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Article

Tasting Tranquility: The Impact of Food and Beverage on Stressed Travelers

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Abstract:
The paper studies the consumer behavior under stress for airport services in terms of consumer rating and recommendation. It takes into account the quantitative and qualitative reviews of travelers to identify the attributes affecting rating and recommendations. The crowd sourced data of 5034 travelers (62 airports ,28 countries, 2012 to 2024) consisted of -numeric ratings on eight airport quality attributes, textual reviews, overall rating and recommendation. multimethod approach was used for data analysis. Airport staff, queuing time, terminal sign and terminal seating emerged as important variables. Additionally, during stressed times, it is food and beverages offerings that tranquilizes consumer.

Keywords: Airport quality, rating & recommendation, textual review, crowdsourcing, NLP, stress, stringency index, pandemic, multimethod approach.

INTRODUCTION

Examining consumer perceptions of quality is a crucial aspect for organizations, as it involves navigating both positive and negative feedback and understanding their consequences. The existing body of literature emphasizes the significance of measuring consumer net promoter scores (NPS) and loyalty, which are pivotal for the long-term profitability and success of an organization (Reichheld, 2003). Metrics like customer satisfaction (CSAT) and NPS can be effectively gauged through consumer reviews and recommendations, providing valuable insights for organizations (Ho-Dac, Carson, and Moore, 2013).

Stress is a pervasive aspect of contemporary society, impacting individuals across diverse backgrounds, circumstances, and age groups. In recent decades, researchers have increasingly focused on understanding how stress influences various aspects of human behavior, including consumer decision-making processes. Understanding the impact of stress on consumer behavior has significant implications for marketers and policymakers. Marketers can leverage insights from research on stress and consumer behavior to develop targeted marketing strategies that resonate with stressed consumers. The relationship between stress and consumer behavior is multifaceted, with psychological factors playing a crucial role in shaping consumer responses to stressors. Research by Smith et al. (2018) found that individuals experiencing high levels of stress exhibited a greater tendency towards impulsive buying behaviors while study by Johnson et al. (2020) identified a positive association between stress levels and consumer preferences for familiar brands.

The COVID-19 pandemic has led to "self-isolation and social lockdown," resulting in heightened mental stress and triggering psychological and behavioral shifts (Witteveen, 2020; Manchia et.al., 2022).The unprecedented global outbreak of corona has dramatically reshaped numerous aspects of everyday life, significantly impacting the travel and transportation sectors (Serrano and Kazda, 2020). Airports, as pivotal nodes of global mobility, have faced unique challenges in managing passenger experiences during and after the pandemic. The pandemic has instigated a shift in passenger expectations, with an increased emphasis on a cleaner and safer airport environment. The heightened risk of human-to-human transmissions in large indoor gatherings has rendered airports vulnerable, prompting health concerns and necessitating a re-evaluation of safety measures (Du et al., 2020; Kraemer et al., 2020). This shift has compelled airport administrations to reinforce quarantine procedures and adapt to evolving circumstances (Serrano and Kazda, 2020). Consequently, these changes have the potential to influence travelers' behaviors and sentiments toward airport services, manifesting in concerns such as queues for temperature checks and sanitation conditions in restrooms. This research aims to explore how stress, induced by the stringency of pandemic lockdowns, affects consumer behavior in rating and recommending airport services.

Understanding consumer behavior under stress is critical for several reasons. Firstly, airports are high-stress environments even under normal circumstances due to factors such as security checks, flight delays, and the inherent anxiety associated with air travel. The additional stress from stringent COVID-19 lockdowns has likely exacerbated these pressures, influencing passengers' perception and behavior in new ways. In navigating this complex and changing environment, two pivotal questions arise for evaluation strategies: (1) What are the key attributes of services that drive passenger satisfaction at airport ? and (2)What are the changes in customer perception of airport quality due to stress?

Addressing the first question, previous research, as outlined by Barakat et al. (2021), has utilized surveys to explore representative samples of passengers' perspectives on airport service quality (Allen et al., 2020; Bezerra and Gomes, 2016; Hong et al., 2020). While traditional survey methods can offer valuable insights into airport service quality, the process of collecting responses is time-consuming and resource-intensive. Furthermore, a significant challenge lies in achieving broad geographical coverage and securing respondents from diverse socioeconomic backgrounds. For the second question, there is a vast and rapidly growing literature that has examined the impact of stress during pandemic on mental health both on the shorter and longer term. But Very few studies in marketing research have examined the role of stress on consumer behavior in service settings in general and airports specifically.

Building on this foundation, the current study employs a lexicon-based sentiment analysis tool to explore the airline service quality reviews and recommendations sourced through www.airlinequality.com.. This study seeks to identify specific stress-induced changes in how passengers rate and recommend airport services. The findings of this research are expected to provide valuable insights for airport administrations. By understanding the nuanced ways in which stress alters consumer expectations and satisfaction, airport services can be more effectively tailored to meet the evolving needs of passengers. Enhanced service delivery, informed by such insights, can lead to better ratings and recommendations, ultimately improving the overall passenger experience and airport reputation.

Furthermore, this study contributes to the broader field of consumer behavior under stress, an area that has been relatively under-explored. The unique context of airport services during a global health crisis offers a compelling case for examining the interplay between stress and consumer decision-making processes. Insights derived from this research may extend beyond the aviation industry, offering implications for other sectors where consumer stress is a significant factor.

The paper begins with discussion on the theoretical model, subsequently the methodology and results of data analysis are delineated ; followed by discussion and understanding of the theoretical and managerial implications of the results. The paper concludes highlighting the limitations of the current study, and scope for future research.

LITERATURE REVIEW

Customer Reviews

The assessment of customer satisfaction through Customer Ratings (CRat) and Customer Recommendations (CRec) stands as a fundamental quantitative metric in evaluating the success of marketing endeavors (Anderson, et al.,1994). Studies have consistently underscored the monetary implications of these metrics, elucidating its role in bolstering consumer purchases, fostering repeat business, and enhancing return on investment (Anderson et al., 1994; Soderlund, 1998,Hallowell, 1996; Chatterjee, et al.,2018). While repeat purchases significantly contribute to an organization's profitability and sustainability (Bandyopadhyay & Martell, 2007); customer recommendations augment the Net Promoter Score. Unveiling the drivers of customer ratings and customer recommendations across diverse contexts has remained a focal point of research (Anderson & Sullivan, 1993; Martensen, et al., 2000; Mouwen, 2015). This scrutiny becomes even more pertinent in service industries characterized by its heterogeneity and varied business models (Grewal, et al., 2010).

The advent of online reviews and ratings has reshaped consumer decision-making processes, with reviews influencing purchasing behaviors and shaping perceptions of products and services (Chevalier & Mayzlin, 2006; Duan, Gu, & Whinston, 2008). Companies often employ strategies to solicit positive reviews, understanding their pivotal role in driving revenue and profitability. However, existing literature primarily focuses on the impact of ratings and recommendations on consumer decisions and economic performance, neglecting the underlying psychological mechanisms and emotional nuances embedded in textual reviews (Hennig-Thurau et al., 2004; Cheung & Lee, 2012).

Analyzing ratings and recommendations in predefined aspects provides valuable insights into an organization's performance in specific areas. However, delving deeper into textual reviews offers a more comprehensive understanding. Textual reviews not only reveal overall sentiments and emotions but also provide insights into how various aspects are evaluated. Exploring the connection between these evaluations, sentiments, and emotions with customer ratings (CRat) and recommendation behavior (CRec) can yield valuable insights (Ye, Zhang, and Law, 2009).

In the context of tourism, online reviews play a crucial role in influencing consumer decision-making and perceptions. Existing literature has extensively discussed the impact of rating on travel-related choices and highlighted the factors that contribute towards favorable online reviews (Sparks and Browning, 2011; Lee, Law, and Murphy, 2011). Despite the significance of online reviews in the tourism sector, there is a notable gap in research regarding the recommendation behavior of consumers in this domain (Siering et al., 2018). This research aims to address this gap and contribute to a deeper understanding of how consumer sentiments and evaluations translate into rating and recommendation behaviors in the tourism sector. Thus the research question addressed in the paper is-

RQ1:.Does customer ratings and customer textual reviews (on airport service attributes) affect customer rating and recommendation behavior across various customer types?

Stress and Consumer Behavior

All areas of life are affected by the presence of stress. Stress can affect the ability to make decisions (Kahn and Baron 1995; Kunreuther et al. 2000; Starcke and Brand 2012) or interpersonal relationships (Bodenmann et al. 2010).

Sources of stress can stem from various aspects of life, including work-related pressures such as tight deadlines, high workloads, and conflicts with colleagues or supervisors (American Psychological Association, 2020). Financial strain is another significant source, with debt, unexpected expenses, and the pressure to meet financial obligations causing considerable anxiety (Mayo Clinic, n.d.). Personal relationships also contribute to stress, conflicts with family or friends, divorce, or the loss of a loved one being common triggers (American Psychological Association, 2020). Health issues, whether chronic illness, injury, or concerns about personal or family health, add another layer of stress (Mayo Clinic, n.d.). The COVID-19 pandemic has introduced new stressors, including fear of infection, social isolation, changes in work or schooling, and uncertainty about the future (Centers for Disease Control and Prevention, n.d.; Harvard Health Publishing, n.d.). Governments worldwide responded to the pandemic by implementing various public health strategies, such as border closures, quarantine initiatives, and the temporary shutdown of schools and non-essential businesses (Talic et al., 2021). While these measures effectively curbed the spread of infections and prevented healthcare systems from becoming overwhelmed, they also brought about significant economic and social repercussions, impacting individual behavior, mental well-being, and societal stability (Talic et al., 2021; Kaye et al., 2021). The stringency of these measures differed across regions and evolved over time, with many countries gradually easing restrictions in response to fluctuating infection rates and hospitalizations. Consequently, the effects of the pandemic and associated interventions varied globally (Prati and Mancini, 2021; Watkins-Martin et al., 2021). More stringent public health COVID-19 measures were associated with higher stress (Lorenzo et.al,). Samson and Voyer (2014) considered the impact of emergency purchase decisions (EPS) on buying and concluded that urgency (in time and needs) leads to stress among consumers, and the resulting stress affects, in turn, the manner of product evaluation. High levels of stress lead to a more heuristic evaluation compared to a reflective evaluation, with the latter being more careful and relying on costs and benefits of the product.

Gordon-Wilson (2021) observed that external factors like the COVID-19 pandemic have impacted consumers' sense of self-control, leading to changes in their shopping habits, preferred store formats, and consumption patterns of unhealthy snacks and alcohol.

Customers' assessments of quality and value, buying decisions, and recommendations are all influenced by emotions under stressful conditions. But too often companies don't adequately anticipate those emotions and therefore can't mitigate negative ones. This is especially true for high-emotion services—those that trigger strong feelings before the service even begins. Services relating to major life events such as birth, marriage, illness, and death fall into this category, as do airline travel, car repair, and home buying, selling, and renovation. This research aims to address this impact of stress on travelers sentiments and evaluations and how they translate into rating and recommendation. The second question that the research addresses is-

- RQ 2: Does customer stress affect customer rating and recommendation of Airport services ?

The study delves deep into the emotional dimensions of consumer reviews, recognizing the profound impact of emotions on customer satisfaction (Siering et al., 2018). By employing text mining techniques such as sentiment analysis and opinion mining, the researchers seek to extract actionable insights from textual data, enriching our understanding of customer sentiment and behavior. Adopting mixed methodology, the study strives to provide a comprehensive analysis of customer sentiment and behavior under stressful conditions, which may help in strategic decision-making and enhancing organizational performance in an increasingly stressful laden world.

METHODOLOGY

Data and Data Processing

Traditional approaches to gauging customer satisfaction often rely on survey-based methods employing Likert scales to measure latent constructs such as service quality, value, and trust (Taylor & Baker, 1994; Oh, H, 1999). However, as technology and internet usage advance, consumers increasingly engage in information sharing on online platforms, expressing their views, giving ratings, and providing recommendations on various services (Park, Gu, Leung & Konana, 2014). Social media and online platforms like Twitter, Facebook, Google Maps, have become popular for individuals to express opinions and sentiments (Heinonen, 2011). These platforms serve as channels that facilitate the quick dissemination of information on a large scale, overcoming social and geographical barriers (Cheung and Thadani, 2010).

Crowdsourcing through online platforms emerges as an innovative avenue for service providers to assess service quality, with applications across various domains like hotel administration (Luo et al., 2021), restaurant management (Mathayomchan and Taecharungroj, 2020a), and airport services (Martin-Domingo et al., 2019). Though crowdsourced information may skew towards certain demographic groups, such as the young and educated population (Barbera´ and Rivero, 2015; Mellon and Prosser, 2017), yet it serves as a valuable means for obtaining quick and geographically diverse information from a large population.

Leveraging consumer-generated ratings and reviews from crowd sourcing offers a novel avenue to understand and analyze customer sentiment free from biases inherent in survey data. The abundance of unstructured textual data poses challenges, but recent developments in data analytics and natural language processing (NLP) have made it feasible to extract valuable insights (Li et al., 2021b, 2022b). Numerous studies highlight the potential of NLP and machine learning techniques in analyzing customer reviews (Cuizon et al., 2018; Lee and Yu, 2018; Luo et al., 2021). Integrating qualitative and quantitative data through text mining techniques is the new imperative, to elucidate the drivers of CRat and CRec comprehensively and bridge the gap in existing literature.

Online data source is one of the major information sources for customer reviews. To facilitate our research and understanding thereof, we have used the data available from online sources to study customer reviews for airports. Data has been collected from airlinequality.com, a website, which collects customer reviews on various airports all over the world. The data contained 10,121 customer reviews of 62 airports from 28 countries (Table 1 and 2). These customer reviews were posted between 2012 and 2024. The dataset contained textual reviews given by travelers, overall rating, recommendation score, along with attribute-wise ratings, on the following eight attributes: terminal cleanliness, terminal seating, terminal sign, food and beverages,airport shopping wifi connectivity, airport staff and queuing time. The overall rating given by the consumers is on a 1 to 10-point rating scale, where 1 means highly dissatisfied and 10 means highly satisfied. The recommended score is captured on a binary scale where 0 means not recommended and 1 means recommended the airport to other customers. The eight attributes mentioned above are scored on a 5 star rating; 1 star means low score and 5 star means a high score. In the data we first looked for missing values and dropped the corresponding rows with missing values in any of the columns from our analysis thereby reducing the sample size to 5123.

Table 1: Countries covered in the study

Australia	Germany	Netherland	Spain
Austria	Hong Kong	New Zealand	Switzerland
Canada	India	Philippines	Thailand
China	Indonesia	Qatar	Turkey
Denmark	Italy	Riyadh	UAE
Finland	Japan	Singapore	UK
France	Malaysia	South Korea	USA

Table 2: Airports covered in the study

Amsterdam Schiphol	Dubai	London Gatwick	Seattle
Atlanta Hartsfield	Dublin	London Heathrow	Seoul Incheon
Auckland	Dusseldorf	London Stansted	Singapore Changi
Bangkok Suvarnabhumi	Edinburgh	Los Angeles LAX	Sydney
Barcelona	Frankfurt Main	Luton	Tokyo Narita
Beijing Capital	Geneva	Madrid Barajas	Tokyo Haneda
Berlin Tegel	Guangzhou	Manchester	Toronto Pearson
Birmingham	Hamad Doha	Manila Ninoy Aquino	Vancouver
Brisbane	Hamburg Lubek	Melbourne	Vienna
Chicago O'Hare	Helsinki Vantaa	Miami	Washington Dulles
Copenhagen	Hong Kong	Mumbai	Zurich
Copenhagen	Houston George Bush Intercontinental	Munich	
Dallas Fort Worth	Istanbul	Paris CDG	
Delhi	Jakarta	Perth	
Denver	Kansai	Riyadh	
Dubai	KLIA Kuala Lumpur International Airport	Rome Fiumicino	
Denver	Las Vegas	San Francisco	

To extract insights from text data, we employed preprocessing techniques. Initially, we cleaned the data by removing special characters, stop-words, spaces, and punctuation through conventional methods. This step aimed to refine the corpus for subsequent data analysis. Previous studies in marketing, information systems, and data science have utilized lexicons developed by computational linguistics researchers to ascertain sentiment and emotion scores from text (Dang, Zhang & Chen, 2010; Taboada, Brooke, Tofiloski, Voll & Stede, 2011; Mostafa, 2013). Although statistical learning-based sentiment prediction methods outperform lexicon-based approaches during training, their generalizability to new samples is comparatively lower (Taboada et al., 2011). Hence, lexicon-based methods are preferable when discerning the linguistic sentiment expressed within text. These lexicons furnish scores pertaining to positive/negative polarity and various emotions associated with words and phrases in a given text. While positive/negative polarity offers a broad indication of the text's valence, emotion scores afford a deeper, affective-cognitive understanding of its content. In our investigation, we utilized the NRC Word-Emotion Association Lexicon (also known as EmoLex) developed by Mohammad and Turney (2013), which assigns scores for emotions (anger, anticipation, disgust, fear, joy, sadness, surprise, trust).

Next, we evaluated the accuracy of sentiment and emotion scores through a preliminary examination involving 100 randomly selected reviews from the dataset. Three independent experts were tasked with reading the reviews and indicating their assessment on a 5-point Likert scale, where 1 signified "strongly disagree" and 5 represented "strongly agree," regarding whether positive/negative sentiment and the eight emotions were expressed in the reviews. The experts' average responses exhibited correlations with the overall sentiment (0.67) and the count of the eight emotions (anger = 0.69, anticipation = 0.75, disgust = 0.88, fear = 0.62, joy = 0.65, sadness = 0.77, surprise = 0.59, trust = 0.61). These findings suggest that the sentiment and emotion scores obtained possess sufficient validity to proceed with further analysis.

We also identified attribute-specific sentiments conveyed within the text. It's common for survey ratings to diverge from sentiments expressed in text, underscoring the importance of discerning consumer opinions regarding various service attributes. These opinions can significantly influence satisfaction levels and subsequent behavior. Following the methodology proposed by Siering et al. (2018), we adopted a two-step approach. Initially, we generated a bag of words tailored to elucidate specific aspects. We began by identifying words that appeared in at least 5% of the entire dataset. Our aim was to focus exclusively on nouns, as aspects are primarily delineated by them. To achieve this, we employed the POS tagging-based aspect selection method. Initially, we tagged the parts of speech of the words using the R package for Ripple Down Rules-based Part-Of-Speech Tagging (RDRPOS). This package is renowned for its pre-trained parts of speech tagging capabilities across 45 languages, including annotation-based parts of speech tagging for English, with its architecture developed by Nguyen et. al, (2016). Subsequently, we curated a subset of words containing only nouns, resulting in a list of 241 nouns..

To extract service aspects from these bags of words , the authors have utilized lexical salience-valence analysis (LSVA) (Taecharungroj and Mathayomchan, 2019), instead of using the approach adopted by Chatterjee (2019) in his study . LSVA aims to discern positive and negative words and their impact on sentiment in tourist attractions based on customer reviews. LSVA employs text mining to analyze the relationships between extracted words and sentiments within reviews by defining the salience and valence of words. In contrast to simply tallying the frequency of words in positive or negative reviews, LSVA enables visualization of word frequencies across the corpus of documents and their influence on overall sentiment. Salience and Valence for the selected 241 bag of words were computed using Python (Table 3). The computed salience and valence values were then subjected to cluster analysis, which resulted in the generation of three clusters. This clustering process was guided by an elbow plot, which exhibited a distinct "kink" at the point corresponding to three clusters. Initially out of 241 words 125, 68 and 48 words populated the first, second and third cluster respectively (Figure 1) which were further narrowed to 11, 9 and 9 in the respective clusters based on their score on salience and valence (Figure 2-4) and their relevance to airport services.

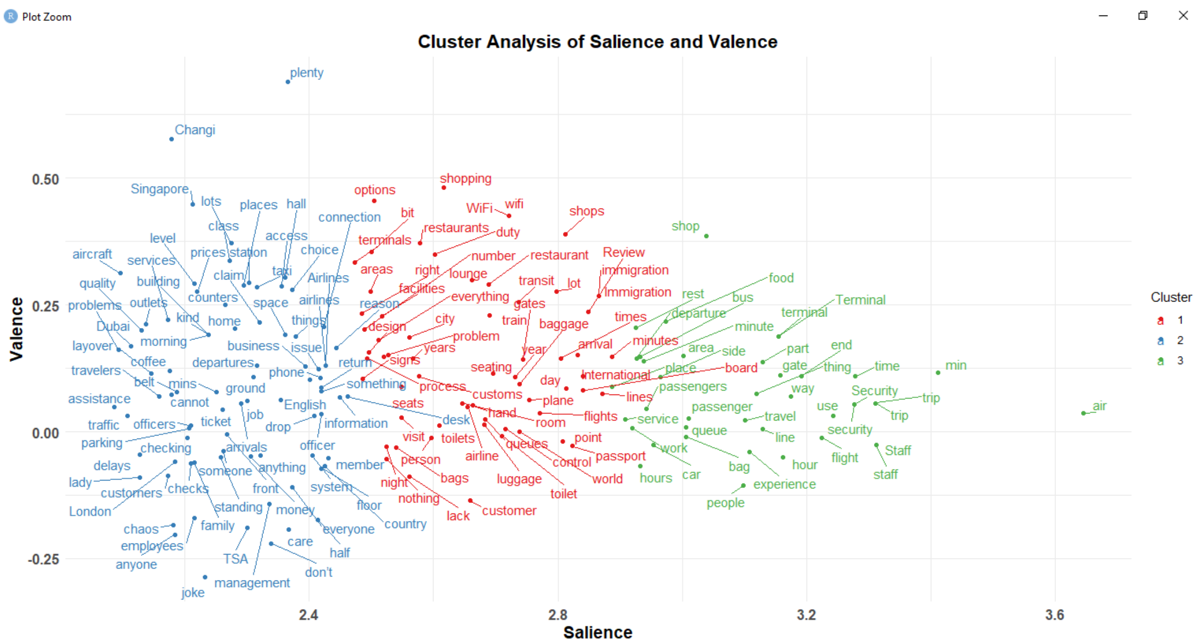

Figure 1: Cluster Analysis of Salience and Valence

Figure 1 Alt Text:The image shows a cluster analysis of salience and valence, categorizing airport-related terms into three clusters based on their emotional tone and significance.

FIGURE 2: BAG OF WORDS FOR CUSTOMER EXPERIENCE

Figure 2 Alt Text:The image shows a cluster analysis of customer experience terms, highlighting positive and negative valence

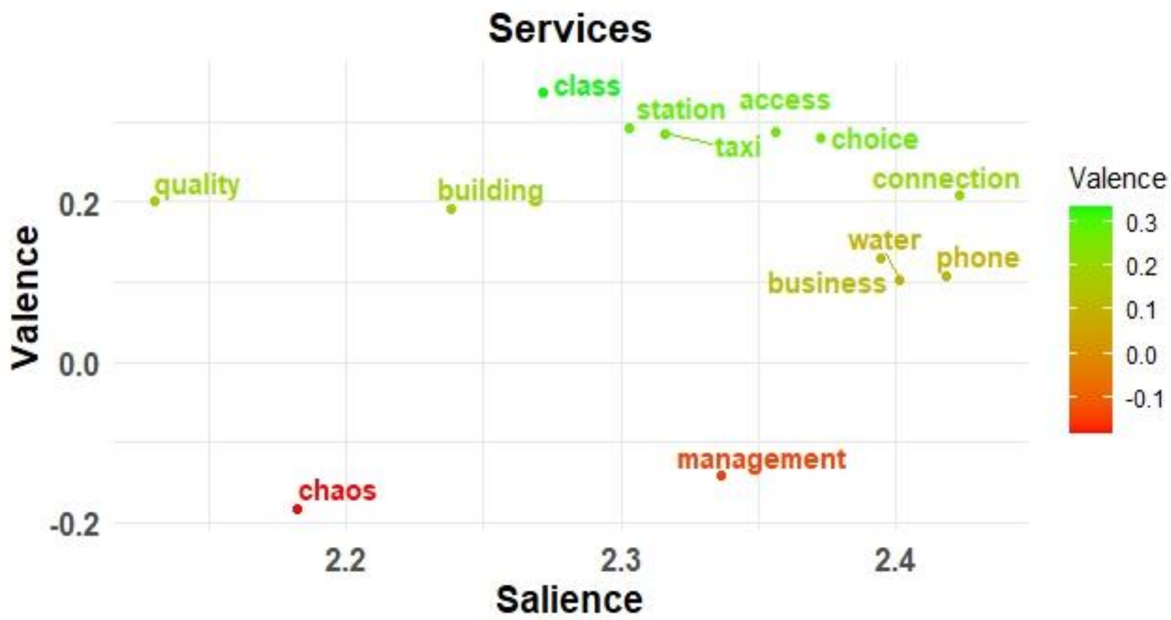

FIGURE 3: BAG OF WORDS FOR SERVICES

Figure 3 Alt Text:The image shows a cluster analysis of service-related terms, with positive valence terms and negative valence terms.

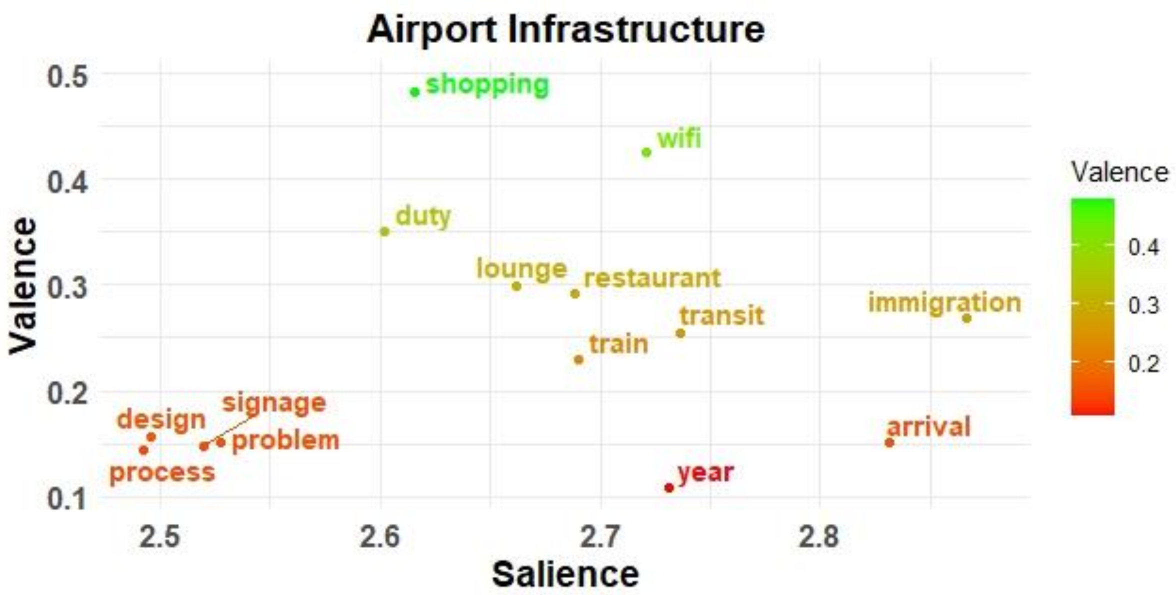

FIGURE 4:BAG OF WORDS FOR AIRPORT INFRASTRUCTURE & PROCESS

Figure 4 Alt Text:The image shows a cluster analysis of airport infrastructure, with positive valence terms and negative valence terms.

Subsequently, words associated with each cluster were identified, and the bag of words was appropriately named based on the predominant themes or characteristics of each cluster namely Airport Infrastructure and Process, Customer Experience and Services (Table 4). The three aspects are in accordance with the findings of Fodness and Murray (2007), who referred to them as- attributes of function (e.g., wayfinding, check-in), interaction (e.g., services), and diversion (e.g., dining, shopping, and internet) .

Table 3: Descriptive Statistics of Salience and Valence of quality aspects

Statistics	Customer experience		Airport infrastructure & process		Services	
	Salience	Valence	Salience	Valence	Salience	Valence
Mean	3.1	0.06	2.65	0.14	2.27	0.05
Standard Error	0.03	0.02	0.02	0.02	0.01	0.02
Median	3.07	0.06	2.65	0.11	2.27	0.07
Mode	3.01	0.03	2.74	0.11	2.42	0.19
Standard Deviation	0.19	0.11	0.12	0.2	0.12	0.21
Range	0.85	0.84	0.57	0.97	0.69	1.68
Minimum	2.86	-0.45	2.37	-0.28	1.8	-0.73
Maximum	3.7	0.39	2.94	0.69	2.49	0.95

Table 4: Bag of Words

S.No	Service Attributes	Bag of Words
1	Airport Infrastructure & Process	Immigration, Shopping, Restaurants, Transit, Gate, Seating, Arrival, Lounge, Signage, WiFi, Facilities
2	Customer Experience	Experience, Staff, Security, People, Time, Passengers, Minute, Rest, Area
3	Services	Service, Connection, Management, Space, Departures, Problems, Place, Access, Officers

After extracting the three service aspects, we proceeded to assess the sentiment associated with each service aspect. The reviews were segmented into sentence-level units and examined whether any word related to a service aspect were present within each sentence. We then extracted the sentiment from sentences that contained at least one word related to a service aspect. By aggregating the frequency of positive and negative words from these sentences, we derived the overall sentiment of the three service aspect expressed in a specific review. Table 2 provides a summary of the variables collected and generated to compile the dataset for our analysis..

Stringency Index

Government-imposed restrictions are known to induce significant stress among people. Research has shown that such measures can disrupt daily routines, limit social interactions, and create economic uncertainty, all of which contribute to heightened stress levels (Brooks et al., 2020). The psychological impact of prolonged restrictions can lead to increased anxiety, depression, and stress, as individuals cope with the uncertainty and changes in their environment (Pfefferbaum & North, 2020). Therefore, the authors have considered government-imposed COVID-19 restrictions as a measure of stress for this study.

The degree of stress is assessed not only by the stringency of the restrictions but also by their duration. The study incorporates data from the Oxford Coronavirus Government Response Tracker (OxCGRT) project (ourworldindata.org/covid-stringency-index), which provides information on the stringency of restrictions. The OxCGRT systematically gathered information on various policy responses implemented by governments to address the COVID-19 pandemic. It evaluated the stringency of these measures and combined them to create a unified Stringency Index. This index serves as a composite measure derived from nine different response metrics, including actions such as school closures, workplace shutdowns, limitations on public events, restrictions on gatherings, public transport closures, stay-at-home mandates, public awareness campaigns, controls on internal movements, and regulations on international travel. It's important to note that this index simply records the strictness of government policies. It does not measure or imply the appropriateness or effectiveness of a country's response. A higher score does not necessarily mean that a country's response is 'better' than others lower on the index. Study takes the average of the stringency Index for the duration that country was under covid restrictions.

Numerous studies show that parents are highly vigilant about their children's safety and tend to avoid sending them into potentially harmful situations. Morrongiello and Matheis (2004) found that parents are generally risk-averse and prioritize their children's safety, often restricting their activities to minimize exposure to danger. Additionally, Schwebel and Gaines (2007) emphasize that parental supervision and intervention are crucial for preventing childhood injuries, reinforcing the notion that parents will only allow their children to participate in activities when they are confident about their safety. Morrongiello and Lasenby-Lessard (2007) further highlight that parents who perceive higher risks are more likely to limit their children's exposure to potentially harmful situations. In light of these findings, it was decided that the day the government declares schools open will be considered the time when the COVID-19 threat has ended. Since different countries announced varying dates for school reopening, we relied on the dates published in major news sources to determine the end of lockdown. In instances where schools were reopened but subsequently closed due to a resurgence of COVID cases, the study considered the date of the last announcement regarding school reopening as the end of the lockdown period.

The OxCGRT computed the daily Stringency Index for each city. However, for our study's objectives, we computed the average stringency during Covid. This average stringency was then multiplied by the duration of the lockdown in that country, to quantify the stress experienced by citizens of that country. The period between the onset of the pandemic (April 1, 2020) and the reopening of schools was designated as the COVID phase

Thereafter the countries were categorized into four groups (Table 5): Category 1 represented the pre-COVID period (with no lockdown stress), Category 2 denoted low stress (stringency Index of less than 15,000), Category 3 indicated medium stress (stringency Index of between 15,000-30,000), and Category 4 reflected high stress (stringency Index of greater than 30,000).

TABLE 5: STRINGENCY INDEX OF VARIOUS COUNTRIES

Country	School opening dates	Average Stringency Index during	Covid Days	Discomfort Factor = Stringency x	Stress Level (Low = A, Med = B, High = C, Precovid = D)
Australia	03- May-20	71	32	2272	A
Austria	01-Feb-21	67.1	306	20532.6	B
Canada	01-Sep-20	70.42	153	10774.26	A
China	01-Sep-22	74.63	883	65898.29	C

Denmark	15-Apr-20	72.22	14	1011.08	A
Finland	14-May-20	69.36	43	2982.48	A
France	21-May-21	64.71	415	26854.65	B
Germany	21-Feb-21	65.54	326	21366.04	B
Hong Kong	29-Sep-20	60.47	181	10945.07	A
India	01-Nov-21	74.02	579	42857.58	C
Indonesia	31-Aug-21	67.66	517	34980.22	C
Italy	01-Sep-20	73.02	153	11172.06	A
Japan	29- Jun -20	38.82	89	3454.98	A
Malaysia	03-Oct-21	70.73	550	38901.5	C
Netherlands	10 Jan 22	59.47	649	38596.03	C
New Zealand	11-May-20	92.17	40	3686.8	A
Philippines	22-Aug-22	65.96	873	57583.08	C
Qatar	01-Sep-20	81.66	153	12493.98	A
Riyadh	30-Aug-20	79.29	151	11972.79	A
Singapore	02-Jun-20	77.83	62	4825.46	A
South Korea	21-Nov-21	53.4	599	31986.6	C
Spain	01-May-21	68.59	395	27093.05	B
Switzerland	11-May-20	71.85	40	2874	A
Thailand	29-Sep-21	57.08	546	31165.68	C
Turkey	06-Sep-21	64.66	523	33817.18	C
UAE	01-Jun-21	59.62	426	25398.12	B
UK	01-Mar-21	73.19	334	24445.46	B
USA	01-Sep-21	64.89	518	33613.02	C

Data Analysis

We aimed to elucidate the determinants of customer ratings and recommendations through a series of linear and logistic regression models, with the overall rating and recommendation as the dependent variable respectively. We employed quantitative ratings for eight service attributes as independent variables, alongside overall sentiment, eight emotions expressed in textual reviews, and three aspect-wise sentiment. The independent variables were regressed on customer rating and recommendation separately across various categories of travelers, namely - (i) low stress, moderate stress and high stress (Covid driven stress) (ii) native and non native (iii) solo, couple, family and business. Each model was subjected to assessments for multicollinearity and heteroscedasticity.

Notably, all variables exhibited a variance inflation factor lower than 4, indicating the absence of multicollinearity in the models. However, the non-constant variance test revealed the presence of heteroscedasticity in the linear models, attributed to the non-continuous distribution of overall ratings. Notably, previous research, such as Siering et al. (2018), commonly employs rating-based independent variables in regression models, as we have done in our study.

Regression Model for travelers under Stress
Rating
When the service quality attributes are regressed under no stress situation i.e. precovid, almost all the quality attributes barring the terminal cleanliness and wifi significantly affect CRat. It is worthy to note that the impact of these attributes has declined during the covid period and some have been insignificant. However food and beverages have continued to significantly affect CRat as food is essential to the survival of mankind. The positive emotions of trust, joy and surprise are marginally significant on CRat. The aspect related sentiments significantly affects CRat when traveler is not under any stress (pre-covid) only to wane during covid stress situations (Table 6).

Table 6: Customer Rating and Recommendation based on Stress Level

	RATING				RECOMMENDATION			
	No	**Low**	**Medium**	**High**	**No**	**Low**	**Medium**	**High**
ADJ. R^2/AIC	0.82	.82	.68	.734	1451.7	103.88	160.4	173.33
INTERCEPT	NA	NA	NA	NA	-8.10***	-17.06***	-10.13***	-10.11***
TERMINAL CLEANLINESS	.02*	0.01	.07*	0.006	0.01	.24	.63	.16
TERMINAL SEATING	0.12***	0.6	.05	.11**	0.41***	.28	.11	.38
TERMINAL SIGNS	0.12***	0.02	.09**	-0.04	0.51***	1.01**	.28	.22
FOOD AND BEVERAGES	0.05***	.19***	.02	.18***	0.25**	1.59**	.53	.76**
AIRPORT SHOPPING	0.06***	-.003	.06	.05	0.17*	-.15	.09	-.21
WIFI CONNECTIVITY	.01*	.03	.007	.03	0.07	.70*	.10	.10
AIRPORT STAFF	0.27***	.30***	.40***	.26***	0.52***	.42	.84***	.65**
QUEUING TIME	0.20***	.25***	.18***	.26***	0.40***	.32	.53**	.60**
TRUST	0.01*	.06*	.01	.07**	-0.003	.23	-.20	.12
JOY	.03***	-.03	-.04	0.001	-0.06	.39	.07	.07
ANTICIPATION	-0.01	.07*	.009	.04	-0.03	.03	-.10	0.02
SURPRISE	0.02*	.04	.04	.04	0.05	-.28	.08	-.16
SADNESS	-0.003	.03	-.01*	-.04	0.02	.03	-.24	-.11
ANGER	0.009	-.08**	.008	-.03	0.13*	-.34	.13	.01
FEAR	0.01	.06	.08	.05	0.03	.27	.13	.35
DISGUST	-0.01	.01	.006	-.07*	-0.12	-.22	-.02	-.12
CUSTOMER EXPERIENCE	0.02**	.003	.001	0.08**	1.9*	7.1	.14	3.17
AIRPORT INFRASTRUCTURE & PROCESS	0.06***	0.05	0.04	-.02	3.4***	5.5	.56	2.31
SERVICES	0.02***	.02	0.05	0.05	1.4	6.0	2.5	1.88
OVERALL SENTIMENT	0.12***	.14***	.11**	.11***	0.09***	.13	.03	.08

Output shows terminal cleanliness has positive relation with customer rating for travelers from medium stress nations (β_{MS} = 0.07, $p<0.05$), terminal seating has positive relation with customer rating for travelers from high stress countries (β_{HS} = 0.11, $p<0.01$) and terminal signs has positive relation with customer rating for travelers with medium stress countries (β_{MS} = 0.09, $p<0.01$). Food and beverages has positive relation with travelers rating for travelers from low and high stress nations. Airport staff and queuing time show positive relation with customer rating for travelers from all 3 categories (all p's <0.001) and the effect is more for airport staff than queuing time. In emotions, trust has positive relation with rating for travelers from low stress countries (β_{LS} = 0.06, $p<0.05$) as well as high stress countries (β_{LS} = 0.07, $p<0.01$) and anticipation has positive relation with rating for travelers from low stress countries (β_{LS} = 0.07, $p<0.05$). Sadness has negative relation with rating for travelers from medium stress countries (β_{MS} = -0.01, $p<0.05$), and emotion of anger has negative relation with rating for travelers from low stress countries (β_{LS} = -0.08, p<0.01). Emotion of disgust has negative relation with rating for travelers from high stress countries (β_{HS} = -0.07, p<0.05). In aspect wise sentiments, airport facility has positive relation with rating for travelers from high stress countries (β_{HS} = 0.08, p<0.001) and other aspects don't have any effect on customer rating. For overall sentiments, travelers rating has positive relations for those coming from low and high stress countries (β_{LS} = 0.14, p<0.001, β_{MS} = 0.11, p<0.01; β_{HS} = 0.11, p<0.001) .

Recommendations behavior

When the service quality attributes are regressed under no stress situation i.e. precovid, almost all the quality attributes barring the terminal cleanliness and wifi significantly affect CRec. The aspect related sentiments except services significantly affect CRec when the traveler is not under any stress (pre-covid) . Emotions do not have any significant effect on CRec, barring anger which has a negative effect on recommendation.

Study shows that airport shopping, WiFi connectivity and Terminal cleanliness are not affecting customers recommendations for travelers under no stress situation (Table 5). Output shows terminal cleanliness and terminal seating are not affecting customer recommendation behavior except terminal signs that have positive relation with CRec (β_{LS} = 1.01, p<0.01) for travelers from low stress countries. Food and beverages has positive relation with travelers recommendation for travelers from low and high stress nations (β_{LS} = 1.59, p<0.01; β_{HS} = .76, p<0.01). WiFi connectivity has positive relation with travelers recommendation from low stress countries (β_{LS} = 0.70, p<0.05). When it comes to effect of airport staff and queuing time on recommendation behavior it is strongly more positive for travelers from medium stress nations (β_{MS} = 0.84, p<0.001; β_{MS} = 0.53, p<0.01) than from high stress countries (β_{LS} = 0.65, p<0.01,; β_{MS} = 0.60, p<0.01). Customer emotions and aspect wise sentiments have no effect on the recommendation behavior.

Regression Model for Native and Non Natives travelers

- Rating
- Regression was carried out to see the effect of airport quality, emotions and aspect wise sentiments and overall sentiments on customer rating for native and non native (foreign) customers (Table 7).

Table 7: Customer Recommendation and Rating for Native and Non-Native Travelers

	Recommendation		**Rating**		
VARIABLES	**Native**	**Non Native**	**Native**	**Non Native**	**VIF**
AIC/ADJ. R²	**840,86**	**1018.8**	**0.787**	**0.822**	
INTERCEPT	**-8.5*** **	**-8.3*** **	**NA**	**NA**	
TERMINAL CLEANLINESS	**0.1**	**0.09**	**0.01**	**0.03** **	**2.64**
TERMINAL SEATING	**.35*** **	**.37*** **	**0.12*** **	**0.09*** **	**3.06**
TERMINAL SIGNS	**.43*** **	**.48*** **	**0.12*** **	**0.07*** **	**2.55**
FOOD AND BEVERAGES	**.22* **	**.42*** **	**0.02**	**0.11** **	**3.47**
AIRPORT SHOPPING	**0.11**	**0.16**	**0.06** **	**0.05*** **	**3.32**
WIFI CONNECTIVITY	**.24** **	**0.004**	**0.03** **	**0.003**	**1.77**
AIRPORT STAFF	**.56*** **	**.51*** **	**0.26*** **	**0.30*** **	**2.75**
QUEUING TIME	**.40*** **	**.43*** **	**0.21*** **	**0.20*** **	**2.34**
TRUST	**0.09**	**-0.06**	**0.03** **	**0.02* **	**1.38**
JOY	**-0.04**	**-0.04**	**0.03** **	**-0.02**	**2.23**
ANTICIPATION	**-0.05**	**-0.02**	**-0.01**	**-0.008**	**2.58**
SURPRISE	**0.06**	**0.03**	**0.01** **	**0.01**	**2.31**
SADNESS	**-0.03**	**0.003**	**-0.006**	**-0.01**	**2.87**
ANGER	**0.1**	**0.12**	**-0.01**	**0.007**	**1.76**
FEAR	**0.07**	**0.08**	**0.03**	**-0.03* **	**2.92**

DISGUST	**0.09**	**-.33*** **	**-0.008**	**-0.02***	**2.01**
CUSTOMER EXPERIENCE	**2.8**	**1.05**	**0.02***	**0.01**	**1.60**
AIRPORT INFRASTRUCTURE & PROCESS	**2.3**	**3.94*** **	**0.06*** **	**0.053*** **	**1.78**
SERVICES	**1.7**	**2.07***	**0.04*** **	**0.02** **	**1.36**
OVERALL SENTIMENT	**.09*** **	**.09*** **	**0.13*** **	**0.12*** **	2.50

Customer rating of airport quality is positively (all p's < 0.000) effected by Terminal Cleanliness and Food and Beverages for Non Native passengers but has no effect for Native customers. Further Terminal Seating, Sign, Airport shopping, Staff and Queuing Time are highly significant (all p's < 0.000) and effect customer rating of airport quality of both passenger categories, though there is marginal change, if any, in beta coefficients except for terminal signs and airport staff , beta coefficients is more for native than non-native passengers (β_N = .12, β_{NN} = .07, p<0.000; β_N = .26, β_{NN} = .30, p<0.000). Interestingly WiFi connectivity significantly effect customer rating for Native and not for non-native customers (β_N = .03, p = 0.01 β_{NN} = .003 p> .05). In aspect wise sentiments, airport infrastructure and process (p=0.05), and services, and overall sentiments positively (all p's < 0.000) effect customer rating of airport quality for both category of passengers, though the effect is more for Native than Non-native passengers (for airport infrastructure and process, β_N = 0.06, β_{NN} = 0.053, and for services β_N = 0.04, β_{NN} = .02). In emotions, Trust significantly effects customer ratings (β_N = .03, p < 0.01 β_{NN} = .02 p< .05) and this effect is more for native than non-native passengers. Emotion of surprise has positive effect for native passengers but no effect for non-native. (β_N = .01, p < 0.01 passengers. However, Disgust is significantly negatively effecting customer rating of airport quality (β_{NN} = -.02, p< 0.05) for non native tourists.

Recommendation

Output shows terminal sign, seating, airport staff and queuing time have strong positive relation (all p's < 0.001) with travelers recommendation of airport in both the categories, namely native and non native (Table 7). The effect of airport staff is more for native than non native while the effect of terminal sign, queuing time and airport seating is more for non-native than native traveler's. Food and beverages has strong positive relation for non-native than native traveller (β_N = 0.22, p <0.05, β_{NN} = .42, p <0.001). WiFi connectivity has significant positive relation for native travelers (p<0.01) but insignificant for non-native traveler. Emotion of disgust has significant negative effect on travelers recommendation for non-native (p<0.001) and insignificant for native passenger and overall sentiment has positive relation for both categories of travelers (all p's <0.001), airport infrastructure and process (p<0.001) and services (p<0.05) has strong positive effect for non-native and no effect for native travelers.

Regression Model for Solo, Couple, Family, Business travelers

Rating

Study assesses customer rating of airport service quality for various categories of traveler's, finding shows terminal cleanliness has positive relationship with customer rating of airport services for couple and family (p's < 0.05), whereas terminal seating and terminal sign has positive relationship with customer rating of airport services for all categories (all p's < 0.001), where the effect of terminal seating is more than terminal sign for all categories of travelers except couples (Table 8). Food and beverages show positive relationship with rating, for all categories (solo, business travelers, couple and family), however the effect is high in business categories. Airport shopping has a positive relationship with rating for solo and couple travelers (p< 0.001) and no relationship for family and business travelers. WiFi connectivity has a positive relationship with rating for business travelers (p < 0.05) and insignificant for others. Airport staff and queuing time has a strong positive relationship (all p's < 0.001) with customer rating of airport services for all categories of travelers and effect is more for airport staff than queuing time. Positive emotion of surprise has positive relation with customer rating for solo and couple travelers (β_S = .03, all p < 0.05, β_C = .04, all p < 0.05) and negative emotion of disgust has negative relation with rating for solo traveler (β_S = -.03, all p < 0.01). Overall sentiment has a positive relation with customer rating for all categories of travelers (all p's < 0.001). Aspect wise sentiments on customer experience has strong positive relation for solo traveler (β_S = .03, p <0.05), similarly airport infrastructure and process has strong positive relation for all category of travelers (all p's < 0.001) except solo where relation is insignificant. For services, the relationship is positive for couples and business travelers (all p's < 0.001) and insignificant for others.

Table 8: Customer Recommendation and Rating for various types of Travelers Services

	RECOMMENDATION	RATING	

VARIABLES	Solo	Couple	Family	Business	Solo	Couple	Family	Business	VIF
AIC/ADJ. R^2	721.09	363.51	411.61	414.06	0.81	0.74	0.84	0.78	
INTERCEPT	-8.18***	-9.5***	-9.3***	-7.9***	NA	NA	NA	NA	
TERMINAL CLEANLINESS	0.006	0.05	0.28	0.01	0.01	.04*	.04*	0.02	2.6
TERMINAL SEATING	.28**	.45**	0.23	.58***	.12***	.07**	.09***	.12***	3.1
TERMINAL SIGNS	.45***	.45**	.48***	.49***	.10***	.12***	.08***	.09***	2.2
FOOD AND BEVERAGES	.34**	0.29	.49**	0.25	.07***	.06*	.07**	.10***	3.2
AIRPORT SHOPPING	0.12	.40*	0.21	-0.01	.07***	.08***	0.03	0.03	2.9
WIFI CONNECTIVITY	.15*	0.02	0.09	0.09	0.02	-0.01	0.01	.03*	1.7
AIRPORT STAFF	.60***	.62***	.46***	.45***	.27***	.28***	.33***	.24***	2.4
QUEUING TIME	.35***	.41***	.49***	.55***	.21***	.18***	.20***	.22***	2.1
TRUST	.14*	-0.11	0.005	-0.09	.02	.02	.01	0.02	1.4
JOY	-0.05	0.06	-0.01	0.003	-.01	.04*	.05**	-.01	2.05
ANTICIPATION	-0.05	0.03	0.001	.13*	-.01	-.0006	.01	-.02	2.4
SURPRISE	0.02	0.05	0.02	0.06	.03*	.04*	.01	.01	2.1
SADNESS	0.01	-0.01	0.04	0.01	-.01	-.01	-.01	.01	2.5
ANGER	-.17*	-0.0009	0.08	0.05	.003	-0.005	.01	-.03*	1.6
FEAR	-0.0001	0.13	0.18	0.14	.02	.01	.02	-.05*	2.5
DISGUST	-0.1	-0.04	-.31*	-0.24	-.03**	-0.005	-.01	-.008	2.1
CUSTOMER EXPERIENCE	1.69	-0.34	2	1.9	.03**	.002	-.0004	.03	1.5
AIRPORT INFRASTRUCTURE & PROCESS	2.74*	8.7***	2.7	2.55	.02	0.1***	.06***	.07***	1.6
SERVICES	1.68	1.7	.7	3.56	.01	0.06***	.02	.04**	2.4
OVERALL SENTIMENT	.08***	.07**	.06**	.15***	.12***	.11***	.15***	.11***	2.4

Recommendation

Study assesses the effect of airport services on customer's recommendation behavior. It shows that terminal seating has a strong relationship with recommendation for business travelers (β_B = 0.58, p<0.001), then for couples and solo (β_C = 0.45, β_S = 0.28, all p's < 0.01). Airport staff, terminal sign and queuing time all have strong and positive relation with travelers recommendations (all p's <0.001) in the stated sequence for solo and couple travelers (Table 8). Queuing time , terminal sign and airport staff all have positive relation with travelers recommendation in the stated sequence for business category. For family travelers airport staff, terminal sign and queuing time all have equal impact on traveler recommendation. The effect of airport shopping has positive relation for couple traveller (β_B = 0.40, p<0.05) and WiFi connectivity has positive relation for solo traveller (β_B = 0.15, p<0.05). Food and beverages positively impact the tourist recommendation , more in case of family travelers than solo travelers (β_F =0.49, β_S= 0.34and p< 0.01). The effect of airport shopping on travelers recommendation is insignificant in all categories of travelers barring couple travelers ($\beta_{C=}$ 0.40, p< 0.05). Emotions of trust has positive relation for solo travelers (β_S = 0.14, p<0.05), anticipation has positive relation with recommendation for business travelers (β_F = 0.13, p<0.05), anger has negative relation for solo traveler (β_B = -0.17, p<0.05) and disgust has negative relation for family traveler (β_B = -0.31, p<0.05). Overall sentiment has statistically significant positive relation with recommendation for solo and business travelers (β_S = 0.08, β_B = 0.15, p's <0.001, β_C = 0.07, β_F = 0.06, all p< 0.01). Airport infrastructure and process has strong positive relationships for couple (β_C = 8.7, p<0.001) and solo ($\beta_{S=}$ 2.74, p<.05).

Managerial Implication

The above findings provide several managerial implications for airport management to enhance the service quality of airports. The primary focus is on the changes in consumer behavior under the stress. Additionally, the study examines customer behavior regarding service quality attributes and sentiments on an aspect-wise basis. It also explores travelers' varied perceptions of different services, influenced by respondent demographics such as native or non-native status and type of traveler. This research will help airport managers identify key attributes to prioritize in order to improve airport service quality. The major implications are discussed below.

Terminal seating, terminal signage, airport staff and queuing time are the important attributes that matter to the travelers primarily. While queuing times are what matter most to business class, courteous airport staff behavior is what the solo and couple travelers look for; terminal signs goes a long way in guiding the non native travelers in foreign lands; good staff behaviour and less queue time helps the stressed customer more than anything else. Thus the airport managers should ensure that airports are having comfortable seating and proper signages, ensuring that travelers don't have to struggle to find ways to their destinations.To enhance customer experience, airports can implement various strategies focusing on training, empowerment, and support for their staff. Comprehensive training programs covering customer service skills, conflict resolution, and communication techniques ensure staff proficiency and adaptability to new procedures and technologies. Empowering frontline employees with decision-making authority fosters prompt issue resolution and personalized assistance tailored to passengers' needs. Cross-training and skill development initiatives enhance staff versatility, enabling them to handle diverse airport operations efficiently. Further airport managers should work on the flow process and automation to reduce the time per workstation, thereby reducing queuing time. Terminal cleanliness, WiFi connectivity are hygiene factors, which are expected as default requirements by travelers.; nevertheless their quality should also be maintained.

The Emotions of trust and disgust seem to affect the customer rating and recommendation across a few categories like native and foreign (non native) traveler's , solo and family travelers. To enhance traveler's trust and reduce disgust, the airport authorities should focus on delivering what they promise in terms of cleanliness, comfort, and positive experiences. This includes well-maintained restrooms, free lounge to frequent flyers and numerous sanitation stations. Offering diverse food options, entertainment, and wellness facilities can make waiting times more pleasant. Friendly and helpful staff, along with engaging activities like cultural events and art displays, further enhance the airport experience. Frequent cleaning of high-traffic areas, restrooms, and food courts, as well as maintaining waste disposal systems to prevent unpleasant odors and sights would help reduce emotion of disgust among traveler's. Regular feedback mechanisms help in continuously improving services and addressing travelers' needs promptly.

Airport infrastructure and process, customer experience and services are the three important aspects that generate sentiments that influence CRat and CRec . While airport infrastructure and process matters to all types of flyers, it is the non native travelers who appreciate these facilities and recommend the airports. The airports should focus on enhancing these aspects significantly to improve the overall customer experience for travelers. Key improvements include implementing efficient check-in processes through self-service kiosks and online options, alongside offering mobile check-in for added convenience. Streamlining security screening with advanced technologies and clear instructions helps passengers navigate checkpoints more efficiently. Terminal facilities can be enhanced by increasing seating areas, providing diverse dining options, and ensuring clean restroom facilities with ample amenities. Improved baggage handling systems minimize mishandled luggage, offering real-time tracking for peace of mind. Enhanced wayfinding tools such as digital signage and interactive maps aid navigation, particularly for international travelers. Efficient boarding processes, including zone-based boarding and clear announcements, reduce gate congestion. Improved customer service with proactive assistance and dedicated help desks addresses passenger needs promptly. Seamless connectivity and technology integration, such as high-speed Wi-Fi and digital apps, enhance connectivity and deliver personalized services. By implementing these improvements, airports create a more seamless and enjoyable travel experience, ultimately boosting customer satisfaction and loyalty. Airports can enhance the food and shopping experience of travelers by offering a diverse range of high-quality options and integrating innovative technology and services. A mix of high-end boutiques, popular chain stores, and local specialty shops caters to various preferences and budgets, while featuring local products provides a unique shopping experience. Including pop-up shops and seasonal stores keeps the selection fresh and exciting. Diverse dining options, from quick bites to sit-down restaurants, ensure that all travelers find something they enjoy, with local flavors and choices for healthy and specialty diets adding to the appeal. Integrating technology, such as digital directories, mobile apps, and augmented reality for interactive experiences and navigation, can make the process more convenient. Excellent customer service through personal shoppers and concierge services assists travelers with tight schedules. Promotions and loyalty programs, including exclusive offers and rewards tied to airline frequent flyer programs, encourage engagement. Additionally, focusing on sustainability and community engagement by offering eco-friendly products and supporting local artisans and small businesses attracts conscientious travelers. By implementing these strategies, airports can create an enjoyable and memorable food and shopping experience, making time at the airport more pleasant and potentially increasing revenue for retailers.

It is seen that under stress situations , the travelers evaluate their satisfaction on the basis of food and beverages, airport staff and queuing time available at the airport. The stressed travelers actually wanted escapade from the situation and found it through indulgence in food. This is a vital revelation in the context of service setting. Service providers need to understand that a customer faces stressful situations in their day to day life and often look for pleasurable indulgences to assuage the effect. Stress often leads to indulgence in food as a coping mechanism, a phenomenon known as emotional eating. Airports can capitalize on emotional eating by offering a variety of comfort foods known to be popular during stressful times, such as pastries, burgers, pizza, and chocolate. By partnering with well-known brands and ensuring high-quality options, they can attract travelers seeking a quick mood boost. Additionally, placing snack kiosks and vending machines in high-traffic areas, like gates and waiting areas, can encourage impulse purchases of indulgent snacks. Creating cozy and inviting dining spaces with comfortable seating, calming decor, and ambient lighting can further enhance the dining experience, encouraging travelers to take a break and enjoy their food in a relaxing environment.

Another finding of this study is that the stressed customers prefer the queuing time to be short so that they get to the destination as soon as possible. Airport authorities need to register this finding. The queuing time to be reduced through automation, multiple facilities , virtual check ins etc. Interestingly the stressed traveler who wants the interaction time in queues to be minimal has more penchant for personal interaction with airport staff in stress than in normal situations. This contradictory finding can be explained in light of human need for affiliation and security in trying times. Personal interactions break the monotony of the situation, diverting the attention to other things. This of course depends primarily on the kind of interaction. Positive , welcome and warm interactions with the staff can go a long way in enhancing the quality of service and vice-versa.

CONCLUSION

limitation and scope for future research

Study carried out to assess rating and recommendation of airport services using reviews of the airport by travelers across various categories (native and non-native, solo-couple-family - business travelers, and travelers witnessing pandemic driven stress-high-medium-low stress) sums up that airport staff, terminal sign, queuing time and terminal seating are strong predictors of customers rating and recommendation behavior. Family traveler’s prefer spending on food and beverages and couples prefer spending time in airport shopping. Interestingly, WiFi and terminal cleanliness are not strong predictors of customers' attitude and behavior.These two may be considered as hygiene factors that traveler’s expect all international airports to have.n comparing various stress situations one important and interesting finding is that food and beverages affect the customer rating of airport services in low and high stress situations, which is 3 to 4 times higher than what it was under no stress condition. Another interesting finding is that emotion on all 3 aspects has absolutely no effect on customer recommendation under all 3 stress conditions.While stress can trigger cravings for comfort foods, indulging in these treats often offers a quick, tangible respite from anxiety. This phenomenon highlights the importance of understanding how food choices during stress can be influenced by the need for immediate comfort rather than emotional fulfillment.

Future efforts could enhance aspect-based sentiment analysis by utilizing advanced NLP and machine learning techniques that take sentence context into account. This improved sentiment analysis would provide more accurate insights into passengers' opinions on airport services. The psychological process behind the manifestation of CRat and CRec may enhance the understanding of customer behavior further and help in enhancing customer satisfaction. A study in this domain may be taken up in future. The effect of stress on buying behavior can be examined in experimental settings. Additionally, further research on how stress influences consumer psychological processes represents another promising area for investigation.

Relying on crowdsourcing can help reduce the bias inherent in participants of an open-ended survey, but it still retains the bias of those who choose to post public comments about airport service (Li et al., 2022). In other words, review writers may not fully represent the target population. Research indicates that young and educated individuals are more likely to post reviews online due to their habits and familiarity with social media and online platforms

(Barberá and Rivero, 2015; Li et al., 2021; Mellon and Prosser, 2017). Additionally, people with either extremely positive or negative experiences are more likely to write reviews (Filieri, 2016), leading to significant variance. Moreover, some individuals may share their experiences on other social media platforms, such as Facebook or Twitter, or may only use ratings without detailed comments to express their views on airport service. These factors can affect data quality and introduce bias into the results.

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