributes.

4.3 IPA Maps

The IPA results reveal that airports' main strength is terminal signs (see Figure 2). This attribute is located in Quadrant I (i.e., "Keep up the good work"). Quadrant II (i.e., "Concentrate here") indicates which attributes are quite important but are low in performance from the passengers' perspective: airport staff and queuing time. Quadrant III (i.e., "Low priority") includes the attributes that reviewers see as less important than average and lower than average performance areas, which in this case are terminal seating, food and beverages, and Wi-Fi connectivity. Quadrant IV (i.e., "Possible overkill") includes the service quality attributes of terminal cleanliness and airport shopping. Both attributes are associated with higher than average performance and lower than average importance.

Insert Figure 2 near here

Analyses based on traveler type revealed that business travelers are more demanding than leisure passengers are with regard to giving priority to specific areas (see Figure 3). Three items are located in Quadrant II for both leisure and business travelers: airport staff, queuing time, and terminal seating. However, the business group also considers improving food and beverages to be a priority. With regard to airport experience category, all groups agree on which areas should be given priority: airport staff, queuing time, and terminal seating (see Figure 4).

Insert Figure 3 near here

Insert Figure 4 near here

The IPA map by region of origin shows heterogeneous priorities (see Figure 5). Airport staff is located in Quadrant II for passengers for Africa, Europe, North America, and Oceania and in Quadrant I for passengers from Asia and South America. Queuing time is positioned in the first quadrant only by passengers from Europe and North America. Terminal seating is placed in Quadrant II by travelers from Europe and Oceania, but food and beverages is located in Quadrant II by reviewers from Africa. The IPA results by traveler type thus verify Hypothesis 2, that is, the areas given priority in terms of improvement interventions vary according to passengers' airport experience category, traveler type, and region of origin.

Insert Figure 5 near here

5. Conclusions

This study examined airport service quality using IPA based on reviews shared by travelers worldwide in the Skytrax platform.

5.1 Discussion

The ANN results used the online overall rating and ratings by product attributes as input to answer the first research question (i.e., What are the most important airport service quality attributes according to online ratings?). The findings revealed that staff and queuing time are the most significant airport characteristics. Although airports are commonly categorized as retail environments (Lin and Chen, 2013), the results also include that aviation services are more important than non-aviation services to passengers. Wi-Fi connectivity is the least important attribute. These results contrast with Gitto and Mancuso's (2017) study, which found that travelers' narratives about European airports are mainly about food and beverages and airport shopping.

The most important attribute overall is airport staff, who can be a significant part of different interactions during passengers' journey. Staff–traveler interactions are thus of utmost importance to airport experiences (Yakut *et al*., 2015; Prentice and Kadan, 2019). Wattanacharoensil *et al*. (2017) similarly found that passengers' negative airport experiences are primarily due to the limited help given by staff (i.e., airline ground staff, security personal, and immigration officers).

Regarding queuing time, the present findings are in accordance with Song *et al*.'s (2020) conclusions: passengers' satisfaction with an airport drops dramatically after a flight delay and the attention they pay to service aspects increases. Martin-Domingo *et al*. (2019), in turn, assert that waiting is the most important airport attribute based on Twitter data.

The second research question (i.e., Do the most important airport attributes vary according to passengers' profile?) was addressed by constructing an ANN for each market segment variable and category. The hypothesis testing confirmed the existence of differences by traveler type, airport experience category, and region of origin. For example, the most important attribute is airport staff for leisure travelers and queuing time for business travelers, which could be explained by how business passengers value time more than leisure passengers do (Suárez-Alemán and Jimérez, 2016). In addition, non-leisure travelers tend to be more sensitive to services' technical aspects. These findings are in accordance with those reported by Bellizzi *et al*. (2018), who found that service quality dimensions' importance varies according to trip purpose.

With regard to region of origin, the importance rankings show that airport staff is the most significant attribute for passengers from all regions except Africa. Travelers from that continent give airport cleanliness the highest indirect importance, after which comes food and beverages. Overall, African passengers' reviews indicate that the food and beverages offered by airports is the most significant component of their experiences (Punel *et al*., 2019).

The third research question (i.e., Which service quality areas should be given priority based on IPA?) was answered by creating a two-quadrant map of the importance ratings generated via the ANN and the average performance ratings for each attribute shared online. The results indicate that passengers consider staff and queuing time to be extremely important and the average ratings for these two attributes are lower than the overall average. These priority areas differ from previous IPA studies using surveys. For instance, Mikulić and Prebežac's (2008) analysis placed ease of finding the way, check-in procedure, and luggage cart availability in the first quadrant. Tseng (2020) reports that baggage delivery time; lost luggage services; smoking policy and/or lounges; terminal comfort, ambience and design; and immigration queuing time and/or system are the most important attributes. The current results are, in contrast, similar to Jiang and Zhang (2016) and Martin-Domingo *et al*.'s (2019) findings that staff and queuing time are significant variables even though they are associated with low performance.

Finally, the findings addressing the fourth research question (i.e., Do these high-priority service quality areas vary according to passengers' characteristics?) reinforce the importance of using a priori market segmentation, confirming its effectiveness as an approach to assessing priorities in airport service quality. For the global sample, the second quadrant includes the dimensions of queuing time and airport staff. The analysis based on travelers' profile revealed that food and beverages are also important, yet these items are considered a poor performance area by business and African travelers. Terminal seating is specifically a priority area for passengers from Oceania.

5.2 Theoretical Implications

The above findings have significant theoretical connotations. First, this study applied an innovative approach that relied on a frequently used methodological framework—IPA—and new types of data—passengers' ratings posted on the Skytrax website. The proposed method offered insights into how marketing researchers can extract valuable information about airport service quality from freely available user-generated content. That is, scholars can combine consumers' perceived airport service quality based on information shared online with importance ratings obtained indirectly through ANNs.

Previous studies of airport service quality have relied on either surveys (Punel *et al*., 2019) or analyses of unstructured text posted online by passengers (Barakat *et al*., 2021). In addition, researchers who have conducted surveys have usually evaluated service quality for specific facilities, such as Dubai Airport (Awad *et al*., 2020) and Melbourne Airport (Jiamg and Zhang, 2016). The present method of analyzing online ratings facilitated an investigation that targeted airports worldwide.

Second, the results offer new insights regarding market segmentation in service quality studies, which continues to be an under-researched area. This study extends Bellizzi *et al*. (2018) findings by showing that researchers should segment passengers not only into domestic or international travelers but also by the region of origin, as has been done in previous studies of airline transportation (Punel *et al*., 2019). The present study thus adds to the literature on airport service quality (Jiang *et al*., 2016; Awad *et al*., 2020; Barakat *et al*., 2021) by testing for differences in both importance ratings and priority areas to facilitate improvements based on market segmentation variables.

5.3 Managerial Implications

Managers can complement traditional periodic surveys with real-time passenger feedback in order to enhance service quality more effectively. Other implications for airport managers include a confirmation of the advantages of checking Skytrax ratings regularly, as previously pointed out by Gitto and Mancuso (2017). The current results should encourage supervisors to use alternative types of user-generated content (i.e., ratings) as opposed to unstructured text to assess service quality. Web ratings are publicly available, and they can be collected faster at a lower cost. Managers can further use the proposed IPA framework or this study's findings to prepare large-scale surveys to determine, among other things, which areas of service quality should be given priority.

IPA using user-generated contents should only be used to process data from social media platforms that provide both overall ratings and service attributes, such as Skytrax. Thus, social media platforms could generate more useful information by offering consumers opportunities to evaluate service attributes online in the post-purchase phase of their experiences.

The approach tested in this research offers airport managers a tool with which to identify the most important attributes that drive passenger satisfaction and to prioritize attributes based on market segments. The proposed methodology facilitates continuous improvement, better management, and more appropriate resource allocation. Airports could benefit by encouraging their passengers to provide feedback online and analyzing the resulting data using the proposed approach. Regarding areas needing further improvement, managers need to identify those attributes that are directly overseen by airports and those that can only be upgraded through third party contracts.

Overall, the above IPA showed that airport staff's service provision should also be prioritized. Airport managers can strengthen their personnel's performance by refining their recruiting and training practices, offering incentives, and supervising career paths. In addition, airports should develop conflict resolution protocols, add more feedback mechanisms, and identify areas for improvement by using observation methods such as the mystery client.

Queuing time is also classified as a second quadrant factor, so managers must map customers' airport journeys to identify pain points related to queues. These problems could be addressed by introducing queue management systems and continuously collaborating with airlines and security agencies.

The above findings confirm that online reviews can be used to refine market segmentation. The IPA by market segment, in particular, highlighted that airports must avoid treating passengers as a homogeneous group. The most important determinants of airport service quality and the areas that should be given priority vary according to traveler type, airport experience, and region of origin. For example, queuing time is the most significant attribute for business travelers, but food and beverages are more important to African travelers. The IPA of priority areas also revealed that passengers from Oceania value terminal seating the most. Based on the results findings, airport managers can improve the passenger journey by defining tailored strategies for each segment.

5.4 Limitations and Avenues for Future Research

The above contributions are significant, but some limitations should be taken into account during applications. First, despite the larger sample used compared with previous studies, the online ratings were generated by a sample of airline passengers who voluntarily shared their reviews via Skytrax. The ratings are skewed toward negative responses, so these scores may not be representative of all travelers' opinions. Second, the data were aggregated by geographical regions instead of countries due to the lack of sufficient data for each country. Last, overall airport experiences may be unfavorably affected by factors related to airline services, such as flight delays (Song *et al*., 2020), which are negatively correlated with both airline and airport assessments.

The present study used an IPA framework to examine service quality from the passengers' (i.e., airline travelers) perspective since they are the end users of airport facilities and services. Airports provide services to not only travelers but also, more importantly, airlines, so future research could target airports' airline market segment (i.e., business-to-business services). IPA can further be used to study service quality in other sectors covered by Skytrax, such as airlines and airport lounges. Reviews shared in social media platforms can additionally provide both overall rating and assessments of specific service attributes. Passengers' geographical origin was shown to be an important market segmentation variable, suggesting that future studies should target airport service quality at the country level. Finally, this study applied an a priori market segmentation approach, which can be refined by testing for latent segments (i.e., post hoc market segmentation) in future research.

Conflict of interest

On behalf of all the authors, the corresponding author can state that no conflict of interest exists.

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Selected IPA airport studies

Reference	Research context	Research design	Assessment of performance	Assessment of importance
Mikulić and Prebežac (2008)	Major airport, Croatia (n = 1,046)	Survey	Arithmetic means	Regression analysis & penalty.reward contrast analysis
Tsai *et al*. (2011)	Taoyuan International Airport, Taiwan (n = 226)	Survey	Arithmetic means	Multi-criteria model
Jiang and Zhang (2016)	Melbourne Airport, Australia (n = 517)	Survey	Arithmetic means	Arithmetic means
Tseng (2020)	Taoyuan International Airport, Taiwan (n = 856)	Survey	Arithmetic means	Arithmetic means
Allen *et al*. (2020); Allen et al. (2021)	International Airport of Lamezia Terme, Italy (n =1,873)	Survey	Arithmetic means	Structural equation modelling (SEM)

Notes: n = sample size

Table II. Importance ratings' sensitivity analysis

Sample	Queuing time	Terminal cleanliness	Terminal seating	Terminal signs	Food and beverages	Airport shopping	Wi-Fi connectivity	Airport staff
No 1	82.6%	43.0%	43.5%	56.9%	43.0%	29.6%	23.6%	100.0%
No 2	73.5%	41.4%	41.8%	56.0%	41.4%	22.4%	19.6%	100.0%
No 3	70.6%	45.9%	54.4%	55.7%	45.9%	27.9%	21.7%	100.0%
No 4	76.1%	44.9%	51.0%	65.1%	44.9%	25.3%	19.2%	100.0%
No 5	77.1%	48.3%	50.9%	55.7%	48.3%	25.7%	19.8%	100.0%
No 6	69.6%	42.3%	45.4%	59.2%	42.3%	23.8%	14.6%	100.0%
No 7	86.1%	44.3%	50.6%	57.0%	44.3%	24.9%	19.4%	100.0%
No 8	77.4%	55.6%	56.8%	71.0%	55.6%	23.2%	22.3%	100.0%
No 9	93.6%	54.1%	56.4%	65.7%	54.1%	25.8%	21.3%	100.0%
No 10	77.3%	45.9%	46.6%	66.3%	45.9%	22.8%	16.9%	100.0%
Average (10-fold)	78.1%	43.4%	49.5%	60.7%	46.3%	25.1%	19.7%	100.0%
Rank (10-fold)	2	6	4	3	5	7	8	1
Partition 70%/30%*	74%	41%	51%	62.0%	49%	30%	20.30%	100%
Rank (Partition 70%/30%)	2	6	4	3	5	7	8	1

% of correct classifications: 91,1% (training); 91,4% (testing)

Table III. Airport service quality attributes' ratings by passenger profile

		Traveller type			Airport experience					Region of origin						
	Number	Business	Leisure	Kruskal-Wallis *H*	Arrival and departure	Arrival only	Departure only	Transit	Kruskal-Wallis *H*	Africa	Asia	Europe	North America	Oceania	South America	Kruskal-Wallis *H*
Queuing time	33.92	2.13	2.31	44.79***	2.48	1.93	2.19	2.24	365.55***	2.72	2.78	2.38	2.43	2.61	3.05	268.56***
Terminal cleanliness (1–5)	33.88	2.81	2.94	30.45***	3.02	2.87	2.79	2.96	115.91***	3.27	3.38	3.04	3.15	3.27	3.48	318.15***
Terminal seating (1–5)	19.17	2.34	2.46	18.14***	2.59	2.30	2.28	2.48	201.15***	2.60	2.84	2.30	2.48	2.49	2.78	238.65***
Terminal signs (1–5)	21.27	2.73	2.80	7.94***	2.95	2.72	2.68	2.65	177.51***	2.94	3.17	2.73	2.71	2.76	3.08	222.91***
Food and beverages (1–5)	17.35	2.38	2.46	7.69***	2.57	2.44	2.28	2.49	170.32***	2.47	2.77	2.32	2.52	2.44	2.81	155.68***
Airport shopping (1–5)	27.93	2.41	2.50	9.07***	2.60	2.46	2.32	2.61	156.96***	2.78	2.88	2.59	2.74	2.70	2.84	110.65***
Wi-Fi connectivity (1–5)	14.77	2.51	2.59	4.81*	2.70	2.45	2.47	2.58	71.58***	2.73	2.86	2.49	2.55	2.60	2.73	243.22***
Airport staff (1–5)	14.77	2.20	2.29	7.16***	2.52	2.10	2.10	2.16	400.1***	2.36	2.66	2.19	2.21	2.36	2.61	551.48***
Rating (1–10)	35.14	3.30	3.61	20.90***	4.11	3.08	3.14	3.47	494.86***	4.46	4.74	3.70	3.71	4.11	4.77	332.26***

Notes: ***. **. * statistically significant at the 5%. 1% and 0.1% level. respectively.

Table IV. Service quality attributes' importance by traveller type

	Traveller type				*Airport experience*								*Region of origin*											
	Business		Leisure		Arrival and departure		Arrival only		Departure only		Transit		Africa		Asia		Europe		North America		Oceania		South America	
	NI	R	NI	R	NI	R	NI	R	NI	R	NI	R	NI	R	NI	R	NI	R	NI	R	NI	R	NI	R
Queuing time	100.0%	1	79.7%	2	68.9%	2	100.0%	1	100.0%	1	54.6%	2	7.0%	8	88.7%	3	91.5%	2	59.9%	2	74.1%	5	36.5%	2
Terminal cleanliness	49.9%	6	51.4%	5	44.8%	5	32.8%	6	54.7%	4	42.0%	6	100.0%	1	76.4%	4	51.7%	6	36.1%	5	32.3%	7	15.0%	7
Terminal seating	79.1%	3	61.3%	3	60.4%	3	69.0%	3	59.4%	3	54.2%	3	15.4%	6	65.1%	5	57.7%	3	46.4%	3	76.1%	3	25.6%	4
Terminal signs	66.2%	5	56.9%	4	51.2%	4	54.1%	4	42.6%	6	52.0%	4	15.0%	7	90.6%	2	52.4%	5	44.1%	4	82.7%	2	32.8%	3
Food and beverages	66.8%	4	36.8%	6	36.3%	6	22.0%	7	49.2%	5	38.0%	7	71.8%	2	48.1%	6	52.9%	4	34.3%	6	40.0%	6	18.1%	6
Airport shopping	34.1%	7	30.0%	7	27.7%	7	35.1%	5	31.5%	7	48.4%	5	21.9%	4	39.3%	7	31.4%	7	10.5%	8	74.4%	4	19.6%	5
Wi-Fi connectivity	18.8%	8	22.2%	8	23.0%	8	19.1%	8	14.9%	8	17.3%	8	21.9%	5	33.9%	8	18.7%	8	29.8%	7	25.6%	8	14.7%	8
Airport staff	85.3%	2	100.0%	1	100.0%	1	74.8%	2	99.5%	2	100.0%	1	62.1%	3	100.0%	1	100.0%	1	100.0%	1	100.0%	1	100.0%	1
R^2	Training: 82% Testing: 80%		Training: 83% Testing: 81%		Training: 86% Testing: 83%		Training: 79% Testing: 78%		Training: 79% Testing: 77%		Training: 84% Testing: 82%		Training: 88% Testing: 85%		Training: 85% Testing: 83%		Training: 90% Testing: 82%		Training: 78% Testing: 81%		Training: 82% Testing: 80%		Training: 80% Testing: 77%	

Notes: NI = normalized importance;

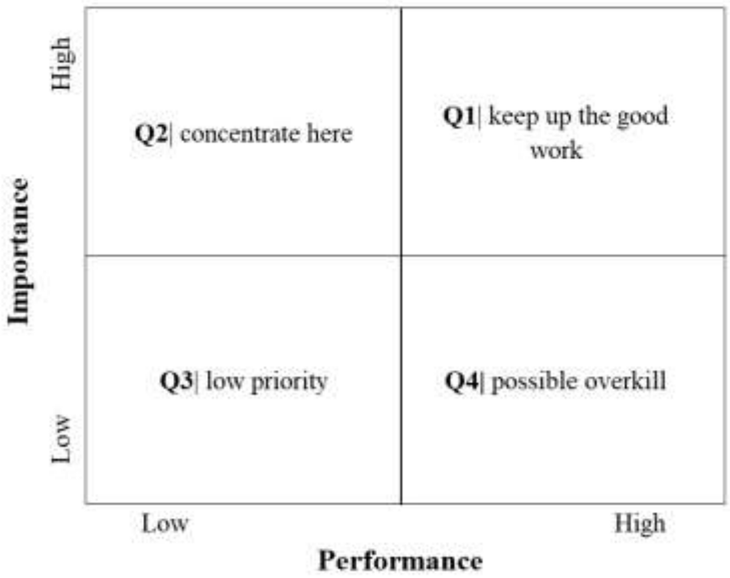

Figure 1. IPA map

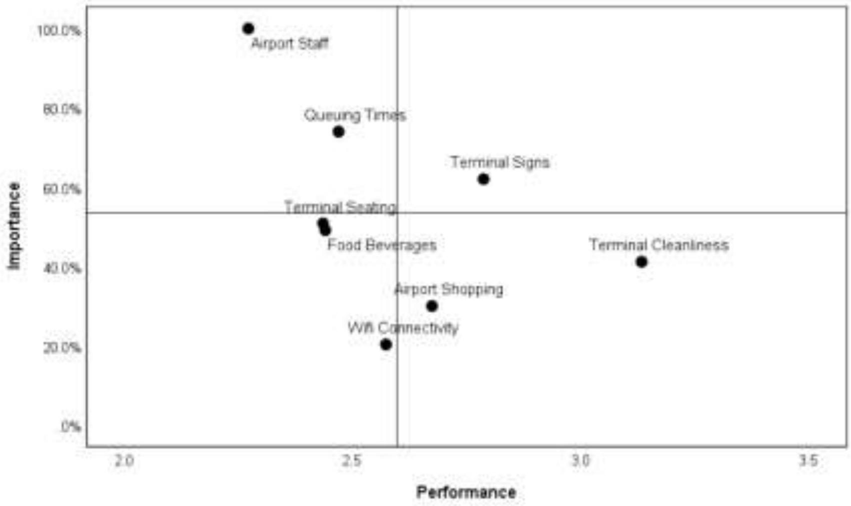

Figure 2. IPA map for the overall sample

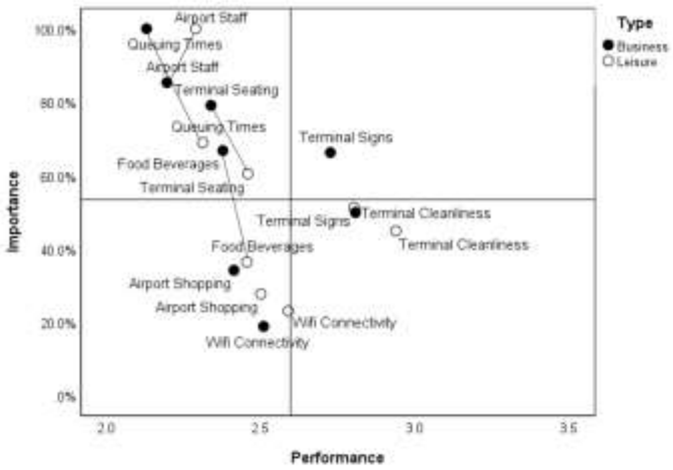

Figure 3. IPA by traveller type

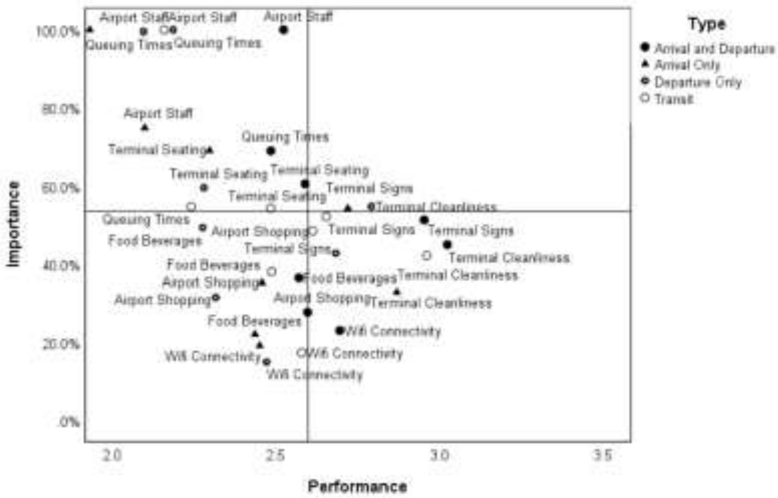

Figure 4. IPA by airport experience

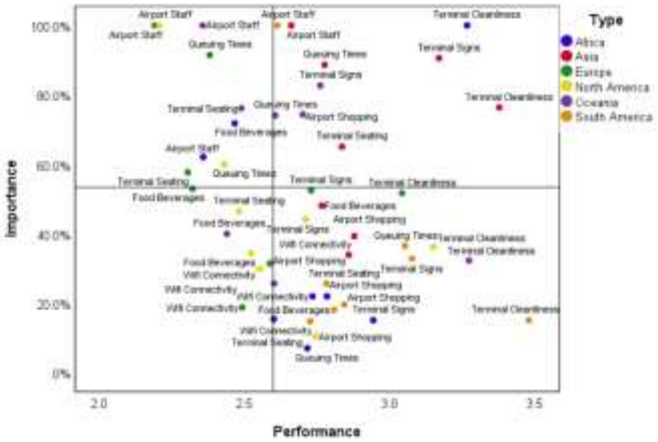

Figure 5. IPA by region of origin