Online review data analytics
to explore factors affecting consumers’
airport recommendations

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Abstract

Purpose – The main objective of this study is to determine the factors that have the greatest impact on travelers’ opinions of airports.

Design/methodology/approach – 11,656 customer reviews for 649 airports around the world were gathered following the COVID-19 outbreak from the website that rates airport quality. The dataset was examined using hierarchical regression, PLS-SEM, and the unsupervised Bayesian algorithm-based PSEM in order to verify the hypothesis.

Findings – The results showed that people’s intentions to recommend airports are significantly influenced by their opinions of how well the servicescape, staff, and services are.

Practical implications – By encouraging air travelers to have positive intentions toward recommending the airports, this research offers airport managers decision-support implications for how to improve airport service quality. This will increase the likelihood of retaining more passengers.

Originality/value – This study also suggests a quick-to-implement visual decision-making mechanism based on PSEM that is simple to understand.

Keywords Airport recommendation, Service quality, Hierarchical regression, PLS-SEM, Bayesian network-based probabilistic structural equation model (PSEM)

Paper type Research paper

1. Introduction

The global air travel infrastructure relies significantly on airports, serving as pivotal hubs for countless travelers. These travelers often engage with and provide feedback on airport services through online forums, leading to the rapid dissemination of user-generated content related to airports. The Airports Council International (ACI) has conducted research indicating that a passenger’s inclination to utilize an airport in the future is substantially influenced by the quality of airport services they have previously encountered (Prentice and Kadan, 2019; ACI, 2016). Airport management companies engage in fierce competition by offering a diverse array of services in their efforts to attract both customers and airlines. Consequently, they regard online reviews as a vital resource for augmenting the quality of their services (Gitto and Mancuso, 2017; Ludwig et al., 2013; Wang and Kim, 2021).

Hence, prior to determining the most effective strategies for meeting these expectations, airport management should acquire a comprehensive understanding of both the services that passengers desire and their distinct attributes (Bezerra and Gomes, 2020; Wattanacharoensil et al., 2017), to ensure that travelers have a positive and satisfactory experience constitutes the primary focal point of business operations at airports (Prentice and Kadan, 2019). Furthermore, perusing reviews can offer valuable insights into the behavior and preferences...
of the target market (Lee et al., 2020; Basili et al., 2017). According to Nghiêm-Phú and Suter (2018), travelers who have a pleasant experience at the airport are more inclined to revisit the facility, while those who have a negative experience are less likely to do so. Moreover, it is noteworthy that readers tend to retain and give more weight to reviews that fail to meet expectations compared to those that surpass them, and negative reviews often leave a more lasting impression and are subject to more in-depth evaluation than positive ones. (Yin et al., 2016; Wang et al., 2017).

Public online reviews posted by customers are a trustworthy indicator of their actual interactions with a company (Zhang et al., 2016; Chen et al., 2022). Reviews of companies and their products can be readily found on various social media platforms, including Twitter and Facebook, as well as dedicated review websites such as Google and TripAdvisor (Barakat et al., 2021). The analysis of online reviews and other forms of user-generated content can offer more profound insights than traditional methods for assessing customer satisfaction and obtaining feedback (Wattanacharoensil et al., 2017; Chen et al., 2022; Baek et al., 2020).

Airports should proactively monitor online reviews to gain a deeper understanding of their customers and to set the benchmark for formulating recommendations. In today’s digital era, electronic word-of-mouth has emerged as the primary means through which modern consumers share their opinions and recommendations with one another. Effectively harnessing the variety of online customer reviews poses a challenge for many businesses (He et al., 2016). Airport managers may often seek assistance in effectively responding to and implementing the suggestions offered by travelers to enhance airport services and operations (Lee and Yu, 2018).

Advancements in data mining and analytics have enabled the examination of extensive datasets, such as those found on review and rating websites (Zhong et al., 2010). Data-driven research is gaining increasing popularity within the travel sector, encompassing areas such as airports, airlines, and hotels (Gitto and Mancuso, 2017; Lee and Yu, 2018; Bunchongchit and Wattanacharoensil, 2021; Siering et al., 2018; Rhee and Yang, 2015). These customer reviews, despite their significant contributions to the airport industry through innovative data analytics methods, do not typically draw from a broader data pool or offer other essential insights (Bunchongchit and Wattanacharoensil, 2021). Instead, field managers often resort to time-consuming and cumbersome ad-hoc survey questionnaires as a means of collecting feedback from travelers (Martin-Domingo et al., 2019).

There exists a significant lack of research in the field of airport management that could provide valuable insights into critical aspects such as customer ratings, review headings, comments, travelers’ experiences during both departure and arrival, visit statistics, traveler demographics, and ratings specific to each service category. Despite airports being early adopters of digital, mobile, and social media platforms to improve service delivery and engage with customers, this trend has endured over time. According to Lee and Yu (2018), Hong and Jun (2006), and Hong et al. (2020), the academic study of the subject of airport service quality is still in its early stages. Hence, this research aims to bridge a critical gap in the existing body of knowledge by scrutinizing the comments and feedback provided by air travelers on review websites.

The primary objective of this study is to ascertain the aspect of airport services that patrons hold in the highest regard. By doing so, this research offers a more profound comprehension of passengers’ recommendations for the overall experience and aids in identifying any misjudgments in the evaluation of individual service components, thereby enhancing decision-making processes, as Bunchongchit and Wattanacharoensil (2021) suggested. This study intends to suggest a more practical and user-friendly application for field practitioners by analyzing the consumer review dataset through three distinct techniques: hierarchical regression, partial least squares structural equation modeling (PLS-SEM), and a Bayesian network-based probabilistic structural equation model (PSEM).
The goal is to provide a solution that is easier to generate, interpret, and implement in real-world settings. We believe that the analysis of online reviews can bolster and complement conventional data analysis methods by incorporating these additional techniques, as former studies tried (Martin-Domingo et al., 2019; Gitto and Mancuso, 2017; Lee and Yu, 2018). Also, to ensure the accuracy of our conclusions, we sought input from professionals in both academia and business. This collaborative approach helped maintain the theoretical and practical relevance of our research. Identifying the factors with the most significant influence on customer satisfaction with airport services, through the utilization of appropriate online reviews and methodologies, could be a valuable resource for aiding airport field managers in their decision-making processes.

The rest of the paper is structured as follows. The next section provides the essential theoretical background and introduces the research hypotheses. Subsequently, three separate studies are presented, each employing distinct statistical techniques: hierarchical regression, PLS-SEM, and Bayesian network-based PSEM (see Figure 1 for the research methodology). Each study includes a relevant research model, findings, and corresponding recommendations. An assessment by subject-matter specialists underscores the significance of the study. Following that, the paper discusses its limitations and offers suggestions for future research endeavors.

2. Theoretical background and hypotheses development
2.1 Practical relevance
Passenger preferences regarding airports hold substantial importance. It is increasingly imperative for business professionals to diagnose airports based on customer insights, as this enables the enhancement of service quality through informed decision-making processes (Fodness and Murray, 2007; Arefieva et al., 2021). Professional reports authored by aviation trade associations play a pivotal role in aiding experts in comprehending the importance of travelers’ assessments regarding the quality of airport services (Fodness and Murray, 2007). Among the reports, the Airport Service Quality (ASQ) program offered by ACI has been widely embraced by both academics and industry professionals as an indispensable decision-support tool for evaluating customer satisfaction with airport services (Tsai et al., 2011; Fodness and Murray, 2007; Pantouvakis and Renzi, 2016; Bezerra and Gomes, 2016). The ASQ program, by collecting data samples directly from passengers at the terminal, possesses a unique advantage in providing an accurate reflection of the airport experience. Utilizing data from the ASQ program, airports can effectively evaluate their own service quality and make meaningful comparisons with other top-performing airports.

![Figure 1. Research process of the study](image-url)
However, in service sectors such as aviation, it is essential to understand the customer’s perspective. The datasets generated by the ASQ program are not directly accessible to actual consumers, making it challenging to analyze data from the customer’s point of view. Due to the sensitive nature of this data, airport operators can typically only obtain regional or national-level data from other airports. Consequently, while the ASQ program serves as a valuable tool for self-diagnosis and high-level benchmarking of airports against one another, relying solely on it may cause airport managers to miss out on insights that could aid in improving service quality through more in-depth analysis. Utilizing alternative solutions such as data analytics, data mining, and machine learning becomes necessary to gain a comprehensive understanding of how customers rate the level of service they receive at an airport.

According to previous studies, customers are increasingly providing more testimonials and reviews (Singh and Winkel, 2012; Chaudhari et al., 2013; Brochado et al., 2019). Online reviews and recommendations that stem from genuine passenger experiences can provide airport management with valuable insights into the quality of their services. Assuming that airports excel in reviewing customer comments and making insightful assessments, they can adapt in response to constructive feedback and proactively implement suggestions. This process of self-evaluation using online reviews has the potential to increase return visits from passengers significantly. Encouraging passengers to return by consistently delivering superior service represents the most effective approach for airports to enhance revenues and elevate overall customer satisfaction levels (Brochado et al., 2019; Prentice and Kadan, 2019).

Indeed, manually reading and analyzing specific customer feedback can be a daunting task for field practitioners, despite its potential usefulness. Moreover, from the perspective of airport managers, relying solely on this manual analysis approach might limit their scope to only the airports they operate or a limited number of airports within their respective countries or regions. Considering that there were over 17,000 airports worldwide as of December 2020, this approach becomes impractical and inefficient. Focusing solely on their own airports could lead managers to overlook significant variations in user reviews for other airports, making it challenging to draw meaningful conclusions. To address these challenges and ensure a more comprehensive understanding of customer feedback, it is crucial to develop decision-making tools for airport administrators that enable them to rapidly and effectively analyze customer reviews. These tools can assist airport managers in identifying key insights, regardless of the vast number of airports globally, and contribute to raising the bar on service quality across the industry.

2.2 Online reviews and recommendations for the airport industry

Reviews penned by genuine customers are increasingly regarded as authoritative and influential by a substantial number of consumers (Salehan and Kim, 2016). The advantages and opportunities of analyzing online reviews could be substantial for consumers, businesses, and researchers, especially during the COVID-19 pandemic when online channels saw increased usage. Airport field managers stand to gain significant insights from relevant online reviews and effective methodologies, particularly if they can pinpoint the key factors that have the most impact on passengers’ recommendations of airport services. This information could prove invaluable in enhancing service quality and decision-making within the airport industry.

Before the Internet’s widespread popularity, only professionals were typically authorized to write reviews for products like high-end electronics and other items that demanded specialized knowledge. In today’s digital age, the quality of a product is often assessed by consumers themselves, who evaluate its features and value based on their own experiences and perspectives (De Chernatony and Riley, 1999). Word-of-mouth (WOM) based on the
experiences of other consumers was also extensively circulated for other regularly purchased products or services, including travel, banking, automobiles, and clothing (Qu and Chau, 2023; Anderson, 1998; Hallencreutz and Parmler, 2021). Furthermore, online reviews from other customers are gaining higher levels of trust among buyers (Salehan and Kim, 2016).

2.3 Data analytics on airport service quality
Online reviews have been used as a secondary data source in a variety of marketing functions, most notably in brand management and price setting (Wang and Kim, 2021). In the aviation sector, online customer reviews have emerged as an alternative evaluation method in recent years, serving as a means to enhance the monitoring of airport service quality (Bunchongchit and Wattanacharoensil, 2021; Sezgen et al., 2019). Researchers have endeavored to utilize online reviews as a data source for evaluating service quality through the application of data analytics, data mining techniques, and machine learning (Lee and Yu, 2018; Filieri and McLeay, 2014). Bunchongchit and Wattanacharoensil (2021) conducted an analysis of data obtained from the Skytrax Airport Review websites to investigate how passengers rated various aspects of airport service. Martin-Domingo et al. (2019) employed sentiment analysis to identify features in tweets related to London Heathrow Airport. Gitto and Mancuso (2017) also used sentiment analysis to analyze customer satisfaction with airport services at Europe’s busiest airports. Likewise, Lee and Yu (2018) mined Google Maps reviews, utilizing sentiment analysis and topic modeling to reveal passengers’ perceptions of airport service quality. Bogicevic et al. (2013) employed a web crawling technique to locate review content from airport websites for the analysis of passenger satisfaction and complaints. The summarized past research on airport ratings is provided in Table 1. According to Lee and Yu (2018), these analyses can help researchers and airport managers find “complementary indicators to cross-validate the ASQ’s survey results, to extract the key attributes of service quality perceived by passengers that can be compared to those from ASQ surveys, and to expand the coverage of analysis beyond the 320 participating airports in the ASQ program.”

2.4 Dependent variable
Customer input is crucial to a company’s success in many ways, including product development and expansion (Siering et al., 2018). Comprehending the thought processes and motivations of passengers, especially concerning their behaviors when making recommendations, is fundamental to the effective operation of a successful airport business. This insight is crucial for tailoring services and making informed decisions that enhance overall customer satisfaction and drive business growth (Albayrak et al., 2016; Han et al., 2018). Although research investigating the influence of airport attributes on passengers’ likelihood to recommend the airport to others is unquestionably essential, it is somewhat surprisingly scarce or limited (Han et al., 2018).

It is widely accepted that word-of-mouth (WOM) marketing, in the form of recommendations, plays a significant role in bolstering a company’s brand and driving revenue growth (Philp and Ashworth, 2020; Ladhari et al., 2011; Akbari et al., 2022; Chen et al., 2022). In other words, word-of-mouth (WOM) can be a powerful avenue for businesses to connect with potential customers and impress them with the excellent quality of their products and services. Especially in the context of services, word-of-mouth recommendations from existing customers encompass positive aspects, experiences, and interactions that customers encounter both before and after making a purchase (Ladhari et al., 2011).

Due to the overwhelming influence of online channels, e-WOM or online word-of-mouth has become increasingly potent and persuasive in the service market setting, including the hospitality, transportation, and tourism industries (Akbari et al., 2022; Yang, 2022; Ahmad et al., 2020).
According to research by Ahmad et al. (2020), there is a noteworthy correlation between the likelihood of a customer making a purchase and the quantity of electronic word-of-mouth (e-WOM) recommendations they receive for airline tickets, particularly those based on the reviewers’ personal experiences. Positive consumer experiences on a cruise, according to Castillo-Manzano et al. (2021), were critical in establishing brand loyalty via e-WOM. Our prediction is that the satisfaction level of passengers with the services they receive at airports will directly influence their likelihood of recommending those airports to others. Consequently, this research considers recommendations as a dependent variable that can be influenced by various aspects of the service provided.
2.5 Explanatory variables

2.5.1 Servicescape. Various aspects of an airport terminal, such as its accessibility by foot, the quality of visual information provided, and the available space, which could play a pivotal role in shaping the overall passenger experience at the airport, have the potential to impact passengers’ satisfaction with the terminal and their inclination to recommend it to others (Bezerra and Gomes, 2016; Lemer, 1992; Tsai et al., 2011; Hong et al., 2020; Chonsalasin et al., 2021; Bakır et al., 2022; Batouei et al., 2020). Bitner (1992) developed the servicescape model to emphasize the significance of the physical setting in which a service process occurs. The servicescape model was created to provide an explanation for customer behavior and make recommendations for improving the service by altering the physical space in which it is delivered. Nonetheless, there remains a shortage of studies that have specifically identified the elements within the servicescape that have been conclusively shown to enhance recommendations for airport passenger terminal services (Park et al., 2020; Hong et al., 2020). Airport operators take care of a variety of physical and environmental factors regarding servicescapes such as check-in and security areas, terminal signs, terminal cleanliness, and sitting options, to ensure passengers have a positive experience (Bitner, 1992). Physical and environmental factors have been identified as having a substantial impact on customers’ assessments of service quality, and these aspects play a crucial role in shaping customers’ perceptions of the services they receive (Rys et al., 1987; Dabholkar et al., 1996; Brady and Cronin Jr, 2001; Chonsalasin et al., 2021; Bakır et al., 2022; Batouei et al., 2020). Before arriving at airports and throughout their journey until departure after boarding the aircraft, passengers engage with the servicescape, which encompasses terminal facilities, to assess the overall service experience, and the servicescape significantly contributes to shaping passengers’ impressions of the airport and the services it provides (Farooq et al., 2018; Zeithaml et al., 2018; Bakır et al., 2022).

Studies in the past (Hong et al., 2020; Fodness and Murray, 2007) have established the basic servicescape construct as consisting of terminal signs, terminal cleanliness, and terminal seating, with a rating scale from one to five stars from airport users. Terminal signs guide travelers through the various steps required for check-in and boarding, ensuring that they can navigate the airport efficiently and catch their flights on time (Hong et al., 2020; Fodness and Murray, 2007). In addition to signs, airline executives consider and respond to passengers’ initial impressions of the terminal’s cleanliness and the available seating options (Hong et al., 2020; Fodness and Murray, 2007). We have also included queuing time at each stage of the airport boarding process (check-in, security checkpoint, boarding gate, and baggage claim) in addition to the other factors, as recommended by the former research (Wu and Mengersen, 2013; Yeh and Kuo, 2003). All these aspects are closely interconnected with the infrastructure and service delivery environments within airports, such as terminal signs and seating arrangements. For example, terminal cleanliness and queuing time are influenced by these physical and environmental amenities. In essence, the servicescape components provided by airport facilities play a substantial role in shaping passengers’ perceptions of the overall quality of airport services.

It is worth noting that the quality of the physical environment within airport terminals may sometimes have a negative impact on the services provided by human agents (Park and Park, 2018; Prentice and Kadan, 2019; Fodness and Murray, 2007). Passengers’ first and last impressions of an airport are shaped by its servicescape because that’s where they interact with airport staff upon arrival and departure. The importance of servicescape, particularly in relation to passengers’ intentions to recommend airports and their overall perceptions of service quality, cannot be overstated. Therefore, servicescape should seriously be considered in airport management decisions. Considering these theoretical contexts, we postulate the following:

H1. Servicescape will positively influence airport recommendations of users in online reviews.
2.5.2 Service. Airport service quality should be defined and measured by passengers rather than by other stakeholders to attain the desired outcomes, as service quality stands as a crucial determinant for operational and managerial success (Yeh and Kuo, 2003; Fodness and Murray, 2007; Hong et al., 2020; Bakır et al., 2022). “Airport service excellence” is an expansive concept that includes every touchpoint between an airport and its passengers (Lee and Yu, 2018; Chonsalasin et al., 2021). Rhoades et al. (2000) employed factor analysis to discern four distinct dimensions comprising a total of twelve characteristics. These factors encompass airport accessibility, encompassing aspects such as parking, rental cars, and ground transportation; the airline-airport interface, which encompasses gate boarding areas, baggage claim, and information display; and the inter-terminal transit, which is considered a single attribute dimension.

Service refers to “what airport users can spend time with while waiting for their flights,” such as food and beverages, airport shopping, and wi-fi connectivity (Fodness and Murray, 2007, p. 498). Users’ perceptions of the quality of an airport’s service may be heavily influenced by the time and effort they are required to invest in using the airport (Fodness and Murray, 2007; Park et al., 2020; Shah et al., 2020; Bakır et al., 2022; Batouei et al., 2020). Passengers are restricted in their exploration of airport amenities by the time they spend at check-in desks and other touchpoints (such as the security checkpoint). Thus, customers’ perception of airport service quality is likely to decline if passengers spend more time than necessary on such measures (Martín-Cejas, 2006). In an alternative phrasing, airports should provide passengers with ample forms of entertainment to ensure that their valuable time is not perceived as being wasted. These enjoyable amenities would be viewed by airport patrons as an additional enhancement to their overall experience, thereby fostering a higher likelihood of their return visits (Kim et al., 2020; Park and Ryu, 2019). There might be no causal link between service and the boarding of planes at airports, but it could be the clincher in ensuring passengers are happy with their overall experience (Hwang et al., 2020).

In this study, we break down service into three elements: food and beverage, airport shopping, and wi-fi connectivity. Airports’ largest source of revenue comes from passengers spending money on food and beverage, and airport shopping while waiting for their flights (Timothy and Butler, 1995). Non-flight-related activities at airports, such as shopping and dining, may contribute to passengers’ overall positive impressions of the airport (Toudert and Bringas-Rábago, 2019). The increasing prevalence of mobile device use necessitates that airports provide and maintain reliable Wi-Fi services for passengers (Nghiêm-Phú and Suter, 2018). Prior research has indicated that user satisfaction with an airport’s services plays a pivotal role in influencing their inclination to recommend the airport to others (Anderson and Sullivan, 1993; Cronin Jr et al., 2000; Patterson and Spreng, 1997). Henceforth, airport managers should judiciously deliberate their decisions concerning the management of these non-aeronautical aspects, aiming to attain the utmost level of customer satisfaction attainable (Del Chiappa et al., 2016). The following hypothesis is formulated based on the aforementioned theoretical underpinnings:

**H2.** Service will positively influence airport recommendations of users in online reviews.

2.5.3 Staff. A passenger’s inclination to recommend an airport could primarily be influenced by their interactions with airport staff. Staff members within the service sector are the individuals responsible for direct customer interaction and the delivery of the services for which they are employed (Bitner, 1992; Brady and Cronin Jr, 2001; Dabholkar et al., 1996; Fodness and Murray, 2007; Oh and Parks, 1996). Airport staffs are individuals who are employed at various passenger contact points, including the check-in counter, security checkpoints, boarding gates, and duty-free shops (Fodness and Murray, 2007). The attitude, friendliness, and responsiveness of service staff, including airline agents, security guards, and information desk clerks, directly serve as indicators of how passengers will assess the quality of airport services (Hong et al., 2020).
The significance of interactions between service providers and customers has also been underscored by previous research (Cronin Jr and Taylor, 1992; Oh and Parks, 1996; Fodness and Murray, 2007; Bakır et al., 2022). In their analysis of 42,137 Google Maps reviews, Lee and Yu (2018) observed that airport staff often served as a frequent source of dissatisfaction among passengers. Furthermore, they highlighted the issue of the helpfulness of airport staff, a concern observed at both large and small airports. According to research conducted by Gitto and Mancuso (2017) and Pantouvakis and Renzi (2016), passengers prioritize their concerns in the following order: the quality of airport services, followed by the performance of airport staff, the condition of airport facilities, and lastly, the availability of airport Wi-Fi. Research conducted by De Barros et al. (2007) among transfer passengers at a major hub in South Asia confirmed the significance of airport staff politeness, especially during screening procedures.

Numerous airports have established dedicated customer service departments staffed by individuals possessing the requisite knowledge and skills to provide assistance to passengers (Misuraca et al., 2020). Implementing effective and suitable human resource allocation strategies, such as prompt responses and a courteous demeanor, ensures the provision of high-quality services to passengers through well-trained front-line staff who can adequately address their requirements (Kennington et al., 1996; Wirtz and Mattila, 2004). Passengers value a passenger-centered approach, even in the context of airport security procedures, and are more inclined to provide positive feedback regarding the quality of services they receive as a result (Park, 2003). Customers tend to develop an appreciation for the proactive measures taken by staff to reduce lines and minimize unnecessary waiting times (Kivela et al., 2000; Antwi et al., 2020). Researchers have reached a consensus that both airports and their customers derive benefits from human agents who possess qualities of friendliness, knowledge, and empathy (De Barros et al., 2007; Liou et al., 2011; Eboli and Mazzulla, 2009; Yeh and Kuo, 2003; Bakır et al., 2022). We posit that passengers’ intentions to recommend airports are influenced by the behaviors of human agents, including their attitudes, communication skills, and kindness, within airport settings. Accordingly, we present the following third hypothesis in this study:

**H3.** Staff will positively influence airport recommendations of users in online reviews.

3. **Research framework**

3.1 **Research model**

The research model is based on theoretical backgrounds in the previous study that utilized the ACI ASQ program (Fodness and Murray, 2007) and hypothesis developments. Previous studies (Fodness and Murray, 2007; Hong et al., 2020) have utilized servicescape, service, and staff to predict passengers’ perceptions of airport service quality. In our research model, we have incorporated similar constructs but have replaced airport service quality with recommendation. Additionally, the research model includes wi-fi connectivity within the servicescape construct, which was not included in previous research. It is noteworthy that during the time of the earlier studies, wi-fi connectivity at airports may not have been considered a critical factor, as smart devices like Apple’s iPhone had just entered the market. The proposed conceptual research model is illustrated in Figure 2.

3.2 **Research data**

In this research, a specialized data collection procedure was utilized to assemble a dataset that provides valuable insights into consumers’ perspectives on airports worldwide. The dataset was compiled through the utilization of a custom-designed web crawling tool, which was
employed to extract consumer reviews from the website Airline Quality (https://www.airlinequality.com). This website serves as a valuable resource by aggregating firsthand experiences and reviews from air travelers regarding airports across the globe. The data collection period spanned from January 2020 to October 2020. The dataset comprised a total of 11,655 reviews submitted by consumers, covering 649 distinct airports from around the world. To ensure a comprehensive analysis, the data collection process focused on nine specific attributes. These attributes encompassed terminal signs (TSI), terminal cleanliness (TCL), terminal seating (TSE), queuing time (QTI), food and beverages (FNB), airport shopping (ASH), wi-fi connectivity (WCO), staff, and recommendation. The attribute “recommendation” served as a representation of consumers’ overall opinions regarding the airports and was recorded as either “yes” or “no”. Meanwhile, the remaining eight attributes were evaluated using a five-point scale, which offered a more thorough understanding of consumers’ assessments. This methodology for exploring consumers’ insights into airport service quality on the website survey is similar to ACI’s ASQ approach. ASQ utilizes the overall service quality of the airport as a conclusive variable, derived from other explanatory variables such as servicescape, service, and staff. Thus, we assigned “recommendation” as a dependent variable of this research, and we assigned the other eight variables (i.e. TSI, TCL, TSE, QTI, FNB, ASH, WCO, and staff) as variables that explain why consumers arrive at a conclusion of their intention to recommend the airport they experienced.

To control for potential confounding factors and to enhance the depth of the analysis, three additional control variables were incorporated into the dataset. These control variables encompassed the type of traveler (e.g. business or leisure), the experience at the airport (e.g. transit, departure, or arrival), and the geographical region of the airport. These variables were deemed essential for contextualizing the data and achieving a more nuanced understanding of the findings.

The dataset has a total of 139,860 data points with 12 rows (i.e. eight independent variables, a dependent variable, and three control variables) and 11,655 columns (i.e. 11,655 reviews). The gathered data, encompassing the nine attributes and three control variables, has been meticulously organized and is presented in Table 2 for the sake of reference and thorough analysis. This methodical approach to data collection has ensured that the study possesses a robust dataset, facilitating an exhaustive analysis of the factors influencing consumers’ airport recommendations, grounded in their real-life experiences.

3.3 Data analysis
The dataset was subjected to analysis employing a hierarchical regression approach, Partial Least Squares Structural Equation Modeling (PLS-SEM), and the unsupervised Bayesian EQ algorithm-based PSEM. These analytical methods were utilized to validate the hypotheses and identify the most significant factors influencing consumers’ recommendations of airports. Hierarchical regression analysis was initially utilized as the primary step to examine

![Conceptual research model](image)

**Figure 2.** Conceptual research model

*Source(s): Figure created by authors*
the factors impacting airport service quality and to assess the validity of the proposed model. Subsequently, SEM was applied using SmartPLS 3.0 on the identical dataset. Although hierarchical regression may be considered a traditional method, it offers three distinct advantages, as follows. Firstly, hierarchical regression possesses the capacity to seamlessly incorporate a diverse array of variables, representing heterogeneous characteristics, into a unified model. This capability facilitates the estimation of their respective significance levels. Secondly, hierarchical regression allows for the assessment of coefficient reliability pertaining to Level 1 variables by considering both within-group and across-group variances. This reliability assessment can subsequently be employed to re-evaluate the coefficients associated with Level 1 variables. Thirdly, the methodology employed in hierarchical regression, which amalgamates individual and aggregate characteristics, mitigates the potential pitfalls associated with debates concerning ecological and atomistic fallacies (Chi and Voss, 2005). The hierarchical regression analysis, conducted using SPSS 26, is particularly pertinent for this research as it examines how different variables in a hierarchical structure explain the variance in the dependent variable, such as recommendation (Cohen et al., 2013). Independent variables were entered in blocks based on their categories or theoretical importance, allowing for the evaluation of the contribution of each set in explaining variance while controlling for other variables (Radmacher and Martin, 2001). In this study, a hierarchical regression framework was meticulously designed to systematically incorporate servicescape, service, and staff variables. This stepwise approach was undertaken to facilitate a comprehensive analysis, allowing for the examination of interactions and the cumulative impact of these factors on recommendation.

Subsequently, the analysis advanced to the application of SEM utilizing the versatile SmartPLS 3.0. This transition was motivated by the recognition that hierarchical regression, while valuable, may encounter limitations related to assumptions of linearity, and the ability to model intricate, multidirectional relationships among variables (Woltman et al., 2012). SEM, on the other hand, provides a more nuanced approach that overcomes these constraints. SEM supports the analysis of multiple relationships simultaneously, including mediating, moderating, and reciprocal relationships, within a single comprehensive model. This approach not only enables the estimation of both direct and indirect effects but also accommodates latent variables, thereby yielding a more robust comprehension of the underlying constructs in the research model. The incorporation of latent variables within

<table>
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<tr>
<th>Variables</th>
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<td>Family leisure</td>
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<td>22.8%</td>
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<td>Experience at airport</td>
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<td>Departure only</td>
<td>4,283</td>
<td>36.7%</td>
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<tr>
<td>Arrival and departure</td>
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<td>Region (where the airport is located)</td>
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<td>Asia-Pacific</td>
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<td>Middle East</td>
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</tbody>
</table>

**Table 2.** Control variables

Online review data analytics
SEM offers the advantage of accounting for measurement errors while providing a more precise modeling of the relationships between observed variables and their underlying constructs. SEM’s capacity to construct and validate theoretical models encompassing both observed and latent variables within a flexible and confirmatory framework positions it as a potent tool in research scenarios necessitating the examination of intricate interactions among constructs, particularly where complex models are essential for a comprehensive understanding of the phenomena under investigation (Hair et al., 2021). SEM has established itself as a prominent methodology for hypothesis testing, especially in studies focused on consumer satisfaction and service quality (Chen, 2020; Eslami et al., 2018). Within the realm of SEM, Partial Least Square Structural Equation Modeling (PLS-SEM) was pinpointed for this study due to its innate ability to comprehensively elucidate the relationships between constructs that are predicated on the hypotheses (Fornell and Larcker, 1981). Another advantage of PLS-SEM is its relatively lenient requirements concerning sample size and measurement scales (Chin and Newsted, 1999), which played a pivotal role in rendering it an exceptionally suitable choice for the seamless analysis of the extensive and data-rich dataset utilized in this study, encompassing 11,656 samples. By strategically deploying both hierarchical regression analysis and SEM, this research could not only analyze data but delve deeper, thereby obtaining a more robust, multifaceted, and nuanced understanding of the determinants of airport recommendations, accentuating the interplay of the involved variables.

Thirdly, our analytical approach incorporated the Probabilistic Structural Equation Model (PSEM), which enhanced the depth and scope of our analysis. A significant advantage of employing a probabilistic SEM through Bayesian networks, as opposed to traditional SEM, is the capacity to compute posterior probabilities for all network nodes in an omnidirectional manner, without being limited by the arc directionality (Gerassiss et al., 2019). SEM harmonizes statistical data with qualitative causal assumptions to establish causal relationships; however, it typically treats these relationships as deterministic, assuming that they have precise cause-and-effect connections (Bollen and Pearl, 2013). In contrast, PSEM treats relationships as probabilistic, acknowledging the inherent uncertainty in causal connections. PSEM could be preferred over SEM or hierarchical regression due to its efficiency in model generation, as it utilizes machine learning algorithms to automatically and swiftly generate models, thereby reducing the time-consuming steps associated with SEM or hierarchical regression. In this study, PSEM using Bayesialab software was employed alongside other methods to leverage its efficient algorithm for automatic model generation and its robust capabilities for conducting in-depth model analysis (Silvera and Smail, 2019). While PSEM shares conceptual underpinnings with traditional SEM (Conrady and Jouffe, 2013), it distinguishes itself by employing a Bayesian network structure as opposed to relying on a series of linear equations. There are three core characteristics of PSEM. To begin, relationships within PSEM inherently embody a probabilistic nature, enabling the modeling of intricate interdependencies among variables. This characteristic proves especially valuable in managing uncertainties often encountered in real-world datasets. Second, PSEM is nonparametric; this quality is vital as it enables PSEM to accommodate and elegantly represent nonlinear relationships between categorical variables, which is of immense value when dealing with multifaceted datasets. The third characteristic of PSEM is its ability to adapt and respond to data-driven information and patterns. Unlike traditional SEM, PSEM’s structure is molded and informed by the data itself, either in part or entirely, rather than being solely guided by theoretical assumptions. This dynamic attribute ensures the development of a model that is more grounded and adaptable, capable of accurately mirroring the underlying patterns and relationships. The incorporation of PSEM was instrumental in revealing insights that are both intricate and firmly rooted in the dataset, thereby enriching the robustness of our findings.
In the study, hyperparameter tuning was conducted for the Probabilistic Structural Equation Model (PSEM) to optimize its performance. Hyperparameter tuning is essential for machine learning models as it enhances their abilities to learn effectively and generalize well to new data (Hutter et al., 2011). In the case of PSEM, which is based on a Bayesian network, specific hyperparameters impact the structure and complexity of the network (Conrady and Jouffe, 2013). We employed grid search and random search techniques (Bergstra and Bengio, 2012) to systematically explore the hyperparameter space and identify the combination that minimized the error metric or maximized the likelihood of the model. Furthermore, cross-validation was employed to assess the performance of the PSEM model using various hyperparameters. This practice is critical for mitigating overfitting and verifying that the model can effectively generalize to new data (Kohavi, 1995). By meticulously tuning the hyperparameters, we were able to enhance the robustness and accuracy of the PSEM model in analyzing the complex relationships among the variables used in this study.

Lastly, expert evaluation was employed to examine the usability of the study. We invited five experts in the field of aviation who had an experience of more than seven years: one from the global representative of world airports, one from the worldwide representative of airlines, one from an airport corporation, one from the airline, and one from academia. These experts' evaluation with qualitative and quantitative feedback plays a decisive role in advancing field knowledge on the objective (airport recommendations), the proposed statistical models, and the results. A revised questionnaire from the research of Aldag and Power (1986) was adopted for the quantitative evaluation with a seven-point Likert scale and validated using the intraclass correlation coefficient (ICC) (Shrout and Fleiss, 1979).

3.3.1 Hierarchical regression analysis. We formulated the hierarchical regression research model based on the developed hypotheses, as presented in Figure 3. Next, we conducted an analysis using SPSS 26 to discover the control variables’ and independent variables’ significance to the dependent variable, recommendation.

First, we inserted control variable groups, including type of traveler, experience at airport, and region (model 1). Second, servicescape groups, including terminal signs, terminal cleanliness, queuing times, and terminal seating (model 2). Then, we added the quantitative ratings for the service group (food and beverages, airport shopping, wi-fi connectivity) in model 3 and staff in model 4.

3.3.2 PLS-SEM analysis. We applied two formative second-order constructs: servicescape (with four dimensions: terminal signs, terminal cleanliness, terminal seating and queuing time)
and service (with three dimensions: food and beverages, airport shopping, wi-fi connectivity) as shown in Figure 4. The repeated indicator approach was employed for analyzing these formative second-order constructs. We could appropriately predict the second-order formative constructs with this two-stage approach without any flooding-out influence (Chin et al., 2003). To evaluate the second-order formative constructs’ significance, bootstrapping with 1,000 samples was utilized to assess the upward dimensional effects. Lastly, three control variables (type of traveler, experience at airport, and region) were tested to exclude any spurious impact.

3.3.3 PSEM analysis. The probabilistic structural equation model (PSEM) is similar to the traditional SEM (Conrady and Jouffe, 2013). However, PSEM is based on a Bayesian network structure a contrast to a series of equations. PSEM has three fundamental characteristics that are distinguished from SEM. First, all relationships in a PSEM are probabilistic. Second, PSEM is nonparametric, which facilitates the representation of nonlinear relationships between categorical variables. Last, the structure of PSEM is partially or fully machine-learned using the dataset.

We attempted five different algorithms, such as Taboo (Heckerman et al., 1995), Sopleq (Zargoush et al., 2014), EQ (Munteanu and Bendou, 2001), Maximum Spanning Tree (Lam and Bacchus, 1994), and TabooEQ (Conrady and Jouffe, 2013), with the dataset to learn a network using Bayesia Lab 9 to find the best algorithm with the smallest MDL scores output. Minimum description length (MDL) scores were measured to optimize while searching for the best possible network. Minimizing this score comprises finding the most appropriate algorithmic approach (Lechien et al., 2020). Therefore, the MDL score has to be minimized to obtain the best solution. The result of MDL indicated that EQ is the most appropriate algorithm for the model; the initial MDL score was 205,319.822 and became the lowest with a score of 163,496.965 after applying the EQ algorithm.

Prior to the full-fledged PSEM analysis, we compared the performance of Bayesian-based EQ to other machine learning methodologies, such as logistic regression (LR), decision tree (DT), support vector machine (SVM), neural network (NN), random forest (RF), adaboost (ADA), bagging (BA), random subspace (RSS), to confirm whether EQ can provide reasonable performance. As shown in Table 3, EQ’s performance is found to be acceptable compared to the different machine learning approaches with higher than 90% measurement scores. Also, considering the significant advantage of the straightforward interpretations with the graphical representation of the Bayesian network, we came to the conclusion that Bayesian EQ can be employed as our research analysis method.

Next, we conducted variable clustering, and four groups were formulated: control variables, servicescape, service, and fundamental. In this step, we found a difference between

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**Figure 4.**

PLS-SEM model

**Source(s):** Figure created by authors
the PLS-SEM and the PSEM. The two second-order constructs in PLS-SEM had three first-order descendant constructs; on the other hand, PSEM had two groups with three sub-variables each, and one group with two sub-variables. Next, we conducted multiple clustering using the EQ algorithm, an unsupervised learning algorithm based on Bayesian network, to finalize the model, as shown in Figure 5. Moreover, Table 4 presents all variables (children nodes) having a relationship with the recommendation, the target node. We could identify the top three variable nodes that affect recommendation are fundamental, servicescape, and service. Control variable nodes had a relatively low relationship with recommendation compared to the highest three nodes. Also, we converted each fundamental, servicescape, and service value to categorical values, high, mid, and low, for an easy interpretation. Based on this unsupervised machine-learning network, we investigate the role of control variables in the analysis.

4. Findings
4.1 Hierarchical regression results
In the first hierarchical regression model, the results found that type of traveler - couple \((\beta = -0.144, p < 0.001)\), type of traveler - family \((\beta = -0.053, p < 0.001)\), and type of traveler - business \((\beta = -0.100, p < 0.001)\) were negative and significant. Experience at airport – arrival and departure \((\beta = 0.134, p < 0.001)\), region – Asia Pacific \((\beta = 0.165, p < 0.001)\), and region – Middle East \((\beta = 0.091, p < 0.001)\) had positive relationships with recommendation. However, the computed variance only with control variable insertion was not sufficiently explained the model (adjusted \(R^2 = 0.061)\).

After including the servicescape group in model 2, the adjusted \(R^2\) was increased to 0.590. Among the control variables, family leisure and Middle East became insignificant. On the other hand, North America \((\beta = -0.034, p < 0.001)\) converted to a significant variable, different from model 1. The other independent variables, TSI \((\beta = 0.058, p < 0.001)\), TCL \((\beta = 0.030, p < 0.001)\), TSE \((\beta = 0.082, p < 0.001)\), and QTI \((\beta = 0.103, p < 0.001)\), had positively significant relationships with recommendation. This result shows that as each variable in the servicescape groups increased, passengers’ intention to recommend the airport would also increase.

In model 3, which accounts for 0.610 adjusted \(R^2\), control variables, showing similar significance in model 2, and the newly inserted group, service, had positively significant effects on recommendation: FNB \((\beta = 0.038, p < 0.001)\), ASH \((\beta = 0.019, p < 0.001)\), and WCO \((\beta = 0.022, p < 0.001)\). Africa \((\beta = 0.049, p < 0.01)\), which was insignificant in the previous, changed to a significant variable.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Accuracy</th>
<th>F-measure</th>
<th>AUC</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>EQ</td>
<td>0.90</td>
<td>0.90</td>
<td>0.94</td>
<td>0.90</td>
<td>0.90</td>
</tr>
<tr>
<td>LR</td>
<td>0.91</td>
<td>0.94</td>
<td>0.97</td>
<td>0.93</td>
<td>0.95</td>
</tr>
<tr>
<td>DT</td>
<td>0.90</td>
<td>0.93</td>
<td>0.91</td>
<td>0.92</td>
<td>0.94</td>
</tr>
<tr>
<td>SVM</td>
<td>0.91</td>
<td>0.94</td>
<td>0.89</td>
<td>0.93</td>
<td>0.95</td>
</tr>
<tr>
<td>NN</td>
<td>0.90</td>
<td>0.93</td>
<td>0.96</td>
<td>0.95</td>
<td>0.91</td>
</tr>
<tr>
<td>RF</td>
<td>0.91</td>
<td>0.94</td>
<td>0.96</td>
<td>0.93</td>
<td>0.95</td>
</tr>
<tr>
<td>ADA</td>
<td>0.90</td>
<td>0.93</td>
<td>0.96</td>
<td>0.93</td>
<td>0.93</td>
</tr>
<tr>
<td>BA</td>
<td>0.91</td>
<td>0.94</td>
<td>0.96</td>
<td>0.93</td>
<td>0.95</td>
</tr>
<tr>
<td>RSS</td>
<td>0.91</td>
<td>0.94</td>
<td>0.96</td>
<td>0.92</td>
<td>0.95</td>
</tr>
</tbody>
</table>

Source(s): Table created by authors
In the final model (model 4), we inserted staff; the final adjusted $R^2$ improved to 0.644. TCL ($\beta = 0.004, p > 0.05$), which was positively significant in previous models, did not have a relationship with recommendation in model 4. Staff ($\beta = 0.090, p < 0.001$) was analyzed to have the most significant effect on recommendation. In addition to the coefficient tests, we evaluated the multicollinearity of each model. The evaluation results suggest that all the variance inflation factors (VIF) are lower than 3.5; thereby, multicollinearity was not found in the model (Kutner et al., 2005). The overall results of hierarchical regression are presented in Table 5.
4.2 PLS-SEM results

First, the results suggest that the first-order constructs (TSI, TCL, TSE, QTI, FNB, ASH, and WCO) that were incorporated in the second-order formative constructs (servicescape and service) are significantly affected ($\beta_{TSI} = 0.286$, $p < 0.001$, $\beta_{TCL} = 0.287$, $p < 0.001$, $\beta_{TSE} = 0.295$, $p < 0.001$, $\beta_{QTI} = 0.286$, $p < 0.001$), as presented in Table 6. Also, the heterotrait–monotrait (HTMT) ratio was utilized to evaluate discriminant validity. Table 7 demonstrated that the HTMT ratio evaluation results are smaller than 1.00 and thus qualified recommended discriminant validity criteria (Henseler et al., 2015).

<table>
<thead>
<tr>
<th>Path</th>
<th>Original $\beta$</th>
<th>Mean $\beta$</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>TSI $\rightarrow$ Servicescape</td>
<td>0.286</td>
<td>0.286</td>
<td>288.327</td>
<td>***</td>
</tr>
<tr>
<td>TCL $\rightarrow$ Servicescape</td>
<td>0.287</td>
<td>0.287</td>
<td>272.413</td>
<td>***</td>
</tr>
<tr>
<td>TSE $\rightarrow$ Servicescape</td>
<td>0.295</td>
<td>0.294</td>
<td>275.982</td>
<td>***</td>
</tr>
<tr>
<td>QTI $\rightarrow$ Servicescape</td>
<td>0.286</td>
<td>0.286</td>
<td>244.642</td>
<td>***</td>
</tr>
<tr>
<td>FNB $\rightarrow$ Service</td>
<td>0.401</td>
<td>0.401</td>
<td>249.082</td>
<td>***</td>
</tr>
<tr>
<td>ASH $\rightarrow$ Service</td>
<td>0.393</td>
<td>0.393</td>
<td>249.071</td>
<td>***</td>
</tr>
<tr>
<td>WCO $\rightarrow$ Service</td>
<td>0.350</td>
<td>0.350</td>
<td>240.345</td>
<td>***</td>
</tr>
</tbody>
</table>

**Note(s):** ***$p < 0.001$  
**Source(s):** Table created by authors

4.2.1 Online review data analytics
Next, the test result of hypothesis 1 found that servicescape significantly positively influences recommendation ($\beta = 0.412, p < 0.001$). In addition to the test result of hypothesis 1, the test result of hypothesis 2 also indicated that the service is significantly positively related to the recommendation ($\beta = 0.128, p < 0.001$). Further, the hypothesis 3 assessment result shows that staff is a substantial factor that positively impacts recommendation ($\beta = 0.309, p < 0.001$). Meanwhile, none of the control variables had a significant influence at $p < 0.05$. In summary, all three hypotheses in PLS-SEM were supported, as presented in Figure 6 and Table 8.

4.3 PSEM results
We found that all control variable nodes had significant relationships with recommendation; however, they had low standardized total effects (STE). In PSEM, STE is critical to consider.

<table>
<thead>
<tr>
<th>Construct</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Servicescape</td>
<td>TSI</td>
<td>0.683</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>TCL</td>
<td>0.677</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>TSE</td>
<td>0.640</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>QTI</td>
<td>0.639</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Service</td>
<td>FNB</td>
<td>0.629</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>ASH</td>
<td>0.618</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>WCO</td>
<td>0.561</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Staff</td>
<td>0.654</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recommendation</td>
<td>0.646</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 7. Discriminant validity using the heterotrait–monotrait (HTMT) ratio

Table 8. Hypothesis test results of PLS-SEM analysis

<table>
<thead>
<tr>
<th>H</th>
<th>Path</th>
<th>$\beta$</th>
<th>$t$-value</th>
<th>$p$-value</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>Servicescape $\rightarrow$ Recommendation</td>
<td>0.128</td>
<td>11.491</td>
<td>***</td>
<td>Supported</td>
</tr>
<tr>
<td>H2</td>
<td>Service $\rightarrow$ Recommendation</td>
<td>0.412</td>
<td>31.538</td>
<td>***</td>
<td>Supported</td>
</tr>
<tr>
<td>H3</td>
<td>Staff $\rightarrow$ Recommendation</td>
<td>0.309</td>
<td>28.481</td>
<td>***</td>
<td>Supported</td>
</tr>
</tbody>
</table>

Note(s): ***$p < 0.001$
Source(s): Table created by authors

Figure 6. PLS-SEM results

Source(s): Figure created by authors
because they reflect the combined direct and indirect influences one variable has on another within a model. STE provides a comprehensive measure of the strength and significance of these relationships, allowing researchers to understand the full impact of predictors on outcomes, including the mediating effects of other variables. This is essential for accurate interpretation and decision-making based on the model’s findings. We regulated each control variable node to identify and analyze how the control variable nodes affected each node. The results are shown in Appendix; we found that the control variable nodes had a slight effect on each factor and recommendation. We could discover the top three variables that affect recommendation were fundamental, servicescape, and service based on STE, as shown in Table 9.

The PSEM standardized total effect (STE) results immediately highlight the importance of the factors relative to the target node (recommendation). Fundamental is the most crucial factor affecting the target node, with a STE score of 0.7357. Servicescape (STE = 0.6655) and service (STE = 0.5988) factors follow after fundamental. In addition to STE analysis, we analyze the probabilistic causes with genetic optimization that are strong arbitrary predictors of the target node. The results discovered that the best solution would be receiving the highest scores for all three indicators (servicescape, service, fundamental) that will finally drive recommendation with a probability of 98.28%.

4.4 Experts’ evaluation results
The mean values of experts’ quantitative evaluation (ICC = 0.956, \( p < 0.000 \)) were 4.80–5.40 for systematic orientation and quality items and 2.00 to 2.40 for general negative affect (see Table 10). In the context of experts’ quantitative evaluation, ICC typically refers to the Intraclass Correlation Coefficient. It is a statistical measure used to assess the reliability or consistency of measurements made by different observers measuring the same quantity. Specifically, it evaluates how much homogeneity or agreement there is in the ratings given by different experts. When used in the assessment of quantitative evaluations by experts, a high ICC indicates a high degree of agreement among the experts’ assessments, signifying that the measure is reliable. This result of quantitative evaluation suggests that the experts mostly agreed with the outcomes of this study. Also, subjective feedback from experts is as follows. First, analyzing passengers’ intentions on airport recommendations using online reviews will provide more rigorous implications because airport managers can discover users’ actual needs with the same perspectives as they have. Second, the third model, PSEM, can be applied in the field straightaway with minimal instruction; thus, it can be a practical application for decision-making.

5. Discussion
The adjusted \( R^2 \) of model 1 demonstrated similarity to that of other models, even though the hierarchical regression analysis had revealed a robust association between control variables

<table>
<thead>
<tr>
<th>Node</th>
<th>Mean</th>
<th>STE</th>
<th>TE</th>
<th>G-test</th>
<th>df</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fundamental</td>
<td>2.4048</td>
<td>0.7357</td>
<td>0.2980</td>
<td>6509.571</td>
<td>1.00</td>
<td>***</td>
</tr>
<tr>
<td>Servicescape</td>
<td>2.7368</td>
<td>0.6655</td>
<td>0.2538</td>
<td>6027.275</td>
<td>2.00</td>
<td>***</td>
</tr>
<tr>
<td>Service</td>
<td>2.4661</td>
<td>0.5988</td>
<td>0.2264</td>
<td>4451.327</td>
<td>2.00</td>
<td>***</td>
</tr>
<tr>
<td>Type of traveler</td>
<td>1.5992</td>
<td>0.1112</td>
<td>0.0451</td>
<td>208.737</td>
<td>3.00</td>
<td>***</td>
</tr>
<tr>
<td>Experience at airport</td>
<td>1.5425</td>
<td>-0.0657</td>
<td>-0.0363</td>
<td>238.568</td>
<td>3.00</td>
<td>***</td>
</tr>
<tr>
<td>Region</td>
<td>2.3285</td>
<td>-0.0386</td>
<td>-0.0131</td>
<td>145.909</td>
<td>5.00</td>
<td>***</td>
</tr>
</tbody>
</table>

Note(s): ***\( p < 0.001 \)
Source(s): Table created by authors

Table 9. The results of the PSEM
and recommendation. In the final model, fewer control factors were incorporated, and the introduction of *servicescape* group variables in model 2 resulted in a noteworthy increase in the adjusted $R^2$ by 0.533. Focusing on H1, which postulated that *servicescape* would have a positive influence on recommendations, our findings align with this hypothesis. Notably, *servicescape* group variables exhibited significance in model 2, contributing to the increase in adjusted $R^2$, and this result suggests a robust and positive relationship between *servicescape* and *recommendation*. Moreover, PLS-SEM analysis underscored that various aspects of the *servicescape*, such as TSI, TCL, TSE, and QTI, are all highly relevant, reaffirming the importance of *servicescape* in how travelers evaluate airport facilities (Hong *et al.*, 2020). Thus, H1 is accepted.

In the second instance, it is noteworthy that model 4 revealed a lack of significant association between TCL and *recommendation*. Given that airports typically maintain a consistent level of hygiene, cleanliness could be considered a standard feature that travelers expect. Consequently, travelers may not place significant emphasis on TCL when making decisions about whether or not to recommend airports. In the context of H2, which posited that *service* would exert a positive influence on *recommendation*, the PLS-SEM analysis corroborated the significance of *service* as a factor to predict *recommendation*. However, it is worth noting that the coefficient for *service*, while significant, does not exhibit as strong an effect as those for *servicescape* or *staff*, signifying a relatively milder positive impact. Therefore, H2 is supported.

Model 4 also unveiled the significance of QTI as a crucial factor influencing recommendations. Waiting in line, both at security checkpoints and at boarding gates, is commonly perceived by passengers as the most tiresome and stress-inducing aspect of the boarding process (Gregghi *et al.*, 2013; Kalakou *et al.*, 2015). Given that the assessment of airports in the dataset occurred in the aftermath of the COVID-19 pandemic, it is essential for travelers to adhere to social distancing measures to mitigate the risk of virus transmission. Queuing, particularly during the boarding of an aircraft, may pose a heightened risk as it can disrupt social distancing protocols. Consequently, travelers may feel compelled to expedite their airport experience to minimize the potential for virus spread, which could further emphasize the importance of efficient queuing procedures. In the context of H3, which posited

<table>
<thead>
<tr>
<th>Item</th>
<th>Question</th>
<th>Mean</th>
<th>STDV</th>
<th>ICC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Systematic orientation</td>
<td>The analyses in the research were very structured</td>
<td>5.40</td>
<td>0.55</td>
<td>0.956***</td>
</tr>
<tr>
<td></td>
<td>Several requirements were seriously considered</td>
<td>5.40</td>
<td>0.55</td>
<td></td>
</tr>
<tr>
<td></td>
<td>There were systematic evaluations of the research</td>
<td>5.00</td>
<td>0.71</td>
<td></td>
</tr>
<tr>
<td>Quality</td>
<td>There were thorough analyses</td>
<td>5.60</td>
<td>0.55</td>
<td></td>
</tr>
<tr>
<td></td>
<td>The results of the research were good ones</td>
<td>4.80</td>
<td>0.84</td>
<td></td>
</tr>
<tr>
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<td></td>
<td>The analyses were generally sloppy</td>
<td>2.40</td>
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<td></td>
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</table>

Note(s): ***$p < 0.001$, ICC was estimated using a two-way mixed average score (McGraw and Wong, 1996) using SPSS 26; the result is “excellent” according to the guidelines from both Cicchetti (1994) and Koo and Li (2016).

Source(s): Table created by authors
that staff would positively influence airport recommendations, the data substantiate this hypothesis. Employees were identified as the most influential independent variable in determining whether or not a customer would recommend an airport (Lee and Yu, 2018; Gitto and Mancuso, 2017; De Barros et al., 2007). The PLS-SEM analysis provided additional support for the assertion that staff significantly influence on recommendation. Consequently, H3 is accepted based on the findings.

Staff emerged as the most influential independent variable in the determination of whether or not a customer would recommend a business. Given that human involvement is requisite for the majority of processes entailed in boarding an airplane, encompassing tasks at the check-in desk, security checkpoint, duty-free shop, and boarding gate, the pivotal role played by employees in shaping the passenger experience becomes evident. Their interactions and behaviors wield substantial influence over travelers’ perceptions, ultimately impacting their decisions to recommend the business. Passengers invariably engage with airport personnel unless they opt for self-service alternatives such as kiosks, mobile boarding passes, and biometric identification. Given this, travelers’ inclination to recommend airports is significantly contingent on their perceptions of the service quality provided by staff. Particularly during the COVID-19 pandemic, there is the potential concern that airport workers may inadvertently transmit the virus to passengers. Consequently, travelers may regard staff as the primary factor in mitigating virus transmission through measures such as social isolation, physical barriers, and the use of personal protective equipment (PPE).

The PLS-SEM analysis unveiled that all three dimensions of airport rating (servicescape, service, and staff) exerted a significant influence on the likelihood of a passengers’ recommendation of the airport. Servicescape was found to be crucial to how travelers evaluate the facilities at an airport, as previous research articulated (Hong et al., 2020). If airports aspire to enhance customer service, allocate resources effectively, and gain a competitive advantage, they must accord customer satisfaction the same level of significance as they do to the profit generation (Hong et al., 2020; Pantouvakis and Renzi, 2016; Yeh and Kuo, 2003; Correia et al., 2008). The findings regarding the significance of staff in the data-driven transformation of the airport industry align with the conclusions drawn in earlier studies on the subject (Lee and Yu, 2018; Gitto and Mancuso, 2017; De Barros et al., 2007). Nonetheless, this research has contributed novel insights by elucidating the influence of staff on passengers’ decision-making, particularly in relation to the recommendations they provide. Concerning non-aviation services, airports have increasingly placed significant reliance on the service industry, with a particular emphasis on food and beverage as well as retail services (Lee and Yu, 2018; Gitto and Mancuso, 2017). Conversely, the study underscores that travelers attach significant importance to the fundamental services provided by the airport.

The PLS-SEM analysis that we conducted demonstrates the high relevance of TSI, TCL, TSE, and QTI as integral components of servicescape. These factors are crucial throughout passengers’ entire airport experience, spanning from the initial stages to the conclusion of their journey, and they are intricately tied to the boarding process by creating a conducive physical environment. The findings articulate the interdependency of these factors, making it impractical to dismiss any of them in isolation. Notably, the coefficient values for the two attributes potentially related to COVID-19 infection (servicescape and staff) were the highest and second-highest, respectively, highlighting their strong associations with passengers’ recommendations. The findings of this study, initiated in the aftermath of the COVID-19 pandemic (as of January 2020), indicate that air travelers may exhibit a heightened level of caution concerning infection risk prevention, such as maintaining a hygienic environment (i.e. cleanliness), adhering to social distancing protocol (i.e. queuing), and mitigating the risk of virus transmission (i.e. human agents). Furthermore, the results show that FNB, ASH, and WCO are all essential components of the service construct. While the coefficient value for
service is the lowest among the three primary constructs (servicescape, staff, and service), the results imply that apprehensions related to the absence of non-boarding amenities at airports are the least influential factor in shaping passengers’ decisions regarding whether to recommend a specific airport to others.

While the coefficients of the independent variables in the hierarchical regression analysis spanned a range from 0.012 to 0.090, the constructs in the PLS-SEM analysis, categorized into three main groups (servicescape, staff, and service), exhibited significantly higher levels of significance, ranging from 0.128 to 0.418 in association with the dependent variable. According to the study’s findings, passengers tend to assess the quality of airport service categories as comprehensive bundles rather than individual components. This observation contrasts with previous studies (Bezerra and Gomes, 2016; Martin-Domingo et al., 2019; Bogicevic et al., 2013) on airport service quality, which often focuses on a subset of the extensive list of 34 attributes utilized in ACI’s ASQ.

In a hierarchical regression analysis, strong positive correlations were identified between recommendation and servicescape components and staff. These findings were further corroborated through the use of PLS-SEM, which also indicated that both the servicescape and the staff played significant roles as predictors of recommendations.

The PSEM model, developed utilizing the unsupervised Bayesian EQ algorithm, was constructed exclusively through statistical computations and machine learning techniques. This stands in contrast to the hypothetical modeling approach employed in the hierarchical regression and PLS-SEM analyses, which was rooted in a review of pertinent literature and theoretical constructs. In another perspective, the PSEM model was autonomously generated, potentially offering a diverse range of outcomes. This machine-learned model, in contrast, has the potential to mitigate the biases inherent in prior studies and provide a more accurate representation of consumers’ authentic perspectives. PSEM findings, however, show that the most significant standard total effect on the target node (recommendation) comes from the fundamental component, which includes staff, queuing times, and wi-fi connectivity as child nodes. When it comes to boarding a flight, passengers are inevitably faced with queues and interactions with airport attendants. Interestingly, the availability of wireless Internet was also identified as a critical factor to consider. This observation underscores the widespread reliance on the Internet, which has become increasingly prevalent among various electronic devices. The significance of digital mediums experienced substantial growth during the COVID-19 pandemic, highlighting that connectivity through wi-fi is no longer considered a luxury but rather a necessity. In line with previous studies that employed sentiment and text mining analysis, our findings also suggest that wi-fi is one of the most important interests for airport visitors.

According to previous studies (Gitto and Mancuso, 2017; Timothy and Butler, 1995), airport shopping is a favored pastime among vacationers. However, service, which includes restaurants and shops, was perceived as the least important factor by passengers, implying that these amenities are more of a “nice-to-have” rather than a critical consideration for airport travelers. This finding is intriguing because airport operators frequently prioritize service as a revenue-generating strategy. However, none of the three models in our study depict service as the most crucial factor in passengers’ recommendations.

5.1 Theoretical and practical implications
This study’s significant contribution can be categorized into three primary areas. Firstly, through the results of the PSEM analysis, this research discovered a novel factor fundamental, composed of staff, queuing times, and wi-fi connectivity, which had not been previously identified in earlier studies. This factor was generated through the application of the unsupervised Bayesian EQ algorithm, which fused a single significant component from
the servicescape, service, and staff constructs. The findings from this study offer valuable insights into the primary considerations of passengers in a situation with risk (e.g., COVID-19) when assessing the quality of airport services and making decisions about recommending airports to others. Hence, we advocate for further research in this domain and encourage practitioners to consider this novel factor fundamental when evaluating and enhancing airport services. Second, as previous research (Hong et al., 2020; Fodness and Murray, 2007) has demonstrated, servicescape exhibited correlations with recommendations in all three models. This result suggests that traditional airport quality indicators, such as the ease of boarding for travelers, remain highly relevant and applicable in the contemporary context. The least significant factor was identified as service, despite the common perspective among airport operators that it is the most pivotal element for revenue generation. These findings could offer valuable guidance to airport managers in striking a more effective balance between profit maximization and passenger satisfaction. Thirdly, our discovery that PSEM constructed using a Bayesian network could potentially assist researchers and practitioners in addressing this complex challenge is noteworthy. The results of the PSEM were somewhat different from those of the regression and PLS-SEM. These disparities can be attributed to the nature of the Bayesian network, which relies exclusively on probabilistic statistics and machine learning. It is important to refrain from prematurely asserting the superiority of PSEM outputs over the results of hierarchical regression or PLS-SEM, as these methods require human interaction and domain expertise from specialists. Nevertheless, academics and industry experts can consider leveraging PSEM as an adjunctive instrument to corroborate the findings obtained through other methodologies. The visual representation capabilities provided by PSEM suggest its potential utility as a practical decision-support tool within the field. This has also received affirmation from industry experts. Therefore, we strongly encourage airport management to contemplate the adoption of our application as a decision-making tool to gain insights into passengers’ perspectives.

For airport managers and other industry professionals, this study has the following implications in addition to its theoretical contributions. First, when evaluating the service quality of airports, professionals in the aviation industry often rely on credible sources, including assessments provided by transportation experts and statistical reports, such as those offered by ACI’s ASQ (Fodness and Murray, 2007). These resources excel in a number of areas, including the provision of up-to-date market trends and a global perspective. Collecting data from passengers at airports, whether for departing passengers rushing to board their flights or arriving passengers eager to return home, can be a demanding endeavor. Respondents may find it challenging to provide calm and considered survey responses amidst the hustle and bustle of their airport experience. Moreover, when passengers complete surveys at the request of a surveyor, there is a greater likelihood for external influences, such as the surveyor’s demeanor or approach, to exert an impact on the responses, compared to when passengers voluntarily decide to participate in a survey. Online reviews, in contrast, are typically submitted voluntarily by travelers. It is more probable that these reviews were composed in a relaxed and unhurried setting rather than in the unfamiliar and potentially stressful environment of an airport. Reviewers are more likely to feel comfortable and undisturbed when sharing their opinions online. This study suggests that professionals should leverage online reviews provided by travelers to conduct a more comprehensive evaluation of airport service quality. Research on the topic indicates that airports can expect a 1.5% rise in non-aeronautical revenue for each 1% increase in passenger satisfaction (ACI, 2016). Given that airport service quality has a profound impact not only on airports’ reputations but also on their financial performance (Halpern and Mwesiumo, 2021), airport operators stand to gain significant advantages from a thorough examination of passengers’ evaluations of airport service quality using online reviews.
The increased focus on fundamental service aspects such as staff, queuing time, and wi-fi connectivity, surpassing the emphasis on traditional physical elements, indicates a paradigm shift in the assessment of airport service quality. This shift aligns with the evolved passenger expectations in the post-pandemic world. This reconceptualization of service quality factors bolsters existing frameworks and guides future strategic priorities in airport management. Unlike the relatively transient aspects of the airport experience, such as shopping, food and beverage, terminal seating, terminal cleanliness, and terminal signs, passengers would be concerned with these fundamental aspects. Airports have been enhancing these fundamental elements by adopting smart boarding devices, such as self-check-in and biometrics, to reduce wait times. They have also expanded Wi-Fi services to improve connectivity and implemented service training programs for staff to enhance in-person interactions. However, airports should continue investing in physical factors such as seating, signage, and shops, even though passengers may place a higher value on interactional service delivery factors like wi-fi, staff, and reduced waiting times. Balancing both physical and service-oriented elements remains crucial for providing a comprehensive and satisfying airport experience (Hong et al., 2020). To enhance service quality, airport management should take a comprehensive approach by reevaluating these fundamental elements. Wi-fi (for online connectivity), staff (for human interaction), and queuing (to ensure social distancing) are indispensable components that require careful management at airports, particularly in the context of the new normal of the post-COVID-19 era.

5.2 Limitations and future studies

Despite the valuable insights gained from this study, there are certain limitations to consider. Firstly, the analysis relies solely on data obtained from the airport quality website, limiting the variables available for examination to terminal signs, terminal cleanliness, terminal seating, food and beverages, airport shopping, staff, queuing times, wi-fi connectivity, and recommendation. It’s important to acknowledge that other significant factors might influence passengers’ ratings of airports that were not explored in this research. Additionally, our analysis was limited to quantitative score evaluations, and we did not delve into passengers’ subjective assessments of airport service quality. Conducting sentiment analysis on user comments from the website would be valuable because qualitative feedback can provide valuable insights and implications beyond numerical ratings alone.

Furthermore, it’s worth noting that while we employed analytical methods such as Probabilistic Structural Equation Modeling (PSEM) and PLS-SEM, the theoretical foundation of our study may be considered somewhat lacking. The absence of established theories in behavioral research like this study could potentially weaken its contribution to the existing literature. However, it is crucial to recognize that this was a deliberate methodological choice, driven by the nature of the data and the analytical objectives in this research. Approach in this study provides a novel perspective on airport service evaluation that complements existing theories rather than diminishing their relevance. Nonetheless, we acknowledge that future research could benefit from a more robust theoretical foundation. Strengthening the theoretical framework could lead to a more comprehensive understanding of the variables influencing consumers’ airport recommendations. It would also enable future studies to assess the applicability of established theories in conjunction with modern analytical techniques like PSEM and PLS-SEM. By doing so, subsequent research could make more substantial contributions to both the theoretical and practical aspects of airport service management. Therefore, we suggest that future studies strive to incorporate a stronger theoretical basis to enhance the depth and breadth of research findings in this domain.

Additionally, there is potential for further granularity within each variable. For example, the staff variable could encompass sub-factors such as staff service quality, response time, kindness,
and interpersonal interactions. However, due to the limitations of the data collected, we were unable to explore these detailed sub-factors for each variable. Therefore, future research should consider breaking down each variable into finer sub-categories to derive more in-depth insights into passengers’ airport experiences and recommendations. Text mining of social media content could be a valuable method for exploring these sub-factors in greater detail.

Lastly, smart airport technologies, including self-check-in, automated bag drop, mobile boarding passes, and biometric identification, as well as passengers’ perceptions of these technologies in relation to service quality, have not been addressed in this study. These innovative technologies are increasingly being implemented at airports to reduce wait times for passengers and improve boarding efficiency. Therefore, it is advisable for future studies to consider incorporating these technologies as factors when predicting passengers’ intention to recommend airports, as they could significantly impact service quality scores. Consequently, the existing gaps in this investigation may be effectively addressed if future research endeavors opt to broaden their focus in this regard.

6. Conclusion
Before the onset of the COVID-19 pandemic, the airline industry stood out as one of the economy’s most rapidly expanding sectors. Following the successful distribution of vaccines, once the aviation industry has fully recuperated from its most severe crisis to date, airports are expected to return to their bustling state, welcoming a surge of travelers. Nevertheless, airports will continue to face the challenge of adapting to the expectations of visitors who have grown accustomed to the “new normal” established during and after the pandemic, characterized by practices such as social distancing and heightened standards of cleanliness. Despite the increased difficulty in meeting the needs of these passengers, airports are poised to assume a more substantial role as intermediaries between travelers and airlines. The primary objective of this study is to develop an effective decision-support tool for airport administrators. This tool will enable them to gain deeper insights into passenger preferences, thereby making more informed decisions and facilitating their contribution to the broader body of research within the aviation industry. The study is designed to investigate the underlying factors that drive passengers to recommend a particular airport, with a specific focus on analyzing online reviews. In order to identify the most optimal strategy, this research employed a combination of statistical techniques, including PLS-SEM, PSEM, and hierarchical regression analysis. The study employed statistical analysis to examine the hypothesis that customer satisfaction with service, staff, and the servicescape would lead to favorable ratings of airports. Furthermore, the study successfully utilized PSEM analysis to reclassify survey items and construct a new construct fundamental.

References


## Table A1.

The PSEM results of the control variable analyses

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Source(s): Table created by authors
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**Source(s):** Table created by authors
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Cheong Kim holds a Ph.D. from SKK Business School, Sungkyunkwan University. His primary research areas encompass neuroscience-based decision-making, business analytics with a particular focus on deep learning mechanisms and computational psychology, with an emphasis on its application to business decision-making. Dr Kim has contributed to the academic community by publishing papers in notable journals, including the International Journal of Information and Management, among others. Cheong Kim is also affiliated with the Department of Business Administration, University of Suwon, Hwaseong, South Korea.

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