Journal of Air Transport Management 105 (2022) 102298

Contents lists available at ScienceDirect

Journal of Air Transport Management

journal homepage: www.elsevier.com/locate/jairtraman

How has airport service quality changed in the context of COVID-19: A data-driven crowdsourcing approach based on sentiment analysis

Lingyao Li [a], Yujie Mao [b], Yu Wang [a,*], Zihui Ma [a]

[a] Department of Civil and Environmental Engineering, A. James Clark School of Engineering, University of Maryland, College Park, MD, USA
[b] Department of Mechanical Engineering, A. James Clark School of Engineering, University of Maryland, College Park, MD, USA

ARTICLE INFO

Keywords:
Airport service quality (ASQ)
Crowdsourcing
COVID-19
Google maps reviews
Sentiment analysis
ASQ driven factors

ABSTRACT

Airport service quality (ASQ) is a competitive advantage for airport management in today's airport market. Since the COVID-19 health crisis has unprecedentedly influenced airport regulations and operations, effective measurement of ASQ has become crucial for airport administrations. Surveying travelers' attitudes is useful for ASQ assessment but collecting responses could be time-consuming and costly. Therefore, this paper adopts a data-driven crowdsourcing approach to study ASQ during the COVID-19 pandemic by investigating Google Maps reviews from the 98 busiest U.S. airports. To do so, this study develops a topical ontology of keywords regarding ASQ attributes and uses a sentiment tool to derive passengers' attitudes. Through sentiment analysis, Google Maps reviews show more positive sentiment toward *environment* and *personnel* but remain constant about *facilities* during COVID-19. The lexical salience-valence analysis (LSVA) is then applied to explain such changes by tracking the sentiment of frequent words in reviews. Through correlation and regression analysis, this study demonstrates that *rating* is significantly related to *check-in*, *environment,* and *personnel* in pre-and post-COVID periods. Additionally, the effect of *access*, *wayfinding*, *facilities*, and *environment* on *rating* significantly differs between the two periods. The findings illustrate the effectiveness of leveraging online reviews and offer practical implications for what matters to air travelers, especially in the COVID-19 context.

1. Introduction

As the connection between passengers and the sky, airports are an indispensable component of the air transportation network (Barakat et al., 2021). Today's passengers demand more extraordinary airport service and are inclined to choose alternative modes of transport once unsatisfied (Halpern and Mwesiumo, 2021). Airports have become highly competitive brands that compete at various levels to attract travelers. In particular, service quality is the determinant for airports to fulfill passengers' needs and influence their intentions to revisit (Prentice and Kadan, 2019). Therefore, airport administrations need reliable information to comprehend passenger expectations about airport services and accordingly facilitate improvement programs (Bezerra and Gomes, 2020; Wattanacharoensil et al., 2017).

Airport services have multiple dimensions and attributes, each of which has varying degrees of impact on passenger satisfaction (Barakat et al., 2021). The Novel Coronavirus Disease (COVID-19) has unprecedentedly influenced air travel, posing new challenges to the aviation industry coming to the forefront (Serrano and Kazda, 2020). Due to large indoor gatherings, airports have become vulnerable places with health concerns about the potential hazards of human-to-human transmissions (Du et al., 2020; Kraemer et al., 2020). As a result, passengers seek a cleaner and safer environment than in the past, reinforcing airport quarantine procedures and forcing airport administrations to accommodate such situations (Serrano and Kazda, 2020). These changes can affect travelers' behaviors and feelings about airport services, such as complaining about queues for temperature checks or sanitation conditions in restrooms. This complex and competitive environment has raised two questions for evaluation strategies: (1) how to understand and measure the key attributes of services that drive passenger satisfaction, and (2) how to explain the changes after the COVID-19 outbreak and allocate resources to thrive airport business.

For the first question, as Barakat et al. (2021) described in their study, prior studies have used surveys to investigate a representative sampling of passengers' viewpoints about airport service quality (Allen et al., 2020; Bezerra and Gomes, 2016; Hong et al., 2020). While conventional survey techniques can help obtain insights into airport service quality, collecting responses could take tremendous time and resources.

* Corresponding author.
E-mail addresses: lli12316@umd.edu (L. Li), ymaopatrik1235@gmail.com (Y. Mao), wangyu@umd.edu (Y. Wang), zma88@umd.edu (Z. Ma).

https://doi.org/10.1016/j.jairtraman.2022.102298
Received 26 March 2022; Received in revised form 23 August 2022; Accepted 26 August 2022
Available online 9 September 2022

Another significant hindrance is the difficulty of covering a sizeable geographical scale with respondents from diverse socioeconomic backgrounds. For the second question, very few studies so far have investigated the changes in customer satisfaction in terms of airport service attributes since the COVID-19 pandemic.

Social media (e.g., Twitter, Facebook) and online platforms (e.g., Google Maps) have been increasingly indispensable for people to communicate opinions and feelings (Heinonen, 2011). These platforms set up a virtual channel that disseminates information faster, broader, and less constrained by social and geographical restrictions (Cheung and Thadani, 2010). Crowdsourcing through online platforms presents a novel source for service providers to investigate service quality. This approach has been implemented to measure customer satisfaction with products and services in multiple domains, such as hotel administration (Luo et al., 2021), restaurant management (Mathayomchan and Taecharungroj, 2020a), and airport service (Martin-Domingo et al., 2019). Crowdsourcing is an inherently imperfect information resource and may overrepresent opinions from certain demographic groups (e.g., young and educated population) (Barberá and Rivero, 2015; Mellon and Prosser, 2017). However, it provides rapid and geographically distributed information from a large population that may complement conventional surveys.

Nevertheless, dealing with this abundant and ever-increasing amount of online data, consisting primarily of unstructured texts, requires effective and efficient techniques to extract information (Barakat et al., 2021). While analyzing such overwhelming data is challenging, advances in data analytics and natural language processing (NLP) have made it viable in recent years (Li et al., 2021b, 2022b). Multiple studies have demonstrated the potential of using NLP and machine learning techniques to analyze customer reviews (Cuizon et al., 2018; Lee and Yu, 2018; Luo et al., 2021). Building on the existing body of knowledge, this study applies a lexicon-based sentiment tool to investigate Google Maps reviews of the 98 busiest airports in the U.S. This study examines the airport service before and after the COVID-19 outbreak and identifies areas for improvement. It further offers insights into the changes in airport services and proposes several suggestions for airport administrations to consider.

2. Literature review

2.1. Airport service quality (ASQ)

Faced with intense competition, airports are vulnerable to competitors' offerings. Delivering high-quality service to customers is important for airport administrations to maintain and expand business advantages (Chen and Hu, 2013; Halpern and Mwesiumo, 2021). For example, Prentice and Kadan (2019) found a significant positive relationship between airport service and customer intentions to revisit an airport. In a commercial report, the Airports Council International (ACI) (ACI, 2016) uncovered that an increase of 1% in global passenger satisfaction could generate an average growth of 1.5% in non-aeronautical revenue based on a worldwide survey over 300 airports with over 550,000 passengers.

Airport Service Quality (ASQ) offers an objective-oriented measurement framework to assist decision-makers in improving their performance and delivering competitive services to customers (Bezerra and Gomes, 2016; DKMA, 2021; Fodness and Murray, 2007). The ASQ initiative – that benchmarks customer satisfaction with services at airports – was developed and managed by DKMA in Switzerland in partnership with ACI in 2005. Since then, DKMA has worked with over 300 airports worldwide to help airport administrators grow non-aeronautical revenue by improving ASQ (DKMA, 2021). In recent years, the topic of ASQ has attracted much attention from scholars. Many studies focusing on ASQ attributes have developed a set of formative ASQ indicators, as exhibited in Table 1. Despite the slight differences regarding ASQ attributes, most studies have used what

Table 1
A selection of typical studies listing ASQ attributes.

Study	ASQ attributes
Fakfare et al. (2021)	signage and layout, terminal environment, flight information screens, check-in, security, facilities, immigration, departure hall, baggage service, leisure and entertainment
Chonsalasin et al. (2021)	access, security, check-in, airport facilities, wayfinding, airport environment, arrival services
ACI (2020)	access, check-in, passport/personal identification control, security, finding your way, airport facilities, environment, and arrivals services
Bezerra and Gomes (2020)	check-in, security, convenience, ambience, basic facilities, mobility
Antwi et al. (2020)	prime services (e.g., check-in), queueing or waiting time, helpfulness and communication, facilities, airport value addition (e.g., access)
Martin-Domingo et al. (2019)	access, check-in, passport, wayfinding, facilities, environmental, arrival, people
Prentice and Kadan (2019)	facilities (e.g., seating, airbridges, retail and dining), check-in (e.g., processes, staff, self-service kiosks), service scape (e.g., signs, layout), ambience (e.g., cleanliness, temperature, noise)
Trischler and Lohmann (2018)	check-in, immigration, information, baggage, gate lounges, amenities, aerobridges, security
Lee and Yu (2018)	overall satisfaction, access, check-in, passport/personal id control, security, finding your way, airport facilities, airport environment, arrival services
Pandey (2016)	access, check-in, security, finding your way, facilities, environment, arrival services
Pabedinskaitė and Akstinaitė (2014)	landing-related services, parking-related services, escort related services, equipment, provision of ground handling services, provision of non-aviation services, services of ensuring the safety
Liou et al. (2011)	convenience, comfort, immigration, customs, quarantine, transportation, courtesy of staff, information visibility, security, price of shop

Fodness and Murray (2007) referred to as attributes of function (e.g., wayfinding, check-in), interaction (e.g., services), and diversion (e.g., dining, shopping, and internet).

2.2. The survey-based approach to studying ASQ

A comprehensive assessment of ASQ is important to decision-makers and related stakeholders (Yeh and Kuo, 2003). Fodness and Murray (2007) suggested that ASQ should be defined and measured by passengers rather than others. Due to the flexibility in question design, survey tools have been extensively applied to evaluate ASQ or identify determinant drivers. One commercial application is the ASQ program – launched by ACI with skills and expertise to measure passenger satisfaction, business performance, and service quality. ACI delivers 640,000 individual surveys per year in 49 languages across 91 countries, with 701 members operating 1933 airports in 183 countries (ACI, 2021).

In the academic field, one direction focuses on unfolding crucial factors of passenger satisfaction based on statistical models or hypothesis testing. For example, through face-to-face interviews of 237 passengers in the baggage claim area at Ataturk International Airport in Turkey, Calisir et al. (2016) discovered that service quality and price were the determinants. In a survey with 503 responses collected from Brazil Congonhas Airport, Bezerra and Gomes (2020) found that airport service and switching costs for changing airports were favorably associated with passenger satisfaction. Hong et al. (2020) conducted hypothesis testing based on a survey of 138 responses from passengers at the Incheon International Airport in South Korea. They stated that passengers were more concerned with convenience attributes, while service providers perceived the environment as a determinant.

The other research direction uses survey tools to disclose satisfiers and dissatisfiers of ASQ. For example, Del Chiappa et al. (2016) surveyed 551 passengers from Olbia-Costa Smeralda Airport in Italy. Their findings revealed that attributes of cleanliness and comfort, provision of entertainment, and staff courtesy showed satisfactory quality, while price acceptability and internal environment needed further improvement. Another study surveyed 625 passengers in Suvarnabhumi and Don Mueang airports in Thailand and reported that check-in process, security inspection, and cleanliness of restrooms needed improvement (Pandey, 2016).

2.3. The crowdsourcing approach to studying ASQ

Online reviews are a form of electronic word-of-mouth that can be communicated to a vast audience through social networks (Cheung and Thadani, 2010). Online ratings and reviews could significantly affect travelers' decision-making in choosing an airport (Casado-Díaz et al., 2017). Researchers have used social media data or online reviews as an alternative information source to assess ASQ. For example, Lee and Yu (2018) stated that Google Maps reviews could complement and cross-validate conventional quality surveys to appraise airport service. Dalla Valle and Kenett (2018) illustrated that integrating airport interview-based surveys with online blogs could enhance information quality and generate a more accurate analysis of customer satisfaction.

Crowdsourcing through online reviews allows airport management to obtain thoughts or concerns from a large, relatively open, and often rapidly evolving group of passengers. By unlocking a diversity of thinking from air travelers based on their knowledge and experience, this approach can facilitate problem-solving and help identify areas for improvement. Among early attempts, Bogicevic et al. (2013) analyzed 1095 traveler comments posted between 2010 and 2013 from an airport review website. They identified cleanliness and environment as the key satisfiers and security-check, signage, and dining as key dissatisfiers.

With the development of machine learning techniques, recent studies have applied state-of-the-art NLP tools to examine online reviews. For example, Martin-Domingo et al. (2019) used sentiment analysis to measure ASQ based on the London Heathrow airport's Twitter account dataset. They showed that the airport provided quality service in Wi-Fi, food, beverage, and lounge but needed improvement in waiting, parking, passport arrival, and airport staff. Barakat et al. (2021) employed deep learning schemes to classify sentiment based on Twitter data from the King Khaled Airport in Saudi Arabia. According to the results, restroom and airport hotel had the best evaluation, while mobile apps, security, and ground transport were among the worst. Park et al. (2022) applied topic modeling and sentiment analysis to examine Google Maps reviews of 64 major hub airports in the U.S. They identified several positive topics, including staff and shopping, but neutral or negative in service and space. Another typical study (Bunchongchit and Wattanacharoensil, 2021) retrieved 7385 reviews from the Skytrax Airport Review website and applied sentiment analysis, text lemmatization, and the least square equation modeling to reveal critical patterns of ASQ. This study investigated each group of passenger types to identify underlying differences in passenger segmentation, particularly among leisure travelers.

2.4. Research gaps and objectives

The research gaps are twofold. First, the survey approach may have limitations given the time and resource. For example, many survey-based studies only target the sampling of travelers from one or several airports, which may not help measure ASQ at a large geographical scale. Second, there has been minimal focus on uncovering the determinant attributes of ASQ using the crowdsourcing approach, especially in the context of the COVID-19 pandemic. To fill these two research gaps, this study investigates Google Maps reviews for the 98 busiest airports in the U.S. and formulates the following research questions:

- Are there significant changes in terms of different attributes of ASQ before and after the COVID-19 outbreak? How to interpret the changes in ASQ?
- What are the key factors contributing to the ASQ based on online reviews of airports in the U.S.? What topics matter to air travelers in the COVID-19 context?

This study presents a fine-grained sentiment approach to extracting information regarding each ASQ attribute. Statistical models and text mining techniques are then used to examine sentiment changes before and after the COVID-19 outbreak. This crowdsourcing approach features rapidity with large data at spatial densities that can complement conventional survey data. This study provides valuable insights for airport decision-makers to consider when planning and improving ASQ and an invaluable crowdsourcing approach to assessing airport services.

3. Data and methods

Fig. 1 presents a graphical illustration of the research scheme applied in this study. The research scheme begins with data preparation, which involves collecting Google Maps reviews of the 98 busiest airports in the U.S. The resulting dataset contains 98 files stored in JavaScript Object Notation (JSON) format with a total of 642,546 reviews and is later converted to Excel files for analysis. Data collection and preparation are explicitly described in Section 3.1. Next, an iterative process is applied to identify eight key ASQ topics, including *access*, *check-in*, *security*, *wayfinding*, *arrival*, *facilities*, *environment*, and *personnel*. The development of topic ontology and the word screening process are documented in Section 3.2. Last, a sentiment tool is applied to calculate the fine-grained sentiment from reviews based on sentence units, as documented in Section 3.3.

3.1. Data collection and preparation

Google Maps is a web mapping platform and consumer application developed by Google, which provides satellite images, aerial photography, street maps, panoramic views, traffic conditions, and route planning (Google Maps, 2022). On Google Maps, people can freely rate a place and share their experiences, feelings, and suggestions about a business site (Munawir et al., 2019), such as a restaurant, scenic spot, commercial district, or airport. Compared to other online platforms (e.g., Yelp or TripAdvisor), Google Maps has seen a more dramatic increase in the number of reviews since 2015 (Munawir et al., 2019). While social media platforms (e.g., Twitter) may have a large number of users posting information about airports, most postings containing the keyword or the hashtag "airport" may not include the type of evaluative messages (Lee and Yu, 2018). By comparison, reviews posted on Google Maps are generally related to customer experiences and feelings about a business place (Lee and Yu, 2018), making Google Maps a trustworthy information resource for the implementation of the crowdsourcing approach.

This study selected the 98 busiest airports in the U.S. as the study target. The list of airports is based on the total number of domestic and international enplaned passengers in 2019, as published by the Bureau of Transportation Statistics (Bureau of Transportation Statistics, 2019). The geographical distribution of airports is shown in Fig. 1. Google Maps reviews were collected and sorted by date. The collection process lasted from November 12 to 17, 2021. Given that Google Maps has collected reviews about airports for more than ten years, all Google Maps reviews of an airport posted before this collection period were downloaded. The resulting dataset contains 642,546 reviews for the 98 investigated airports.

Each downloaded Google Maps review contains information about a reviewer's username, rating, the number of likes, review text, and posted images. A Google rating appears on a five-star rating scale from one star (poor) to five stars (excellent). It should be noted that Google Maps shows the time of a customer review as "hours ago," "days ago," "months

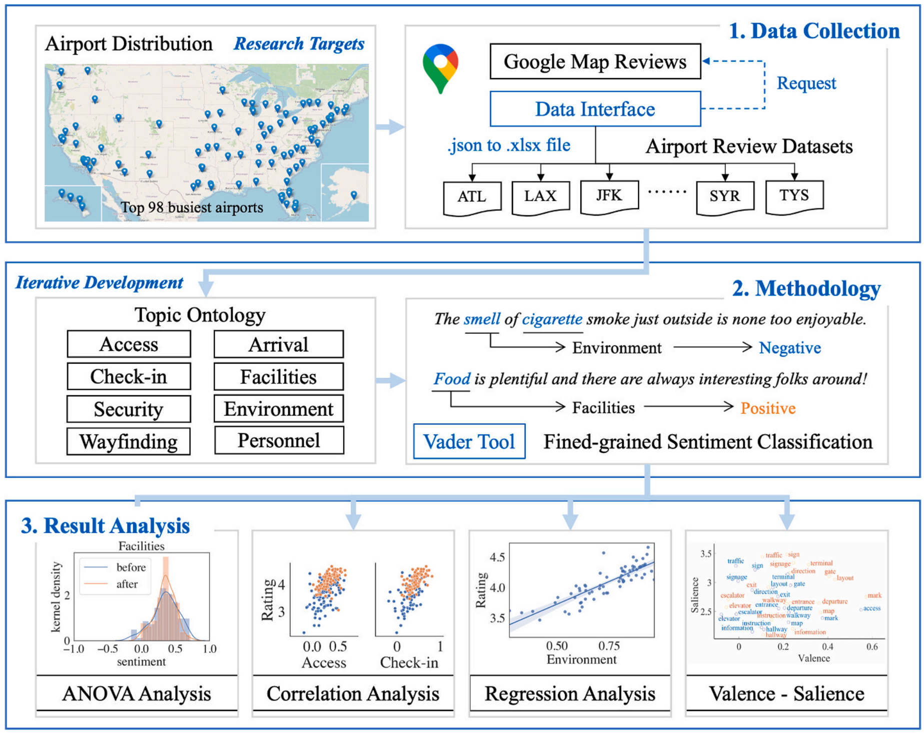

Fig. 1. Research scheme for the implementation of this study.

ago," and "years ago" rather than an actual date and time. Given that some reviews were possibly not written in English, the collection process captured the translated message by Google (translated to English) for the text analysis.

Since one research goal is to identify sentiment before and after the COVID-19 outbreak, the key is to split the dataset. The scheme for data split is presented in Fig. 2, in which the blue bar represents the number of reviews with specific comments while the orange bar represents the number of all Google Map reviews posted in a year. Given that the collected data was sorted in chronological order, it was possible to make a reasonable split by using the year information and tracking the first COVID-19-related word in the dataset. First, the study period was set from November 2015 to November 2021. Reviews posted before November 2015 were removed for analysis to minimize the bias resulting from timing factors (e.g., social development, technological advances). Second, reviews posted between "two years ago" and "five years ago" (i.e., from November 2015 to November 2019) were considered "pre-COVID-19 outbreak" reviews ("blue box" in Fig. 2). Third, for reviews post between "one year ago" and the time of data collection, reviews posted after the date when the first COVID-19-related word (words listed in the "grey box" in Fig. 2) appeared in the dataset were treated as "post-COVID-19 outbreak" reviews ("orange box" in Fig. 2) and reviews posted before the appearance of the first COVID-19-related word were discarded. This handling was due to the

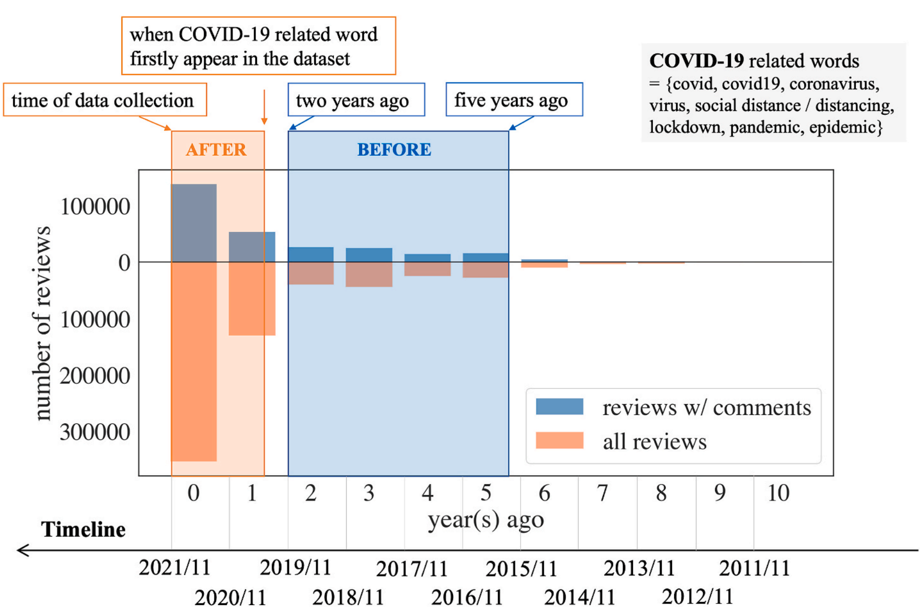

Fig. 2. Scheme for data split.

difficulty to identify whether a review labeled as "one year ago" (i.e., from November 2019 to November 2020) was exactly posted after the COVID-19 outbreak. Although this handling resulted in partial loss of data, it could guarantee that the resulting dataset accurately reflected travelers' opinions that emerged before or after the COVID-19 outbreak.

This process resulted in a dataset containing 462,135 reviews after the COVID-19 outbreak and 138,411 reviews before the COVID-19 outbreak. Given that some users only left ratings without comments mentioning any ASQ topics, these reviews did not include helpful information and were removed for sentiment analysis. As a result, the dataset contains 179,187 and 82,861 reviews after and before the COVID-19 outbreak, respectively. Although significantly fewer passengers traveled during the first months of the pandemic, there were significantly more reviews posted after the COVID-19 outbreak (illustrated by a dramatic increase of reviews in the most recent two years in Fig. 2). This is possibly because more people have used Google Maps to leave customer reviews in recent years. As an earlier study reported (Munawir et al., 2019), Google Maps has seen a dramatic increase in the number of reviews since 2015. Another supporting evidence is from ReviewTrackers, reporting that Google was the top review site where searches significantly rose in 2020, and review interaction was up by 50% from pre-pandemic levels (ReviewTrackers, 2021).

3.2. Topic ontology and word screening

This study implements a top-down process to establish the topic ontology, which is built on previous studies. For example, Martin-Domingo et al. (2019) categorized 108 words into nine ASQ topics, including access, check-in, passport, wayfinding, facilities, environmental, arrival, and people. Antwi et al. (2020) assessed ASQ based on five primary indicators: check-in, queueing, helpfulness, facilities, and airport value addition. Lee and Yu (2018) estimated ASQ based on nine first-level ASQ topics, including access, check-in, passport, security, finding your way, facilities, environment, and arrival services, and 34 second-level service attributes. Based on a thorough investigation of these studies (listed in Table 1), it was found that ASQ topics identified by these researchers somehow overlapped. For example, most studies have included security, check-in, wayfinding, facilities, and personnel. Building on the existing body of knowledge in terms of ASQ topics (primarily based on the study conducted by Martin-Domingo et al. (2019) and the report released by ACI (2020) in Table 1), the selection of ASQ attributes acknowledges eight first-level topics, including *access*, *check-in*, *security*, *wayfinding*, *arrival*, *facilities*, *environment*, and *personnel*, and 19 second-level attributes.

Word collection was completed based on a manual screening of the 10,000 most occurrent words in the dataset. This handling can help ensure the coverage of most keywords (excluding common and ambiguous words). To perform this manual screening, all the terms were first ranked based on their frequencies in the 262,048 (179,187 + 82,861) reviews. Since words with higher frequency reflect what travelers care about, the screening process can help gain insights into the determination of topics, which works as a bottom-up process to understand the word coverage of each topic. The authors formed two groups, with each group of two authors manually assigning each related word to the identified topics.

Next, the word library was reviewed by each author to make alterations and to ensure the coverage of related words under each ASQ topic. The word library was finalized with three iterative loops of development and alterations. The final lexicon-based ontology is presented in Table 2, in which the symbols "/" (or), "+" (and) were used to show combinations of word patterns. For example, patterns "access + freeway" and "park + car" can extract information for the topic *access*. These signs help understand how different word combinations were used to classify topics from a comment. Moreover, words with more than one form were included to ensure the accuracy of topic identification from a review, such as "checkin," "check-in," and "checking in" under

Table 2
Topic ontology and word collections.

Topics	Sub-topics	Keywords
Access	Ground transportation	access + freeway, airtrain, amtrak, bus, cab, commuter, dropoff/drop-off/drop off, ground transportation, lightrail, lyft, metro, people mover, pickup/pick-up/pick up, railway, rental + car, ride share/rideshare, shuttle, skytrain, subway, taxi, taxiway, train, tram, tramway, uber, van
	Parking	garage, park + car/vehicle, parking, to park, toll booth
Check-in	Check-in service	baggage/luggage + pre-check/check, checkin/check-in/check in/checking in/checked in, check + congestion/line/queue/wait, id check, pre-check lane/precheck lane, ticketing, ticket + agent/counter/kiosk/scanner
Security	TSA service	bag check, checkpoint/check point, fingerprint, inspection, metal detector, scan machine, scanner, scanning, security, tsa + congestion/line/queue, tsa precheck/tsa pre check/tsa -pre, tsa + package, tsa + process, tsa + scan/screen/screening, x-ray/xray
Wayfinding	Signs & Directions	direction, instruction, labeled, layout, map, marked, navigate, navigation, sign, signage, signal
	Flight information	announcement, display + board, flight + monitor, information + board
	Mobility	access + gate/terminal, arrivals, corridor, departures, elevator, entrance, escalator, exit, get through, hallway, maneuver, movement, pedestrian, roads, traffic, tunnel, walkway
Arrival	Passport control & Customs	border + control/protect, customs, documentation, immigration, mobile passport, license, line + customs/passport/immigration, paperwork, passport control, passport + inspect/machine/system, visa
	Arrival service & Baggage claim	arrival service/experience, baggage/luggage + claim/cart/kiosk, baggage counter/area, carousel, find + baggage/luggage, get + baggage/luggage, line + baggage/luggage, lose/lost + baggage/luggage, luggage counter/storage, pickup/pick up + baggage/luggage, pick up area, trolley, wait + baggage/luggage
Facilities	Food & Beverage	applebees, bagel, bakery, bar, barbecue, beef, beer, beverage, bistro, breakfast, buffet, burger, burrito, café/cafeteria, catering, cheeseburger, chick-fil-a, chicken, chipotle, clam, coffee, croissant, dining, dinner/dinning, dominos, donut, drink/drinking, drinking/water fountain, dunkin, eatery, eating, espresso, fast food, food, fries, hot dog, latte, lettuce, lunch, mcdonald, meal, meat, milkshake, noodle, onion, oyster, panda express, pepsi/coke, pizza, potato, pretzel, pub, refreshment, restaurant, salad, sandwich, sausage, sausage, seafood, shrimp, snack, soup, spice, starbucks, steak, sugar, sushi, sushi, taco, tequila, tomato, vegetable, vegetarian, vendor/vending, wendy, wine
	Washrooms	bath, bathroom, men's room, paper towel, restroom, soap, toilet, washroom, women's room
	Retail & Shopping	alcohol, bookstore, boutique, clothes + shop, commodity, duty-free, gift, grocery, jewelry, lego, liquor, nike, retail, shopping/shops, souvenir, store, underwear
	Phone & Wi-Fi access & Electronic	charge + device, charge station, charger, charging port, device(s), electrical outlet, phone + charging, power/electrical/

(*continued on next page*)

Table 2 (*continued*)

Topics	Sub-topics	Keywords
		charge/charging outlet, television, wifi/ wi-fi
	Waiting & Relax area	amenities, armrest, cushion, entertainment, facilities, facility, lounge, massage, playground, rest + place, seat, seating, sky club, sleep + chair, smoking area, sofa, studio, waiting room
	Pet relief	animal relief, pet area, relief area
	Accessible	disability, disabled, handicap, wheelchair
Environment	Cleanliness & Environment	ambiance, atmosphere, clean, cleanliness, construction, dirty, environment, hygiene, neat, organized, sanitary, sanitation, sanitized, surrounding, tidy, unsanitary
	Air quality & noise	air conditioner, air conditioning, air quality, cigarette, cold, musty, noise/ noisy, smell, ventilated, ventilation
	Modernization & Aesthetics	aesthetic, airport + old, architecture, arrangement, art installation, artistic, artwork, beautiful, carpet, ceiling, decorate, decoration, design, expansion, gallery, garden, infrastructure, landscape, lighting, modern, modernization, modernize, museum, open air, outdated, renovation, resort, revamp, rundown, scenery, scenic, style, technology, ugly
Personnel	Personnel & Service	administrator, agent, assistant, attendance, attendant, cashier, clerk, concierge, crew, employee, employer, everyone, front desk, information booth, manager, officer, officials, people + desk, people + work, personnel, police, policeman, porter, reception, receptionist, screener, server, shuttle driver, skycap, staff, supervisor, ticket counter, tsa folk, valet, volunteer, waiter, waitress, worker

the topic *check-in*. This word screening process also captured specific meanings of the same word used in different contexts. For example, “TSA” could help identify either topic *personnel* with the word “attitude” or topic *security* with the word “scanner.”

3.3. Fine-grained sentiment classification

A sentence was selected as the fundamental unit for sentiment analysis since a review can include multiple topics. First, this handling can help identify the polarity of a sentence according to the semantic information for each topic. Second, such fined-grained sentiment classification is advantageous when a person expresses opposite sentiments regarding different topics in a review (as illustrated by the examples in Table 3). Therefore, each review was chunked into multiple sentences, and distinctive ASQ topics were extracted based on word patterns in Table 2. Then, a sentiment tool was used to compute the sentiment given a topic. Examples of sentiment classification are presented in Table 3.

Each review was split by the sentence endings, namely a period (.), a semicolon (), a question mark (?), an exclamation point (!), and an ellipsis (…). Illustrative examples are presented in Table 3. Topics extracted from the first review include *facilities*, *personnel*, and *wayfinding*; topics from the second review include *access*, *check-in*, *security*, and *facilities*; topics from the third review include *environment* and *facilities*, and topics from the fourth review include *security* and *personnel*.

The sentiment tool Valence Aware Dictionary and Sentiment Reasoner (VADER) (Hutto and Gilbert, 2014) was leveraged to identify the polarity of sentiment. Vader is a completely open-sourced and lexicon-based sentiment analysis tool implemented under the MIT license that was exceptionally trained on social media data. Vader can help interpret conversations and categorize a text into positive, negative, or neutral emotion classifications by returning a compound score between −1 and 1. The compound score is calculated by adding the sentiment scores of each word in the sentence and then normalized to a value between −1 (i.e., most extreme negative) and 1 (i.e., most extreme positive) (Hutto and Gilbert, 2014). According to its documentation, the thresholds for categorizing a sentence as either positive, neutral, or negative are (Hutto and Gilbert, 2014):

$$sentiment = \begin{cases} positive \quad sentiment \in [0.05,\ 1.00] \\ neutral \quad sentiment \in (-0.05,\ 0.05) \\ negative \quad sentiment \in [-1.00,\ -0.05] \end{cases} \tag{1}$$

As Table 3 shows, R1.3, R2.4, R3.1, and R4.1 were identified as positive for the topics *wayfinding* (“navigate”), *facilities* (“chicken”), *facilities* (“food”), and *security* (“security”). R1.2, R2.1, R2.2, R2.3, R3.1, and R4.2 were classified as negative for the topics *personnel*

Table 3
Examples of sentiment analysis from Google Maps reviews.

Comment	No.	Chunked Sentence	Topics	Vader score	Sentiment
R1. Unfortunately, if you’re flying early - or arriving late these days it seems like most of the restaurants and shops are closed. The airport needs to do something about it, or the employers need to pay more and get these businesses open. Overall the airport is very easy and quick to navigate.	R1.1	Unfortunately, if you’re flying early - or arriving late these days it seems like most of the restaurants and shops are closed.	Facilities	0.0258	Neutral
	R1.2	The airport needs to do something about it, or the employers need to pay more and get these businesses open.	Personnel	−0.1027	Negative
	R1.3	Overall the airport is very easy and quick to navigate.	Wayfinding	0.4927	Positive
R2. Parking, check-in, security all were terrible experiences. 2 stars only because it’s a nice airport and got Popeyes chicken.	R2.1	Parking, check-in, security all were terrible experiences.	Access	−0.1779	Negative
	R2.2	Parking, check-in, security all were terrible experiences.	Check-in	−0.1779	Negative
	R2.3	Parking, check-in, security all were terrible experiences.	Security	−0.1779	Negative
	R2.4	2 stars only because it’s a nice airport and got Popeyes chicken.	Facilities	0.4215	Positive
R3. Not quite one of my favorites as far as airports go, however it’s not bad. It gets really busy, though that’s not their fault. Even so, the smell of cigarette smoke just outside is none too enjoyable. Otherwise, food is plentiful (though expensive), and there are always interesting folks around!	R3.1	Even so, the smell of cigarette smoke just outside is none too enjoyable.	Environment	−0.3412	Negative
	R3.2	Otherwise, food is plentiful (though expensive), and there are always interesting folks around!	Facilities	0.4019	Positive
R4. Security was efficient; however Southwest was HORRIBLE! 70 or so people in Line for full service & only (2) Reps working between 4:30a 5:15a CRAZY.	R4.1	Security was efficient;	Security	0.6369	Positive
	R4.2	70 or so people in line for full service & only (2) reps working between 4:30a 5:15a crazy.	Personnel	−0.3400	Negative

("employers"), *access* ("parking"), *check-in* ("check-in"), *security* ("security"), *environment* ("smell + cigarette"), and *personnel* ("people + working"). The accuracy of sentiment classifications depends on the development of topic ontology and the reliability of sentiment tools. For example, R1.1 was identified as neutral by VADER but negative might be a more precise classification. Limitations of sentiment analysis are specifically discussed in the Discussion section. In the subsequent analysis, this study treated negative sentiment values as "-1," neutral as "0," and positive as "1," respectively.

3.4. Lexical salience-valence analysis (LSVA)

With sentiment classified from each review, the underlying words in reviews and their impacts on the overall sentiment of ASQ topics were further explored in this study. A tool called lexical salience-valence analysis (LSVA) (Taecharungroj and Mathayomchan, 2019) was applied to analyze words in reviews. This definition was proposed by Taecharungroj and Mathayomchan (2019) to identify positive and negative words and impacts on sentiment in tourist attractions based on TripAdvisor reviews. Then, they applied this concept to examine customer experience on restaurant attributes using Google Maps reviews (Mathayomchan and Taecharungroj, 2020b). The LSVA conducts text mining and analyzes the relationships between words and sentiments of reviews through the definition of salience and valence of words. Compared to the simple frequency of words appearing in positive or negative reviews, the LSVA method can help visualize the frequency of words in the corpus of documents and their impacts on the overall sentiment (Taecharungroj and Mathayomchan, 2019). The LSVA defines the salience and valence of a word as below,

$$Salience|_{word_i} = log_{10}(N_{total})|_{word_i} \tag{2}$$

$$Valence|_{word_i} = \frac{N(positive) - N(negative)}{N_{total}}|_{word_i} \tag{3}$$

where

N_{total} represents the total number of reviews where $word_i$ appears
$N(positive)$ denotes the number of positive reviews where $word_i$ appears
$N(negative)$ denotes the number of negative reviews where $word_i$ appears

The salience of a word is computed by the logarithm with base 10 function of the frequency of each term. The valence of a word is computed as $N(positive) - N(negative)$ divided by its total count N_{total}, which measures how positive a particular word is in a corpus (Taecharungroj and Mathayomchan, 2019). Reviews that contain words with highly positive valence are more likely to be positive reviews than those with negative words.

4. Results

The subsections seek answers to the proposed research questions by exploring Google Maps reviews to ultimately figure out what aspects of airport service make a hit to air travelers in the context of COVID-19 ("Result Analysis" in Fig. 1). In response to the first research question, Section 4.1 presents the overall analysis for each ASQ topic and compares statistical results before and after the COVID-19 outbreak. ANOVA analysis is further implemented to reveal the significant sentiment changes regarding each ASQ topic. In response to the second research question, Section 4.2 unfolds the underlying relationships of identified topics through correlation analysis and performs regression analysis to find the determinant factors. Section 4.3 interprets the sentiment changes based on word analysis. For consistency, the following analysis treats analysis done before the COVID-19 outbreak as pre-COVID-19, while analysis done after the COVID-19 outbreak as post-COVID-19.

4.1. Descriptive statistical analysis

This section followed the approach documented in Section 3.3 to classify ASQ topics from a review and applied the Vader sentiment tool to calculate sentiment scores. The sentiment concerning each topic for an airport is the average of sentiments of related Google Maps reviews in that topic, as expressed in the equation below.

$$S_{i,n} = \frac{(Pos)_{i,n} - (Neg)_{i,n}}{N_{i,n}} \tag{4}$$

where

$(Pos)_{i,n}$ denotes the number of positive reviews given a topic i and airport n
$(Neg)_{i,n}$ denotes the number of negative reviews given a topic i and airport n
$(Neu)_{i,n}$ denotes the number of negative reviews given a topic i and airport n
$N_{i,n}$ denotes the sum of the reviews, $N_{i,n} = (Pos)_{i,n} + (Neg)_{i,n} + (Neu)_{i,n}$
$S_{i,n}$ represents the averaged sentiment given a topic i and a course n

The sentiment analysis aims to understand the relationship between passengers' overall satisfaction (i.e., review ratings) and their perception of individual ASQ topics embedded in the reviews (i.e., sentiment scores for ASQ topics). Based on Equation (4), sentiment scores corresponding to each topic were calculated for 98 airports, presented as heatmaps in Fig. 3. Outliers were likely to result from a small sampling of reviews, so observations with less than 15 comments for an airport were not included in the following analysis, displayed as blank values in Fig. 3.

Overall, *security*, *personnel*, and *environment* have higher sentiment scores than other ASQ topics, as demonstrated by the darker orange color (also illustrated by the average sentiment scores in Table 4). A horizontal comparison reveals significant variances among different airports, allowing a quick assessment of satisfactory and unsatisfactory aspects. For example, LaGuardia Airport (LGA) during the pre-COVID-19 period shows the lowest sentiment in *wayfinding* and the highest sentiment in *security* (Fig. 3a). This observation implies that passengers were less satisfied with signages in LGA, so more effective flight information and signpost were needed. However, LGA has shown a significant sentiment increase since the COVID-19 outbreak (Fig. 3a and b), possibly due to several major modernization millstones in recent years (Airport Technology, 2022).

This study further grouped 98 investigated airports (listed in Fig. 3) for sentiment analysis based on FAA categorization (i.e., large (P-L), medium (P-M), and small (P–S)) (FAA, 2022) using the "post-COVID-19" review data. This analysis can help interpret the sentiment analysis from a different perspective given airport hubs. The hub type of each airport is listed in Appendix Table A1. The sentiment distribution for each topic and the rating distribution are displayed in Fig. 4.

The medium and small hubs show a higher rating than the large hub (i.e., the distribution falls to the right). In particular, the small hub shows a significantly higher sentiment than the large hub on *access*, *check-in*, *wayfinding*, *environment*, and *personnel*. The medium hub also shows a higher sentiment, although less than the small hub, than the large hub on *check-in*, *wayfinding*, *environment*, and *personnel*. One possible reason is that getting through access, check-in, or security at medium or small hubs is generally faster and more efficient. Meanwhile, it may be more efficient to manage the environment and hygiene conditions due to the small scale, and the personnel may show more politeness and patience. However, the topic of *facilities* does not show

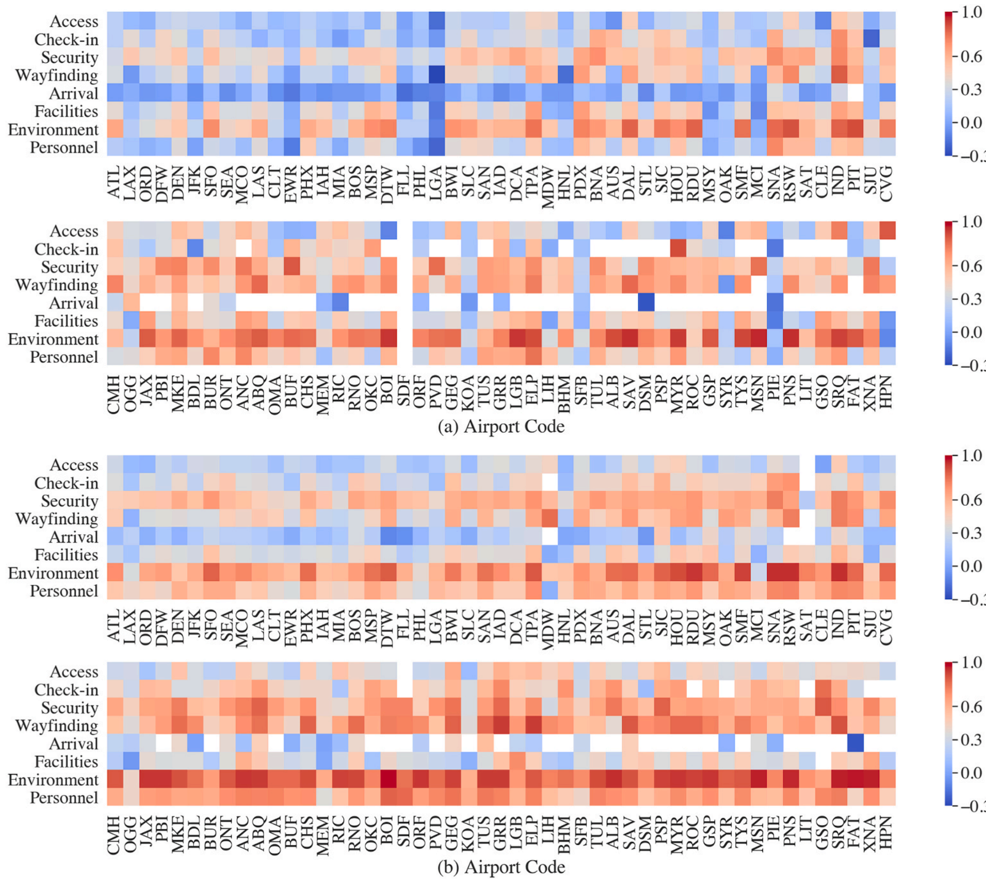

Fig. 3. Heatmap of sentiment scores. (a) Heatmap of sentiment scores for ASQ topics of the 98 airports during the pre-COVID-19 period. (b) Heatmap of sentiment scores for ASQ topics of the 98 airports during the post-COVID-19 period.

Table 4
Descriptive statistics of rating and sentiment in ASQ topics.

	Pre-COVID-19				Post-COVID-19				Change
	No. of reviews	No. of obs.	Mean	S.D.	No. of reviews	No. of obs.	Mean	S.D.	
Rating		98	3.55	0.491		98	4.13	0.292	0.58
Access	11331	97	0.26	0.195	16435	96	0.31	0.136	0.05
Check-in	4762	79	0.30	0.203	6768	90	0.43	0.154	0.13
Security	15249	97	0.51	0.159	18692	98	0.61	0.123	0.10
Wayfinding	12038	95	0.44	0.245	21574	97	0.56	0.191	0.12
Arrival	4650	61	0.04	0.159	5326	70	0.19	0.153	0.15
Facilities	24328	97	0.37	0.203	33269	97	0.35	0.143	−0.02
Environment	19723	97	0.61	0.259	42877	98	0.77	0.151	0.16
Personnel	20254	97	0.36	0.215	30985	98	0.60	0.134	0.24

any clear difference between these three types of hubs during the pandemic.

Table 4 summarizes descriptive statistics regarding the rating and sentiment scores in both periods. Fig. 5 visualizes distributions of the rating and sentiment scores for each ASQ topic. In each subfigure, the distribution plot presents sentiment scores in pre- and post-COVID-19 periods, in which the y-axis shows the fitted density by Gaussian kernel (Waskom, 2021). The lower box chart shows the spread of sentiment scores with quartiles.

Based on the number of reviews (the second and the sixth columns in Table 4), passengers paid more attention to *facilities*, *environment*, and *personnel*. In addition to these three topics, passengers showed an increasing concern about *wayfinding* (the number of reviews on this topic almost doubled). Compared to the pre-COVID-19 period, the average rating after the COVID-19 outbreak increases from 3.55 to 4.13. Correspondingly, the sentiment score for most ASQ topics significantly increases, except for *facilities*. In particular, the average sentiment of *personnel* displays the largest increase (0.24) from pre-COVID-19 to post-COVID-19. Passengers were more satisfied with airport service and personnel after the COVID-19 outbreak, reflecting that most airports have increased customer loyalty and satisfaction through better personalization and service delivery. In addition, *check-in*, *wayfinding*, *arrival*, *and environment* show a remarkable increase in sentiment, possibly because of the reduced volume of passengers and good managerial capabilities during the COVID-19.

The topic *environment* (0.77) shows the highest average sentiment score, implying that passengers were satisfied with environment and aesthetics. However, *arrival* has the lowest average sentiment score (0.19) in both periods, possibly because many passengers were unsatisfied with the baggage claim or passport control process. It is also worth noting that *facilities* barely displays any improvement, which signifies that most investigated airports have made little progress in enhancing

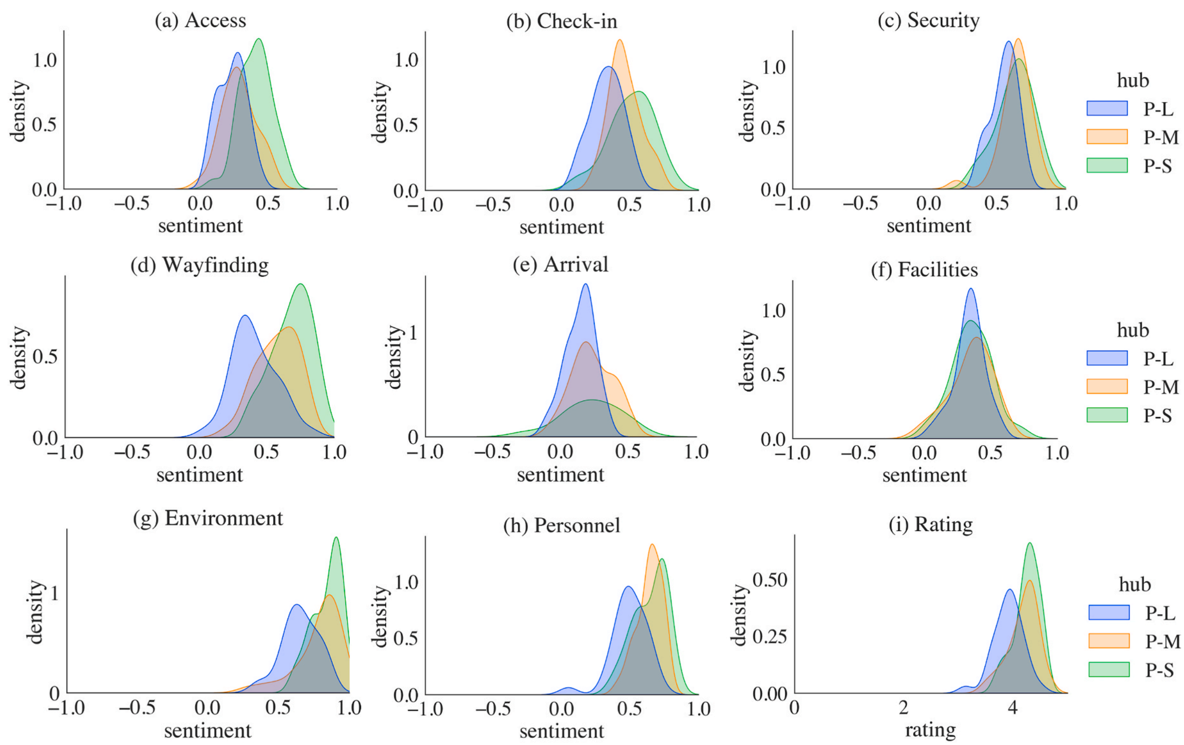

Fig. 4. Sentiment and rating distributions in terms of airport hub types.

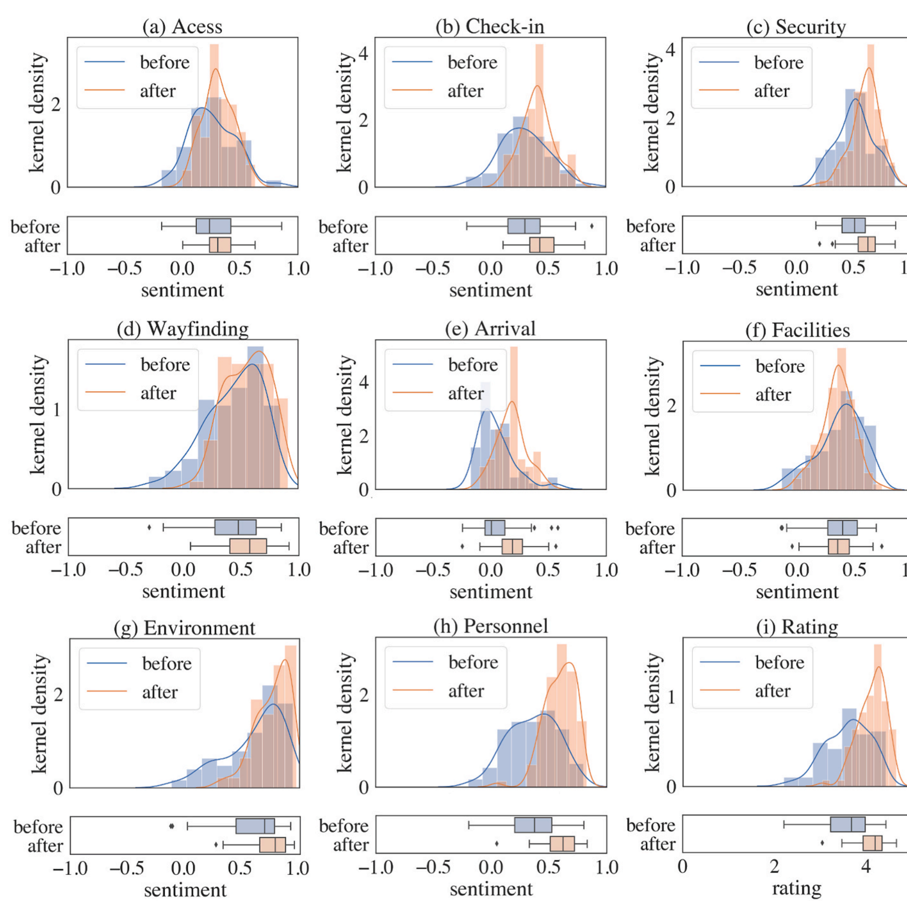

Fig. 5. Comparison of sentiment and rating distributions in pre-COVID-19 and post-COVID-19 periods.

infrastructure in the past six years.

The sentiment change is compared with the North America Airport Satisfaction Study released by J.D. Power. J.D. Power is a pioneer in consumer insights and provides data analytics for industrial companies to understand customer interactions with their brands and products (J. D. Power, 2021). Table 5 presents some statistics summarized from J.D. Power's annual airport satisfaction study. In comparison with previous years, the average score for U.S. airports increased in 2020 and 2021, and the standard deviation decreased. These changes are consistent with those reported in this study.

In addition, the presence of sentiment values and the volume of online reviews imply what ASQ topics are important to travelers. Topics with consistently high sentiment scores (high average with low standard deviation) and large volumes of reviews indicate what matters for air travelers. For example, the topic *personnel* has a high average sentiment score, a comparatively low standard deviation, and a high discussion volume. This observation suggests that *personnel* is crucial for portraying a positive airport image among passengers. Further, a high sentiment score with a small standard deviation indicates that most travelers are consistently positive about the ASQ topic. By contrast, a low sentiment score with a small standard deviation implies a consistently negative sentiment about the ASQ topic, such as *access* based on Table 4, further suggesting that decision-makers should enact plans to enhance the service.

A comparison of the standard deviations (Table 4) shows that ratings and sentiment scores differ less among airports in the post-COVID-19 period (orange histograms display a narrower distribution in Fig. 3). This decrease implies that passengers' evaluations were more consistent, reaffirming that they were more satisfied with airport service during the post-COVID-19 period. This observation shows consistency with the airport satisfaction reported by J.D. Power, as illustrated by a slightly smaller standard deviation in Table 5.

A one-way analysis of variance (ANOVA) was further performed to test whether there is a significant difference between the averaged sentiment scores in the two periods. The result presented in Table 6 manifests a significant difference in the averaged star ratings between pre-COVID-19 and post-COVID-19 periods ($p < 0.001$). Regarding the averaged sentiment scores of ASQ topics, the difference is significantly higher for *check-in*, *security*, *wayfinding*, *arrival*, *environment*, and *personnel* at the 0.001 level and *access* at the 0.05 level. No significant difference is observed in terms of *facilities*.

4.2. Correlation and regression analysis

In this section, a correlation analysis was conducted to describe the linear relationship between variables, as presented in Fig. 6. The bar chart on the diagonal shows the distribution of sentiment for ASQ topics, and the scatter plot shows a relationship between two different ASQ topics. The correlation r-value measures the strength of the linear relationship of sentiment scores between two ASQ topics.

The dependent variable *rating* correlates with sentiment scores for each ASQ topic (illustrated by p-value < 0.05). In particular, it shows a strong correlation (an apparent linearity with $r > 0.7$ (Asuero et al., 2006)) with the topics of *wayfinding* ($r = 0.78$), *environment* ($r = 0.85$), and *personnel* ($r = 0.85$). This observation suggests that travelers positive about these three ASQ topics were very likely to leave a high rating on Google Maps. Travelers were concerned about the quality-of-service delivery, environment and aesthetics, and the effectiveness of wayfinding signs in an airport. Moreover, *wayfinding* is fundamental in guiding efficient movement in an airport. Effective wayfinding signs can help guide efficient movement through the facilities, reduce congestion, and decrease the risks of delays to airport services. Therefore, passengers perceive *wayfinding* as a significant factor in driving ASQ satisfaction.

Table 5
Summarized statistics based on the North America Airport Satisfaction Study.

Resource	Year	Number of Airports	Mean	S.D.
J.D. Power (2016)	2016	60	745	32.1
J.D. Power (2017)	2017	58	761	29.4
J.D. Power (2018)	2018	56	772	27.2
J.D. Power (2019)	2019	53	776	35.1
J.D. Power (2020)	2020	57	794	28.4
J.D. Power (2021)	2021	39	804	18.3

Table 6
ANOVA for pre-COVID-19 and post-COVID-19 periods.

Topic	No. of observations in each topic	F
Rating	98	103.112***
Access	96	4.720*
Check-in	74	14.163***
Security	97	23.304***
Wayfinding	94	13.297***
Arrival	54	23.796***
Facilities	96	0.477
Environment	97	27.078***
Personnel	97	84.199***

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

A few pairs of independent variables deliver remarkably high correlations as well, including *access* and *wayfinding* ($r = 0.73$), *environment* and *wayfinding* ($r = 0.75$), *personnel* and *wayfinding* ($r = 0.73$), and *security* and *personnel* ($r = 0.74$). This is possible because these ASQ topics are tightly associated within reviews. For example, passengers were likely to mention *security* and *personnel* in the same reviews since the service from TSA officers could play an important role in shaping passengers' impression of the security process.

Next, a multi-linear regression was implemented to reexamine the relationship between rating and eight ASQ topics (i.e., identify which ASQ topics could explain the change in ratings). The regression model uses a linear relationship to evaluate the relationship between a dependent variable and two or more independent variables. In this multi-linear regression model, the dependent variable is the average airport rating, and the independent variables are the average sentiment scores for the identified ASQ topics.

The data to fit the regression model was taken as panel data. For each of the 98 airports, its average rating and sentiment scores for eight ASQ topics were observed during two periods (i.e., pre-COVID-19 and post-COVID-19). An airport could have unique features (e.g., location, scale, or condition) that may not change over two periods. Such features become omitted variables when they are absent from the model, affecting the dependent and independent variables in an unobservable manner and causing heterogeneity across groups (i.e., refer to differences across investigated airports). To address this issue, the fixed-effects model can help remove such time-invariant heterogeneity across groups by assuming a fixed group (Torres-Reyna, 2007). Therefore, a fixed-effects regression model was performed in this study, aiming to reduce the impact on the dependent variable *rating* resulting from each airport's unobservable time-invariant characteristics. The mathematical equation of a fixed-effects regression is listed below,

$$Y_{it} = \alpha_i + \beta_1 X_{1,it} + \ldots + \beta_k X_{k,it} + \varepsilon_{it} \tag{5}$$

where

i = airport (1–98)
t = period (0 = pre-COVID-19, 1 = post-COVID-19)
Y_{it} is the dependent variable (the average rating of airport i at period t)
$X_{k,it}$ is the kth independent variable (the sentiment score of the kth ASQ topic)
α_i is the unobserved time-invariant individual effect for airport i
β_k is the coefficient for the kth independent variable
ε_{it} is the error term

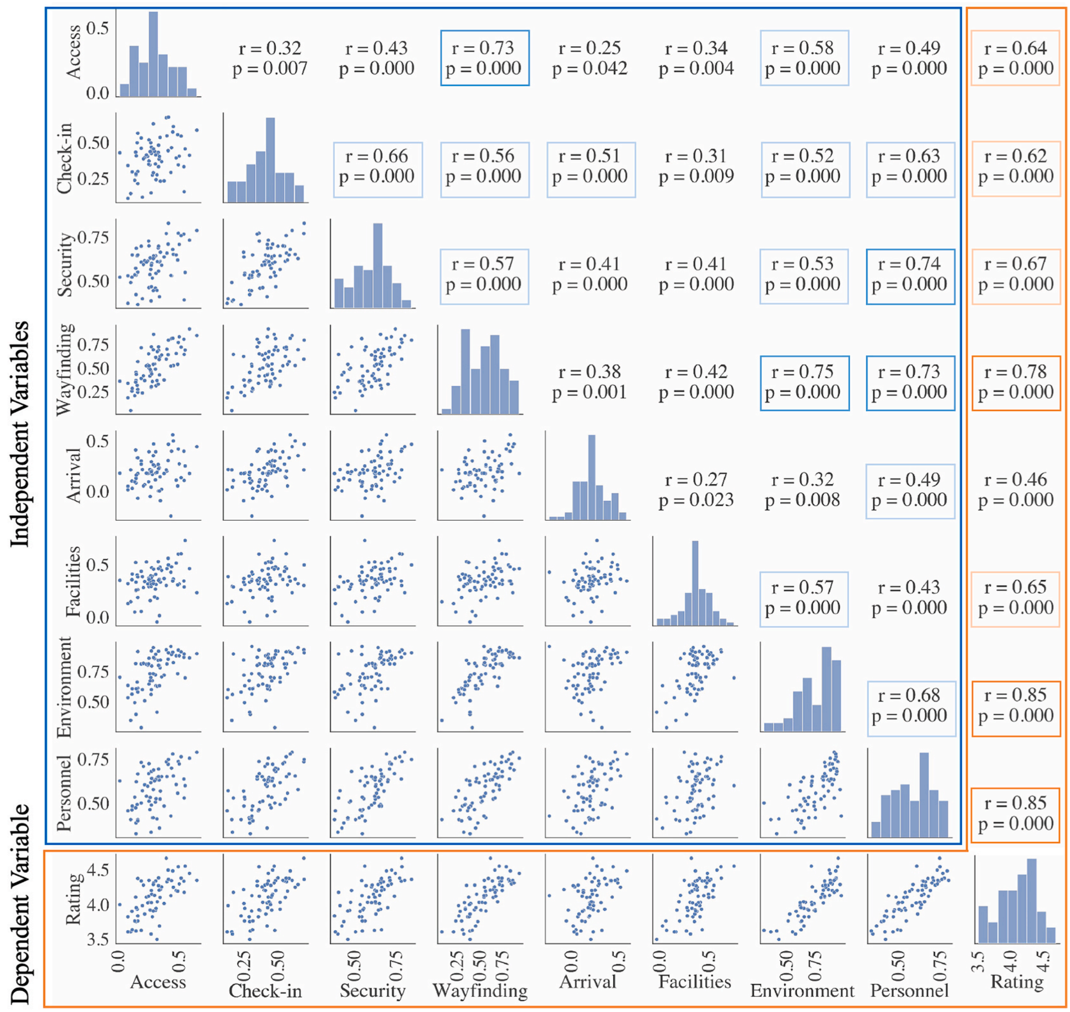

Fig. 6. Correlation results between ASQ topics and the service rating.

For each period, an observation was removed from the dataset prior to fitting the regression model when an airport dataset has less than 15 comments in each ASQ topic. Following this, $i = 60$ observations in the pre-COVID-19 group and $i = 69$ observations in the post-COVID-19 group were retained. It is worth noting that the fixed-effects regression model assumes errors ε_{it} to be independently and identically distributed (i.e., heteroskedasticity is not present). Before building the model, a modified Wald statistic was calculated using Stata command xttest3 to detect whether groupwise heteroskedasticity existed in the regression model (Baum, 2001). As a result, the test rejected the null hypothesis of homoskedasticity, revealing the presence of heteroskedasticity. Robust standard errors were then applied to control the heteroskedasticity (Hoechle, 2007).

The regression result is shown in Model 1, as presented in Table 7. Model 1 investigates the relationships between independent variables (i.e., eight ASQ attributes plus *period*) and the dependent variable *rating*. As a result, *check-in* (p-value < 0.05), *environment* (p-value < 0.001), and *personnel* (p-value < 0.001) show significant relationships with *rating* regardless of the impacts of COVID-19 periods. Such significant relationships of *personnel* and *check-in* revealed by the regression model are consistent with Halpern and Mwesiumo's (2021) findings that a passenger is unlikely to be a promotor of that airport when the service relative to airport staff and queueing times fail. Their study also suggests that shopping and Wi-Fi service play an unessential role in airport service, which supports the insignificance of *facilities* based on the regression result.

The coefficient (0.185**) of the binary variable *period* (0 = pre-COVID-19, 1 = post-COVID-19) manifests that *rating* is significantly higher after COVID-19 compared to that before COVID-19. This indicates that customers were less likely to blame an individual airport for increased restrictions during the pandemic, given that this problem might be pervasive in many service industries. For example, Sun et al. (2021) investigated China's hotel industry and found that customers became more tolerant of the hotel service during the COVID-19 pandemic. This regression analysis is consistent with the ANOVA result in Section 4.1, implying that airport service has gained more positive sentiment from passengers in the aftermath of the COVID-19 outbreak.

Model 2 investigates how each ASQ topic affects the change of *rating* over the two periods and tests the interaction between each ASQ topic and the binary variable *period*. The result is presented in Table 7. It suggests that the effect of *facilities* on *rating* has decreased (a negative coefficient with p-value < 0.05). A possible explanation is that passengers spent less time dining and shopping since many restaurants and shops at airports temporarily closed or restricted service hours during the pandemic, thereby weakening the importance of *facilities* as an evaluation criterion of service quality. While there might be an expectation that subcategories of *environment*, such as cleanliness and air quality, would have a more significant impact on *rating* during the COVID-19 pandemic (Halpern and Mwesiumo, 2021), our result shows that *environment* remains an important attribute for *rating* in both periods.

Table 7
Fixed-effects regression analysis.

Independent variables	Model 1		Model 2		Model 3a		Model 3b		Model 3c	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Access	0.341	0.173	0.552**	0.159	0.421*	0.170	0.343	0.177	0.353*	0.173
Check-in	0.254**	0.085	0.100	0.099	0.235**	0.082	0.258**	0.081	0.235*	0.098
Security	0.059	0.195	0.269	0.228	0.081	0.191	0.060	0.198	0.142	0.253
Wayfinding	0.252	0.158	0.214	0.143	0.236	0.162	0.249	0.166	0.248	0.161
Arrival	0.198	0.125	0.254*	0.119	0.230	0.126	0.202	0.126	0.225	0.124
Facilities	0.112	0.212	0.185	0.213	0.048	0.205	0.108	0.198	0.104	0.203
Environment	0.868***	0.175	0.754***	0.199	0.929***	0.159	0.868***	0.173	0.824***	0.193
Personnel	0.748***	0.135	0.649**	0.182	0.653***	0.154	0.744***	0.143	0.719***	0.146
Period	0.185**	0.058	0.403**	0.122	0.251**	0.080	0.191*	0.091	0.277*	0.135
Access × Period			−0.165	0.167	−0.223*	0.112				
Check-in × Period			0.169	0.200			−0.015	0.138		
Security × Period			−0.046	0.245					−0.151	0.194
Wayfinding × Period			0.064	0.196						
Arrival × Period			0.245	0.169						
Facilities × Period			−0.344*	0.147						
Environment × Period			−0.104	0.177						
Personnel × Period			−0.132	0.195						
Constant	2.39***	0.074	2.371***	0.067	2.392***	0.073	2.394***	0.076	2.393***	0.074
Observations	129		129		129		129		129	
F	456.75***		281.62***		522.77***		458.54***		451.49***	
R^2	0.950		0.955		0.949		0.950		0.951	

Independent variables	Model 3d		Model 3e		Model 3f		Model 3g		Model 3h	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Access	0 .366*	0.159	0.350	0.178	0.451**	0.150	0.459**	0.159	0.386*	0.167
Check-in	0.260**	0.080	0.252**	0.082	0.169*	0.076	0.223**	0.079	0.261**	0.082
Security	0.081	0.191	0.081	0.186	0.162	0.172	0.178	0.365	0.070	0.191
Wayfinding	0.303	0.158	0.280	0.164	0.173	0.139	0.184	0.138	0.222	0.157
Arrival	0.223	0.119	0.145	0.117	0.374**	0.113	0.304**	0.112	0.228	0.117
Facilities	0.003	0.202	0.096	0.218	0.300	0.201	0.007	0.206	0.063	0.197
Environment	0.903***	0.159	0.860***	0.174	0.703***	0.180	0.950***	0.163	0.852***	0.169
Personnel	0.668***	0.144	0.776***	0.141	0.625***	0.143	0.610***	0.144	0.745***	0.140
Period	0.282***	0.076	0.161*	0.073	0.369***	0.066	0.380***	0.087	0.319**	0.101
Access × Period										
Check-in × Period										
Security × Period										
Wayfinding × Period	−0.204*	0.081								
Arrival × Period			0.103	0.142						
Facilities × Period					−0.428***	0.116				
Environment × Period							−0.274**	0.089		
Personnel × Period									−0.245	0.143
Constant	2.402***	0.076	2.374***	0.076	2.429***	0.068	2.374***	0.075	2.415***	0.076
Observations	129		129		129		129		129	
F	435.90***		440.91***		409.94***		455.59***		379.95***	
R^2	0.949		0.947		0.948		0.947		0.950	

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

It is worth noting that Model 2 includes 17 independent variables, giving rise to a concern that including too many variables may impair the power of the analyses especially when the sample is small (Tabachnick and Fidell, 2012, p. 11). Therefore, Model 3a through 3h were implemented to provide supplementary analyses in addition to Model 2, as presented in Table 7. These eight models include only one interaction term (i.e., the interaction between one of the ASQ topics and *period*) at a time. As suggested by the result of Model 3a, Model 3d, Model 3f, and Model 3g, the effects of *access*, *wayfinding*, *facilities*, and *environment* have significantly decreased since COVID-19. This result implies that passengers were more likely to give consistently high ratings during the COVID-19 pandemic, weakening the impact of individual ASQ topics on *rating*. This is also consistent with the increased averaged *rating* and decreased standard deviation as presented in Table 4, which further suggests that passengers might become less sensitive when evaluating airport service during the COVID-19 pandemic.

4.3. LSVA word analysis

This section continues to explore what factors in ASQ topics could contribute to the sentiment changes by extracting textual information from customer reviews. Following the LSVA approach introduced in Section 3.4, Fig. 7 shows each word's relative importance in each ASQ topic. A higher salience indicates that a word is more widely mentioned in the dataset, and a higher valence implies that a word receives a more positive sentiment from customer reviews.

For the topic *access* (Fig. 7a), terms of high salience include "park," "car," "shuttle," "train," "rental," and "bus." Although these words are frequently mentioned, their valences are not high. By contrast, the terms "metro" and "access," although less mentioned in the reviews, are more favorable according to the valence. Compared to the pre-COVID-19 period, most words (especially "transportation") show a higher valence during the post-COVID-19 period. One possible explanation is that the number of visiting passengers was significantly reduced due to government agencies' travel restrictions. As recorded, there was about a 90% decrease in year-over-year available seat kilometers (Suau-Sanchez et al., 2020). This sharp decline in air travel could save rooms for

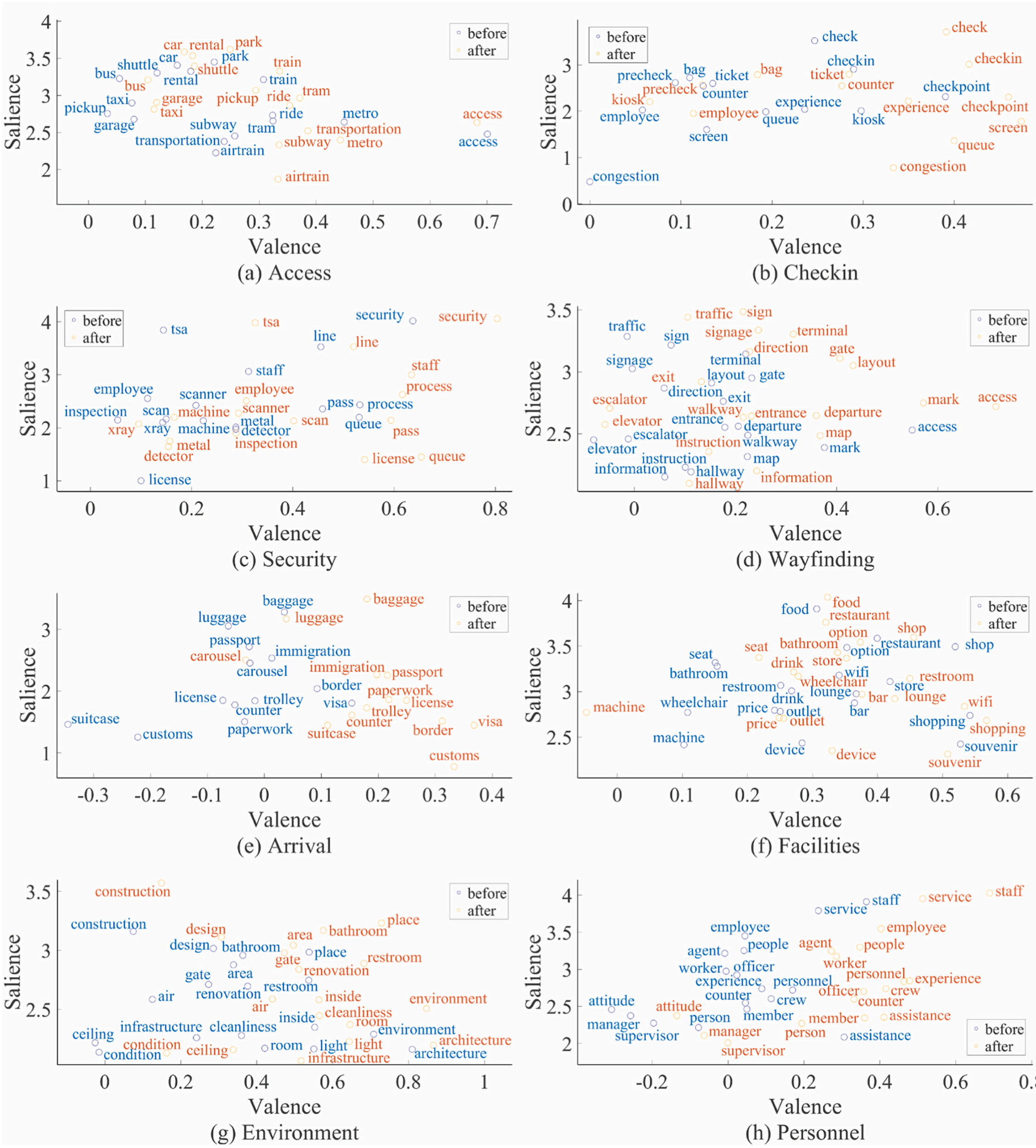

Fig. 7. Relative importance of each attribute in ASQ topics proxied by the LSVA approach.

parking and transportation traffic, which improved customer satisfaction with airport accessibility. Meanwhile, the travel restriction policy could affect public transportation services, and the valence of some words in this topic (e.g., "rental" and "metro") dropped.

Passengers spend much time from check-in through security screening until boarding; hence the efficiency of these mandatory processes significantly impacts passengers' perceptions of airport service. The *check-in* topic (Fig. 7b) shows multiple positive terms, such as "screen," "checkpoint," and "check-in." In particular, the valence of words, including "screen," "check," and "check-in," exemplifies a significant increase, confirming the improvement of check-in process during the COVID-19 pandemic. Such increase possibly results from the optimization of queueing process by implementing preventive measures (e.g., safety distancing, wearing masks, and restricting enforcement (Harvard and Chan School of Public Health, 2020)). Meanwhile, technical devices (e.g., facial recognition and iris scanning) that help combat the COVID-19 transmission hazards (Serrano and Kazda, 2020) might contribute to the overall customer satisfaction in the check-in process. However, the word "kiosk" shows a decreased valence during the COVID-19 pandemic, implying that the airport administration might not deliver constant and consistent effort in improving the check-in facilities.

The topic *security* focuses on the TSA screening process. Terms including "line," "staff," and "security" display a high salience and valence in both pre-COVID-19 and post-COVID-19 periods, implying that travelers were satisfied with airport security management. Terms including "security," "queue," "tsa," "license," "scan," and "staff" have shown a significant increase in sentiment since the COVID-19 pandemic (Fig. 7c). The TSA officers might have used a variety of procedures (e.g., social distance) to limit physical contact for both TSA agents and travelers who went through security screening (Lanzito, 2021). As a result, customer satisfaction with *security* was enhanced. Another interesting observation is that some facility-related words, such as "x-ray" and "machine," show a decrease in valence. This observation is consistent with the previous statement that the airport administration might not put extra effort into improving the security facility, possibly due to a shortage of labor or funding.

For the topic *wayfinding*, passengers have paid much attention to the aspects of "traffic," "sign," "signage," "terminal," "gate," and "direction" (Fig. 7d). Travelers need sufficient information to navigate to terminals and gates. As Prentice and Kadan (2019) emphasized, improving airport signage and information screens could feed more positive comments from passengers. An airport with a well-structured layout, explicit signage, and smooth traffic could facilitate the boarding process and save time for passengers to switch airlines. This statement especially holds for the LSVA result in the post-COVID-19 period, as illustrated by a noticeable increase in valence for words "signage," "sign," "mark," "layout," "direction," "terminal," "gate," and "map." Such sentiment increase in *wayfinding* possibly results from the reduced volume of passengers and effective management during the COVID-19 pandemic. However, the valence of "escalator" and "elevator" is decreased and slightly negative, suggesting that wayfinding facilities need further improvement.

Airport *arrival* services refer to the assistance to arriving passengers, including passport and identification card checks at the immigration checkpoint, customs inspection, and luggage delivery. All terms in the *arrival* domain show increased valence after COVID-19, as illustrated by Fig. 7e. In particular, terms including "visa," "passport," and "license" show higher valence as compared to other words, implying that airport administrations performed well in the passport control process. Terms relative to baggage claim, including "baggage," "trolley," and "luggage," show a significant increase, suggesting a boost in passengers' satisfaction with baggage service. Again, such improvement could result from reduced passenger traffic or improved airport management during COVID-19. Regardless of the positive changes, the valence of "carousel" decreases to negative, which suggest that baggage claim facilities demand improvement.

For the topic *facilities*, no noticeable changes are observed throughout the periods regarding beverage and food-related words, such as "bar," "option," "drink," and "food." The valence of the terms "shopping," "shop," "souvenir," and "outlet" approximately remains identical within the two study periods. This observation is consistent with a prior study stating that shopping services have little influence on passengers' satisfaction (Halpern and Mwesiumo, 2021). Nevertheless, the valence regarding terms "bathroom," "restroom," "wheelchair," and "seat" presents a significant difference between the two periods, which reveals that hygiene-related and accessible facilities have been improved.

For the topic *environment* (Fig. 7g), the valence of terms related to hygiene conditions, such as "bathroom," "restroom," "air," and "cleanliness," has significantly increased. Cleanliness in the airport is particularly important during the COVID-19 pandemic since a clean and sanitary environment could help reduce virus transmission and make travelers feel secure when traveling (Tuchen et al., 2020). Bogicevic et al. (2013) also suggested that a pleasant and clean environment is the key satisfier to attracting more passengers. As illustrated by the increase in valence, cleanliness and environment have obtained a higher evaluation from airport customers since the COVID-19 outbreak. Other terms relative to airport physical outlook like "architecture," "light," "design," "ceiling," and "renovation," although less mentioned, have also gained more positive sentiment from air travelers.

Last, the topic *personnel* is important for customer satisfaction. In line with the ANOVA result in Section 4.1, the valence of frequently mentioned words in *personnel* domain presents a significant increase (Fig. 7h, almost all words in blue color locates right to their counterparts in orange color). In particular, the valence of terms "staff," "service," "employee," "people," "agent," "officer," "counter," "crew," and "worker," is significantly greater than that from the pre-COVID-19 period. This reflects that air travelers have received more satisfactory service and assistance from airport staff. Nevertheless, it should be noted that terms "attitude" and "manager" remain negative in valence, *albeit* slightly increase during COVID-19, which reveals a challenge for airport staff to enhance workplace attitudes and a necessity for managers to improve managerial skills.

5. Discussion

Effectively measuring ASQ is crucial for airport management. Learning from the "voice of the customer" allows airport administration to understand and meet customers' needs and expectations. Therefore, this study proposes a crowdsourcing framework for ASQ assessment and investigates ASQ of the 98 busiest U.S. airports via Google Maps reviews. This research framework intends to extract valuable insights learned from unstructured online reviews. By doing so, this research develops a topic ontology to identify critical topics in ASQ and applies NLP sentiment analysis to classify customer reviews. Regarding the first research question, this study finds that *environment* and *personnel* have significant differences in sentiment after the COVID-19 outbreak according to ANOVA result. However, *facilities* does not show a significant change in the post-COVID-19 period. Regarding the second research question, this study shows that *check-in*, *environment*, and *personnel* are the key ASQ attributes that demonstrate significant relationships with *rating* in both in pre- and post-COVID periods. With regards to the change over the two periods, the effect of *access*, *wayfinding*, *facilities*, and *environment* has decreased. Overall, our findings reveal the potential of the data-driven crowdsourcing approach in the field of ASQ and imply helpful strategies for airport operators to consider in the context of the COVID-19 pandemic.

5.1. Theoretical and practical implications

This study provides several theoretical contributions to the research on information extraction of online reviews relevant to airport management. First, this study has presented an iterative process to inform a topic ontology with mapping words. The subjects of this ontology were determined using a top-down process based on subject matter expertise, and the mapping words were collected from a bottom-up process by manually reviewing the most occurring words from learner reviews. This topic ontology can serve as a library for the machine to capture valuable information from a large dataset of online reviews. Using this ontology, this study has discussed the applications of using an NLP sentiment tool to obtain topic-level sentiment for granular insights. In addition, this study has provided insights regarding the applications of crowdsourcing learned from the "voice of the customer" to understand holistic airport management. The result analysis has demonstrated the utility of online reviews to find what ASQ topics matter to fliers, especially in the COVID-19 pandemic.

For practical implications, this study first sheds light upon several implications regarding the airport improvements for decision-makers to consider, especially in the context of COVID-19. The implications are twofold. For individual airports, this approach allows airport administrations to quickly assess satisfactory and unsatisfactory areas. For example, the LaGuardia Airport (LGA) has a low sentiment in *wayfinding* (Fig. 2a), which implies that air passengers are less satisfied with direction signs in LGA, so more effective flight information and signages should be needed. For the airport industry in the U.S., one noteworthy point is that most investigated airports have improved in ASQ except for *facilities* after the COVID-19 outbreak. This implies that airport management has maintained a safe and hygienic environment and enhanced service but might not put enough effort into facility operations.

This study also provides some practical implications regarding airport hubs, as illustrated by Fig. 4. For example, decision-makers from large hubs may need to focus more on improving the efficiency of airport check-in and wayfinding processes. Environmental conditions and personnel's service are the other challenges for large hubs to consider enhancing their competitiveness. Moreover, words analysis from online reviews suggests that fundamental management in the airport, such as bathroom cleanliness, staff courtesy, and security check-in, are crucial to

ASQ during COVID-19. Given that the valence of facility-related words in *wayfinding*, *access*, *arrival*, and *security* is not high, there is an opportunity to improve passenger traveling experience during COVID-19 by deploying more advanced technologies, such as mobile apps, self-service kiosks, and AI-powered chatbots.

In addition, this study provides some practical insights to help airport administrations consider the determinants of passenger satisfaction. Due to the COVID-19 crisis, the airport management is facing unprecedented changes and challenges, such as the rising financial tensions across sectors (Choi, 2021). This study shows that *check-in*, *environment*, and *personnel* are critical for passenger satisfaction. This insight can help airport administration better invest money and time and ensure those that do matter are appropriately addressed. It also implies that airport administrations need a deeper understanding of passengers when determining operation policy, such as securing a clean and safe environment or improving membership services. From a broader point of view, this crowdsourcing approach provides a quick assessment for airport operators to prioritize capital and labor resources in response to the management challenges resulting from the COVID-19 pandemic.

5.2. Limitations and future work

Several limitations within this data-driven crowdsourcing approach are worthy of note. One limitation is associated with the data preparation. During the data collection process, it was noticed that a few airports only have limited reviews regarding specific ASQ topics. These observations were removed from the analysis to avoid the small sampling issue in which a few sentiment classifications could significantly affect the assessment. The scheme for data split could be another limitation. Since the downloaded Google Maps review data does not have an accurate date, reviews posted after the first COVID-19-related word appeared in the dataset were treated as "post-COVID-19" reviews. This handling could result in some loss of review data, although it ensures the accuracy of opinions posted before and after the COVID-19 outbreak.

In addition, the topic ontology was developed based on manual reviews of the top 10,000 most frequent words. This word screening process was based on the authors' interpretations of airport management expressed in online reviews. As a result, the library might not include all terms describing ASQ topics. More importantly, relying on words or word patterns might not always accurately identify ASQ topics from a review in different contexts. For example, for the review "*Parking garages cost 5 bucks for the first hour and the first 15 min are free though and that helps relieve some of the congestion*," the word "congestion" could imply an issue for access traffic or movement inside the terminal.

Another significant limitation comes from the sentiment analysis. First, sentiment analysis can only help classify the emotion of a review. Some helpful information from a customer review, such as the reasons for an unsatisfied service or the anticipated needs to improve service, cannot be captured by sentiment tools. In other cases, the lexicon-based sentiment tool may incorrectly detect the sentiment. For example, the analysis may not be able to correctly identify ironic words or judge argots. The sentiment analysis also subjects to the capability of Google translation. In the collected dataset, many reviews were written in other languages, such as Chinese, French, and Spanish. A passenger's attitude could be misclassified due to the limitation of translation. Last, the sentiment score in this study was calculated based on sentence unit, but a sentence could include conflicting sentiments given different ASQ topics.

Relying on crowdsourcing can help reduce the bias of those choosing to participate in an open-ended survey, but it still has the bias of those choosing to post a public comment (Li et al., 2022) about the airport service. In other words, people who write reviews may not fully represent the target population. It has been reported that young and educated people are more likely to post reviews online, given their habits and experience using social media and online platforms (Barberá and Rivero, 2015; Li et al., 2021; Mellon and Prosser, 2017). In addition, people who have an extremely good or bad experience are more likely to post reviews (Filieri, 2016), which could result in a significant variance. In other cases, people may share their experiences on other social media platforms, such as Facebook or Twitter, or many of them only use ratings rather than writing down experiences to express their attitudes toward airport service. These cases can affect the data quality and make results biased.

Last, some potential future work is worthy of consideration. First, data from other sources can be integrated with the current assessment to reduce the impacts of imbalanced data. For example, combining data from Google Maps and Twitter could refine the data quality by dealing with the bias from a more widely representative population. Another future work could focus on developing a complete topic ontology by reviewing more words. Last, future work could pay attention to the improvement of the aspect-based sentiment analysis by applying more state-of-the-art NLP and machine learning techniques that consider the sentence context. The advanced sentiment analysis could generate a more accurate analysis regarding passengers' insights into airport service.

Author contributions

- Li, L. contributed to conceptualization, data curation, methodology, formal analysis, visualization, writing – original draft, and writing – review & editing.
- Mao, Y. contributed to investigation, data curation, visualization, writing – original draft, and writing – review & editing.
- Wang, Y. contributed to methodology, data curation, data analysis, writing – original draft, and writing – review & editing.
- Ma, Z. contributed to conceptualization, data curation, writing – original draft, and writing – review & editing.

Declaration of completing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

A list of 98 airports is presented in Table A1. It includes the following information: (1) rank (based on the number of reviews downloaded from Google Maps review), (2) airport full name, (3) airport code, (4) airport location, (5) enplaned passengers in 2019 based on the Bureau of Transportation Statistics (Bureau of Transportation Statistics, 2019), (6) hub type based on Federal Aviation Administration data portal (FAA, 2022), (7) pre-COVID-19 rating (calculated based on Google Maps reviews from the pre-COVID-19 period), (9) post-COVID-19 rating (calculated based on Google Maps reviews from the post-COVID-19 period), and (10) whether upgraded during the study period (based on information collected from online news).

The upgrade status of airports is based on authors' judgment on related news reporting on the upgrade of infrastructure or layout in airports. For example, the Department of Palm Beach International Airport reported multiple facility improvement projects to the infrastructure airport, such as terminal roof and escalator replacement (Beebe, 2020). In this case, the upgrade status is identified as "Y" in Table A1. The upgrade status is also identified as "Y" if there is an ongoing renovation to an airport. For example, Fresno Yosemite International Airport has expanded its terminal by adding two gates and a baggage makeup system (Q & D Construction, 2022). If no news or reports are available online relative to the renovation during the study period, then the status is identified as "N." As a result, 37 airports upgraded their infrastructure or layout for better service during the study period. The sentiment increases for some airports after the COVID-19 outbreak, as reported in Section 4.1, could result from airport renovations. For example, the LGA has shown a significant sentiment increase since the COVID-19 outbreak (Fig. 3), possibly resulting from several major modernization millstones in recent years (Airport Technology, 2022).

Table A1
The list of 98 airports.

Rank	Airport	Airport full name	Code	Location	Passenger enplanements (2019, million)	Hub type	Pre-COVID-19 rating	Post-COVID-19 rating	Upgraded?
1	Atlanta	Hartsfield-Jackson Atlanta International Airport	ATL	Atlanta, GA	53.49	P-L	3.34	3.91	N
2	Los Angeles	Los Angeles International Airport	LAX	Los Angeles, LA	42.88	P-L	2.96	3.61	Y
3	Chicago O'Hare	O'Hare International Airport	ORD	Chicago, IL	40.87	P-L	3.00	3.82	Y
4	Dallas/Fort Worth	Dallas/Fort Worth International Airport	DFW	Dallas, TX	35.76	P-L	3.27	3.82	Y
5	Denver	Denver International Airport	DEN	Denver, CO	33.58	P-L	3.56	3.86	N
6	New York JFK	John F. Kennedy International Airport	JFK	New York, NY	31.04	P-L	2.86	3.95	N
7	San Francisco	San Francisco International Airport	SFO	San Francisco, CA	27.70	P-L	3.57	4.27	N
8	Seattle	Seattle-Tacoma International Airport	SEA	Seattle, WA	24.96	P-L	3.01	4.03	Y
9	Orlando	Orlando International Airport	MCO	Orlando, FL	24.55	P-L	2.96	3.92	N
10	Las Vegas	McCarran International Airport	LAS	Las Vegas, NV	24.41	P-L	3.57	4.03	N
11	Charlotte	Charlotte Douglas International Airport	CLT	Charlotte, NC	24.18	P-L	2.82	3.75	N
12	Newark	Newark Liberty International Airport	EWR	Newark, NJ	23.14	P-L	2.36	3.58	N
13	Phoenix	Phoenix Sky Harbor International Airport	PHX	Phoenix, AZ	22.41	P-L	3.58	4.02	Y
14	Houston Bush	George Bush Intercontinental Airport	IAH	Houston, TX	21.90	P-L	3.29	3.90	N
15	Miami	Miami International Airport	MIA	Miami, FL	21.29	P-L	2.99	3.84	N
16	Boston	Boston Logan International Airport	BOS	Boston, MA	20.68	P-L	3.34	3.93	N
17	Minneapolis	Minneapolis–Saint Paul International Airport	MSP	Minneapolis, MN	19.15	P-L	3.67	4.15	N
18	Detroit Metro	Detroit Metropolitan Wayne County Airport	DTW	Detroit, MI	18.12	P-L	3.86	4.22	N
19	Fort Lauderdale	Fort Lauderdale-Hollywood International Airport	FLL	Fort Lauderdale, FL	17.94	P-L	2.83	3.76	Y
20	Philadelphia	Philadelphia International Airport	PHL	Philadelphia, PA	15.99	P-L	2.78	3.62	N
21	New York LaGuardia	LaGuardia Airport	LGA	New York, NY	15.39	P-L	2.13	3.98	Y
22	Baltimore	Baltimore/Washington International Thurgood Marshall	BWI	Baltimore, MD	13.23	P-L	3.57	4.10	Y
23	Salt Lake City	Salt Lake City International Airport	SLC	Salt Lake City, UT	12.83	P-L	3.76	3.64	Y
24	San Diego	San Diego International Airport	SAN	San Diego, CA	12.64	P-L	3.35	4.21	N
25	Washington Dulles	Dulles International Airport	IAD	Washington, DC	11.86	P-L	3.34	4.01	N
26	Washington Reagan	Ronald Reagan Washington National Airport	DCA	Washington, DC	11.58	P-L	3.55	4.03	Y
27	Tampa	Tampa International Airport	TPA	Tampa, FL	10.92	P-L	4.10	4.50	Y
28	Chicago Midway	Chicago Midway International Airport	MDW	Chicago, IL	10.06	P-L	3.13	3.13	Y
29	Honolulu	Daniel K. Inouye International Airport	HNL	Honolulu, HI	9.89	P-L	2.79	3.61	Y
30	Portland	Portland International Airport	PDX	Portland, OR	9.79	P-L	4.29	4.26	N
31	Nashville	Nashville International Airport	BNA	Nashville, TN	8.92	P-M	3.69	3.95	Y
32	Austin	Austin-Bergstrom International Airport	AUS	Austin, TX	8.50	P-M	3.26	4.10	N
33	Dallas	Dallas Love Field Airport	DAL	Dallas, TX	8.07	P-M	4.05	4.33	N
34	St. Louis	St. Louis Lambert International Airport	STL	St. Louis, MO	7.75	P-M	3.04	3.92	N
35	San Jose	Norman Y. Mineta San Jose International Airport	SJC	San Jose, CA	7.68	P-M	3.72	4.25	N

(continued on next page)

Table A1 (*continued*)

Rank	Airport	Airport full name	Code	Location	Passenger enplanements (2019, million)	Hub type	Pre-COVID-19 rating	Post-COVID-19 rating	Upgraded?
36	Houston	William P. Hobby Airport	HOU	Houston, TX	7.06	P-M	3.75	4.20	Y
37	Raleigh/Durham	Raleigh-Durham International Airport	RDU	Raleigh/Durham, NC	6.91	P-M	3.77	4.38	N
38	New Orleans	Louis Armstrong New Orleans International Airport	MSY	New Orleans, LA	6.86	P-M	2.59	4.10	Y
39	Oakland	Oakland International Airport	OAK	Oakland, CA	6.54	P-M	3.12	4.04	N
40	Sacramento	Sacramento International Airport	SMF	Sacramento, CA	6.45	P-M	3.60	4.34	Y
41	Kansas City	Kansas City International Airport	MCI	Kansas City, MO	5.75	P-M	2.38	3.63	N
42	Santa Ana	John Wayne Airport	SNA	Santa Ana, CA	5.15	P-M	4.24	4.67	Y
43	Fort Myers	Southwest Florida International Airport	RSW	Fort Myers, FL	5.04	P-M	3.85	4.51	N
44	San Antonio	San Antonio International Airport	SAT	San Antonio, TX	5.02	P-M	3.75	3.78	Y
45	Cleveland	Cleveland Hopkins International Airport	CLE	Cleveland, OH	4.88	P-M	3.11	4.00	Y
46	Indianapolis	Indianapolis International Airport	IND	Indianapolis, IN	4.68	P-M	4.24	4.55	Y
47	Pittsburgh	Pittsburgh International Airport	PIT	Pittsburgh, PA	4.68	P-M	4.16	4.34	Y
48	San Juan	Luis Muñoz Marín International Airport	SJU	San Juan, PR	4.54	P-M	3.15	3.76	Y
49	Cincinnati	Cincinnati/Northern Kentucky International Airport	CVG	Cincinnati, OH	4.40	P-M	3.53	4.12	N
50	Columbus	John Glenn Columbus International Airport	CMH	Columbus, OH	4.16	P-M	3.68	4.13	N
51	Kahului	Kahului Airport	OGG	Kahului, HI	3.78	P-M	3.10	3.49	N
52	Jacksonville	Jacksonville International Airport	JAX	Jacksonville, FL	3.47	P-M	3.89	4.38	Y
53	West Palm Beach/ Palm Beach	Palm Beach International Airport	PBI	West Palm Beach/ Palm Beach, FL	3.45	P-M	3.99	4.48	Y
54	Milwaukee	General Mitchell International Airport	MKE	Milwaukee, WI	3.36	P-M	4.16	4.33	N
55	Hartford	Bradley International Airport	BDL	Hartford, CT	3.32	P-M	3.55	4.27	Y
56	Burbank	Bob Hope Airport	BUR	Burbank, CA	2.99	P-M	4.18	4.24	N
57	Ontario	Ontario International Airport	ONT	Ontario, CA	2.72	P-M	3.83	4.35	N
58	Anchorage	Ted Stevens Anchorage International Airport	ANC	Anchorage, AK	2.65	P-M	4.28	4.38	N
59	Albuquerque	Albuquerque International Sunport Airport	ABQ	Albuquerque, NM	2.64	P-M	4.07	4.36	N
60	Omaha	Eppley Airfield Airport	OMA	Omaha, NE	2.45	P-M	3.42	4.34	N
61	Buffalo	Buffalo Niagara International Airport	BUF	Buffalo, NY	2.45	P-M	3.92	4.28	N
62	Charleston	Charleston AFB/International Airport	CHS	Charleston, SC	2.38	P–S	3.86	4.29	N
63	Memphis	Memphis International Airport	MEM	Memphis, TN	2.31	P–S	3.00	3.69	N
64	Richmond	Richmond International Airport	RIC	Richmond, VA	2.19	P–S	3.84	4.17	N
65	Reno	Reno/Tahoe International Airport	RNO	Reno, NV	2.16	P–S	3.82	4.34	N
66	Oklahoma City	Will Rogers World Airport	OKC	Oklahoma City, OK	2.13	P–S	3.64	4.08	N
67	Boise	Boise Air Terminal Airport	BOI	Boise, ID	2.05	P–S	4.29	4.56	N
68	Louisville	Louisville Muhammad Ali International Airport	SDF	Louisville, KY	2.04	P–S	3.83	4.22	N
69	Norfolk	Norfolk International Airport	ORF	Norfolk, VA	1.99	P–S	3.43	4.20	N
70	Providence	Theodore Francis Green State Airport	PVD	Providence, RI	1.97	P–S	4.08	4.22	Y
71	Spokane	Spokane International Airport	GEG	Spokane, WA	1.94	P–S	3.55	4.35	Y
72	Kona	Ellison Onizuka Kona International at Keahole Airport	KOA	Kona, HI	1.93	P–S	3.09	3.80	N
73	Tucson	Tucson International Airport	TUS	Tucson, AZ	1.85	P–S	4.04	4.48	Y
74	Grand Rapids	Gerald R. Ford International Airport	GRR	Grand Rapids, MI	1.78	P–S	3.82	4.52	Y
75	Long Beach	Long Beach Airport	LGB	Long Beach, CA	1.75	P–S	4.37	4.55	Y
76	El Paso	El Paso International Airport	ELP	El Paso, TX	1.74	P–S	4.11	4.45	N
77	Lihue	Lihue Airport	LIH	Lihue, HI	1.63	P–S	3.53	4.13	N
78	Birmingham	Birmingham-Shuttlesworth International Airport	BHM	Birmingham, AL	1.51	P–S	3.61	3.96	N
79	Sanford	Orlando Sanford International Airport	SFB	Sanford, FL	1.51	P–S	3.07	3.91	Y

(*continued on next page*)

Table A1 (*continued*)

Rank	Airport	Airport full name	Code	Location	Passenger enplanements (2019, million)	Hub type	Pre-COVID-19 rating	Post-COVID-19 rating	Upgraded?
80	Tulsa	Tulsa International Airport	TUL	Tulsa, OK	1.50	P–S	3.68	4.34	N
81	Albany	Albany International Airport	ALB	Albany, NY	1.50	P–S	3.70	4.32	N
82	Savannah	Savannah/Hilton Head International Airport	SAV	Savannah, GA	1.46	P–S	4.02	4.31	N
83	Des Moines	Des Moines International Airport	DSM	Des Moines, IA	1.42	P–S	3.88	4.26	N
84	Palm Springs	Palm Springs International Airport	PSP	Palm Springs, CA	1.31	P–S	3.94	4.48	Y
85	Myrtle Beach	Myrtle Beach International Airport	MYR	Myrtle Beach, SC	1.28	P–S	4.08	4.37	N
86	Rochester	Greater Rochester International Airport	ROC	Rochester, NY	1.28	P–S	3.53	4.34	Y
87	Greenville-Spartanburg	Greenville-Spartanburg International Airport	GSP	Greer, SC	1.27	P–S	4.09	4.56	N
88	Syracuse	Syracuse Hancock International Airport	SYR	Syracuse, NY	1.27	P–S	3.10	4.17	N
89	Knoxville	McGhee Tyson Airport	TYS	Knoxville, TN	1.24	P–S	3.56	4.40	N
90	Madison	Dane County Regional-Truax Field Airport	MSN	Madison, WI	1.15	P–S	4.15	4.29	N
91	St. Petersburg	St Pete Clearwater International Airport	PIE	St. Petersburg, FL	1.13	P–S	2.71	4.19	Y
92	Pensacola	Pensacola International Airport	PNS	Pensacola, FL	1.10	P–S	3.75	4.37	N
93	Little Rock	Bill and Hillary Clinton Nat Adams Field Airport	LIT	Little Rock, AR	1.08	P–S	3.19	3.77	N
94	Greensboro/High Point	Piedmont Triad International Airport	GSO	Greensboro/High Point, NC	1.07	P–S	4.00	4.28	Y
95	Sarasota/Bradenton	Sarasota/Bradenton International Airport	SRQ	Sarasota/Bradenton, FL	0.97	P–S	4.28	4.55	N
96	Fresno	Fresno Yosemite International Airport	FAT	Fresno, CA	0.97	P–S	3.23	4.13	Y
97	Fayetteville	Northwest Arkansas Regional Airport	XNA	Fayetteville, AR	0.89	P–S	3.79	4.53	N
98	White Plains	Westchester County Airport	HPN	White Plains, NY	0.86	P–S	3.11	3.93	N

References

ACI, . Research report: does passenger satisfaction increase airport non-aeronautical revenue? Comphrehensive Assessment.

ACI, 2020. ASQ survey – methodology. https://silo.tips/download/asq-survey-benchmarking-the-global-airport-industry-airports-council-internation.

ACI, 2021. World's best airports for customer experience revealed—ACI World. https://aci.aero/2021/03/01/worlds-best-airports-for-customer-experience-revealed/.

Airport Technology, 2022, June. Terminal B Redevelopment. *LaGuardia Airport*, New York, USA. https://www.airport-technology.com/projects/terminal-b-redevelopment-laguardia-airport/.

Allen, J., Bellizzi, M.G., Eboli, L., Forciniti, C., Mazzulla, G., 2020. Latent factors on the assessment of service quality in an Italian peripheral airport. Transport. Res. Procedia 47, 91–98. https://doi.org/10.1016/j.trpro.2020.03.083.

Antwi, C.O., Fan, C., Ihnatushchenko, N., Aboagye, M.O., Xu, H., 2020. Does the nature of airport terminal service activities matter? Processing and non-processing service quality, passenger affective image and satisfaction. J. Air Transport. Manag. 89, 101869 https://doi.org/10.1016/j.jairtraman.2020.101869.

Asuero, A.G., Sayago, A., Gonzalez, A.G., 2006. The correlation coefficient: an overview. Crit. Rev. Anal. Chem. 36 (1), 41–59.

Barakat, H., Yeniterzi, R., Martín-Domingo, L., 2021. Applying deep learning models to twitter data to detect airport service quality. J. Air Transport. Manag. 91, 102003 https://doi.org/10.1016/j.jairtraman.2020.102003.

Barberá, P., Rivero, G., 2015. Understanding the political representativeness of twitter users. Soc. Sci. Comput. Rev. 33 (6), 712–729. https://doi.org/10.1177/0894439314558836.

Baum, C.F., 2001. XTTEST3: Stata module to compute Modified Wald statistic for groupwise heteroskedasticity. In: Statistical Software Components. Boston College Department of Economics. https://ideas.repec.org/c/boc/bocode/s414801.html.

Beebe, L., 2020, December 17. Palm Beach international airport update. https://www.palmbeachtpa.org/static/sitefiles/meeting/2020_DEC_17_TPA_PBC_Airports_Update.pdf.

Bezerra, G.C.L., Gomes, C.F., 2016. Measuring airport service quality: a multidimensional approach. J. Air Transport. Manag. 53, 85–93. https://doi.org/10.1016/j.jairtraman.2016.02.001.

Bezerra, G.C.L., Gomes, C.F., 2020. Antecedents and consequences of passenger satisfaction with the airport. J. Air Transport. Manag. 83, 101766 https://doi.org/10.1016/j.jairtraman.2020.101766.

Bogicevic, V., Yang, W., Bilgihan, A., Bujisic, M., 2013. Airport service quality drivers of passenger satisfaction. Tourism Rev. 68 (4), 3–18. https://doi.org/10.1108/TR-09-2013-0047.

Bunchongchit, K., Wattanacharoensil, W., 2021. Data analytics of Skytrax's airport review and ratings: views of airport quality by passengers types. Res. Trans. Business Manage. 41, 100688 https://doi.org/10.1016/j.rtbm.2021.100688.

Bureau of Transportation Statistics, 2019. Airport rankings 2019. https://www.bts.gov/airport-rankings-2019.

Calisir, N., Basak, E., Calisir, F., 2016. Key drivers of passenger loyalty: a case of Frankfurt–Istanbul flights. J. Air Transport. Manag. 53, 211–217. https://doi.org/10.1016/j.jairtraman.2016.03.002.

Casado-Díaz, A.B., Pérez-Naranjo, L.M., Sellers-Rubio, R., 2017. Aggregate consumer ratings and booking intention: the role of brand image. Service Business 11 (3), 543–562. https://doi.org/10.1007/s11628-016-0319-0.

Chen, P.T., Hu, H.H.S., 2013. The mediating role of relational benefit between service quality and customer loyalty in airline industry. Total Qual. Manag. Bus. Excel. 24 (9–10), 1084–1095. https://doi.org/10.1080/14783363.2012.661130.

Cheung, C.M.K., Thadani, D.R., 2010, June. The effectiveness of electronic word-of-mouth communication: a literature analysis. BLED Proceedings. https://aisel.aisnet.org/bled2010/18/.

Choi, J.H., 2021. Changes in airport operating procedures and implications for airport strategies post-COVID-19. J. Air Transport. Manag. 94, 102065 https://doi.org/10.1016/j.jairtraman.2021.102065.

Chonsalasin, D., Jomnonkwao, S., Ratanavaraha, V., 2021. Measurement model of passengers' expectations of airport service quality. Int. J. Trans. Sci. Technol. 10 (4), 342–352. https://doi.org/10.1016/j.ijtst.2020.11.001.

Cuizon, J.C., Lopez, J., Rose Jones, D., 2018. Text mining customer reviews for aspect-based restaurant rating. Int. J. Comput. Sci. Inf. Technol. 10, 43–52. https://doi.org/10.5121/ijcsit.2018.10605, 06.

Dalla Valle, L., Kenett, R., 2018. Social media big data integration: a new approach based on calibration. Expert Syst. Appl. 111, 76–90. https://doi.org/10.1016/j.eswa.2017.12.044.

Del Chiappa, G., Martin, J.C., Roman, C., 2016. Service quality of airports' food and beverage retailers. A fuzzy approach. J. Air Transport. Manag. 53, 105–113. https://doi.org/10.1016/j.jairtraman.2016.02.002.

DKMA, 2021. Our story & people—airport market research & advisory services—DKMA. http://www.dkma.com/en/index.php/why-dkma/people.

Du, Z., Wang, L., Cauchemez, S., Xu, X., Wang, X., Cowling, B.J., Meyers, L.A., 2020. Risk for transportation of Coronavirus Disease from wuhan to other cities in China. Emerg. Infect. Dis. 26 (5), 1049–1052. https://doi.org/10.3201/eid2605.200146.

FAA, 2022. Welcome to the airport data and information portal (ADPI). https://adip.faa.gov/agis/public/#/airportSearch/advanced.
Fakfare, P., Wattanacharoensil, W., Graham, A., 2021. Exploring multi-quality attributes of airports and the asymmetric effects on air traveller satisfaction: the case of Thai International Airports. Res. Trans. Business Manage. 41, 100648 https://doi.org/10.1016/j.rtbm.2021.100648.
Filieri, R., 2016. What makes an online consumer review trustworthy? Ann. Tourism Res. 58, 46–64. https://doi.org/10.1016/j.annals.2015.12.019.
Fodness, D., Murray, B., 2007. Passengers' expectations of airport service quality. J. Serv. Market. 21 (7), 492–506. https://doi.org/10.1108/08876040710824852.
Google Maps, 2022. Explore and navigate your world. https://www.google.com/maps/about/#!#jump-link.
Halpern, N., Mwesiumo, D., 2021. Airport service quality and passenger satisfaction: the impact of service failure on the likelihood of promoting an airport online. Res. Trans. Business Manage. 41, 100667 https://doi.org/10.1016/j.rtbm.2021.100667.
Harvard, T.H., Chan School of Public Health, 2020. Assessment of risks of SARS-CoV-2 transmission during air travel and non-pharmaceutical interventions to reduce risk—phase one report: gate-to-gate travel onboard aircraft. https://cdn1.sph.harvard.edu/wp-content/uploads/sites/2443/2020/10/HSPH-APHI-Phase-I-Report.pdf.
Heinonen, K., 2011. Consumer activity in social media: managerial approaches to consumers' social media behavior: consumer activity in social media. J. Consum. Behav. 10 (6), 356–364. https://doi.org/10.1002/cb.376.
Hoechle, D., 2007. Robust standard errors for panel regressions with cross-sectional dependence. STATA J.: Promote Commun. Stat. Stata. 7 (3), 281–312. https://doi.org/10.1177/1536867X0700700301.
Hong, S.-J., Choi, D., Chae, J., 2020. Exploring different airport users' service quality satisfaction between service providers and air travelers. J. Retailing Consum. Serv. 52, 101917 https://doi.org/10.1016/j.jretconser.2019.101917.
Hutto, C.J., Gilbert, E., 2014. VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text, p. 10.
Kraemer, M.U.G., Yang, C.-H., Gutierrez, B., Wu, C.-H., Klein, B., Pigott, D.M., , Open COVID-19 Data Working Group, du Plessis, L., Faria, N.R., Li, R., Hanage, W.P., Brownstein, J.S., Layan, M., Vespignani, A., Tian, H., Dye, C., Pybus, O.G., Scarpino, S.V., 2020. The effect of human mobility and control measures on the COVID-19 epidemic in China. Science 368 (6490), 493–497. https://doi.org/10.1126/science.abb4218.
Lanzito, C., 2021, December. TSA Announces New Airport Scree*ning Procedures*. AARP. In: https://www.aarp.org/travel/travel-tips/safety/info-2020/new-tsa-security-procedures.html.
Lee, K., Yu, C., 2018. Assessment of airport service quality: a complementary approach to measure perceived service quality based on Google reviews. J. Air Transport. Manag. 71, 28–44. https://doi.org/10.1016/j.jairtraman.2018.05.004.
Li, L., Erfani, A., Wang, Y., Cui, Q., 2021a. Anatomy into the battle of supporting or opposing reopening amid the COVID-19 pandemic on Twitter: a temporal and spatial analysis. PLoS One 16 (7), e0254359. https://doi.org/10.1371/journal.pone.0254359.
Li, L., Ma, Z., Cao, T., 2021b. Data-driven investigations of using social media to aid evacuations amid Western United States wildfire season. Fire Saf. J. 126, 103480 https://doi.org/10.1016/j.firesaf.2021.103480.
Li, L., Johnson, J., Aarhus, W., Shah, D., 2022a. Key factors in MOOC pedagogy based on NLP sentiment analysis of learner reviews: what makes a hit. Comput. Educ. 176, 104354 https://doi.org/10.1016/j.compedu.2021.104354.
Li, L., Zhou, J., Ma, Z., Bensi, M.T., Hall, M.A., Baecher, G.B., 2022b. Dynamic assessment of the COVID-19 vaccine acceptance leveraging social media data. J. Biomed. Inf. 129, 104054 https://doi.org/10.1016/j.jbi.2022.104054.
Liou, J.J.H., Tang, C.-H., Yeh, W.-C., Tsai, C.-Y., 2011. A decision rules approach for improvement of airport service quality. Expert Syst. Appl. 38 (11) https://doi.org/10.1016/j.eswa.2011.04.168. S0957417411006956.
Luo, J.M., Vu, H.Q., Li, G., Law, R., 2021. Understanding service attributes of robot hotels: a sentiment analysis of customer online reviews. Int. J. Hospit. Manag. 98, 103032 https://doi.org/10.1016/j.ijhm.2021.103032.
Martin-Domingo, L., Martín, J.C., Mandsberg, G., 2019. Social media as a resource for sentiment analysis of Airport Service Quality (ASQ). J. Air Transport. Manag. 78, 106–115. https://doi.org/10.1016/j.jairtraman.2019.01.004.
Mathayomchan, B., Taecharungroj, V., 2020a. How was your meal?" Examining customer experience using Google maps reviews. Int. J. Hospit. Manag. 90, 102641 https://doi.org/10.1016/j.ijhm.2020.102641.
Mathayomchan, B., Taecharungroj, V., 2020b. How was your meal?" Examining customer experience using Google maps reviews. Int. J. Hospit. Manag. 90, 102641 https://doi.org/10.1016/j.ijhm.2020.102641.
Mellon, J., Prosser, C., 2017. Twitter and Facebook are not representative of the general population: political attitudes and demographics of British social media users. Res. Pol. 4 (3), 205316801772000 https://doi.org/10.1177/2053168017720008.
Munawir, Koerniawan, M.D., Dewancker, B.J., 2019. Visitor perceptions and effectiveness of place branding strategies in thematic parks in bandung city using text mining based on Google maps user reviews. Sustainability 11 (7), 2123. https://doi.org/10.3390/su11072123.
Pabedinskaitė, A., Akstinaitė, V., 2014. Evaluation of the airport service quality. Proc. Soc. Behave. Sci. 110, 398–409. https://doi.org/10.1016/j.sbspro.2013.12.884.
Pandey, M.M., 2016. Evaluating the service quality of airports in Thailand using fuzzy multi-criteria decision making method. J. Air Transport. Manag. 57, 241–249. https://doi.org/10.1016/j.jairtraman.2016.08.014.
Park, J.Y., Mistur, E., Kim, D., Mo, Y., Hoefer, R., 2022. Toward human-centric urban infrastructure: text mining for social media data to identify the public perception of COVID-19 policy in transportation hubs. Sustain. Cities Soc. 76, 103524 https://doi.org/10.1016/j.scs.2021.103524.
Power, J.D., 2016. Airports rise to challenge of higher traveler volume, aging infrastructure. https://www.jdpower.com/business/press-releases/2016-north-america-airport-satisfaction-study.
Power, J.D., 2017. North American airports effectively navigating construction, capacity challenges. J.D. Power Finds (in%20Orange,with%20a%20score%20of%20810. https://www.jdpower.com/business/press-releases/jd-power-2017-north-america-airport-satisfaction-study#:~:text=Airport%20Satisfaction%20Rankings&text=John%20Wayne%20Airport%20.
Power, J.D., 2018. North America airports set record for passenger satisfaction amid surging passenger volumes and ongoing construction projects. J.D. Power Finds. https://www.jdpower.com/business/press-releases/2018-north-america-airport-satisfaction-study.
Power, J.D., 2019. North American airports struggle to keep travelers happy amid construction delays and surging passenger volumes. J.D. Power Finds. https://www.jdpower.com/business/press-releases/2019-north-america-airport-satisfaction-study.
Power, J.D., 2020. Traveler satisfaction with North American airports soars to record high—for all the wrong reasons. J.D. Power Finds. https://www.jdpower.com/business/press-releases/2020-north-america-airport-satisfaction-study.
Power, J.D., 2021. Labor shortage, rising passenger volumes drag on airport traveler satisfaction. J.D. Power Finds. https://www.jdpower.com/business/press-releases/2021-north-america-airport-satisfaction-study.
Prentice, C., Kadan, M., 2019. The role of airport service quality in airport and destination choice. J. Retailing Consum. Serv. 47, 40–48. https://doi.org/10.1016/j.jretconser.2018.10.006.
Q & D Construction, 2022. Fresno yosemite international airport (FAT) terminal expansion—Q&D construction. https://qdconstruction.com/projects/fresno-yosemite-international-airport-fat-terminal-expansion/.
ReviewTrackers, 2021. Online reviews statistics and trends: a 2022 report by ReviewTrackers. Inmoment Company. https://www.reviewtrackers.com/reports/online-reviews-survey/.
Serrano, F., Kazda, A., 2020. The future of airports post COVID-19. J. Air Transport. Manag. 89, 101900 https://doi.org/10.1016/j.jairtraman.2020.101900.
Suau-Sanchez, P., Voltes-Dorta, A., Cugueró-Escofet, N., 2020. An early assessment of the impact of COVID-19 on air transport: just another crisis or the end of aviation as we know it? J. Transport Geogr. 86, 102749 https://doi.org/10.1016/j.jtrangeo.2020.102749.
Sun, S., Jiang, F., Feng, G., Wang, S., Zhang, C., 2021. The impact of COVID-19 on hotel customer satisfaction: evidence from Beijing and Shanghai in China. Int. J. Contemp. Hospit. Manag. 34 (1), 382–406. https://doi.org/10.1108/IJCHM-03-2021-0356.
Tabachnick, B.G., Fidell, L.S., 2012. Using Multivariate Statistics, sixth ed. Pearson Education.
Taecharungroj, V., Mathayomchan, B., 2019. Analysing TripAdvisor reviews of tourist attractions in Phuket, Thailand. Tourism Manag. 75, 550–568. https://doi.org/10.1016/j.tourman.2019.06.020.
Torres-Reyna, O., 2007. Panel Data Analysis: Fixed and Random Effects Using STATA. Data & Statistical Services, Princeton University. http://dss.princeton.edu/training.
Trischler, J., Lohmann, G., 2018. Monitoring quality of service at Australian airports: a critical analysis. J. Air Transport. Manag. 67, 63–71. https://doi.org/10.1016/j.jairtraman.2017.11.004.
Tuchen, S., Arora, M., Blessing, L., 2020. Airport user experience unpacked: conceptualizing its potential in the face of COVID-19. J. Air Transport. Manag. 89, 101919 https://doi.org/10.1016/j.jairtraman.2020.101919.
Waskom, M., 2021. seaborn: statistical data visualization. J. Open Sor. Software. 6 (60), 3021. https://doi.org/10.21105/joss.03021.
Wattanacharoensil, W., Schuckert, M., Graham, A., Dean, A., 2017. An analysis of the airport experience from an air traveler perspective. J. Hospit. Tourism Manag. 32, 124–135. https://doi.org/10.1016/j.jhtm.2017.06.003.
Yeh, C.-H., Kuo, Y.-L., 2003. Evaluating passenger services of Asia-Pacific international airports. Transport. Res. E Logist. Transport. Rev. 39 (1), 35–48. https://doi.org/10.1016/S1366-5545(02)00017-0.