A STUDY OF PASSENGER SATISFACTION IN SOUTHEAST ASIA AIRPORTS THROUGH AIRPORT USER-GENERATED CONTENT

THITINAN PHOLSOOK

A Thesis Submitted in Partial Fulfillment of the Requirements for the
Degree of Doctor of Philosophy in Energy and Logistics Management Engineering
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การศึกษาความพึงพอใจของผู้โดยสารที่มีต่อท่าอากาศยานในภูมิภาคเอเชียตะวันออกเฉียงใต้โดยใช้คำวิจารณ์จากผู้โดยสาร

นางสาว ฐิตินันท์ ผลสุข

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิศวกรรมศาสตรดุษฎีบัณฑิต
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Suranaree University of Technology has approved this thesis submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy.

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การตรวจสอบความพึงพอใจของผู้โดยสารที่ท่าอากาศยานในเอเชียตะวันออกเฉียงใต้มีการดำเนินการอย่างเป็นระบบเมื่อโลกก้าวข้ามจากวิกฤติโควิด-19 ไปสู่สถานะปกติใหม่ โดยมีการเปิดเผยข้อมูลจากสภาท่าอากาศยานนานาชาติ (Airports Council International, ACI) ว่าภูมิภาคเอเชีย-แปซิฟิกมีการฟื้นฟูเศรษฐกิจในอุตสาหกรรมการบินล่าช้าเมื่อเทียบกับภูมิภาคอื่นๆ ในการศึกษานี้ได้บูรณาการวิธีการวิเคราะห์ข้อมูลจากผู้โดยสาร ซึ่งเป็นข้อมูลจากเนื้อหาที่ผู้โดยสารวิจารณ์ในเว็บไซต์ของสกายแทร็กซ์ ซึ่งประกอบด้วย การวิเคราะห์การถดถอยพหุคูณ ทฤษฎีความน่าจะเป็นแบบเบย์ และโครงข่ายประสาทเทียม โดยวิเคราะห์ปัจจัยหลักจำนวนแปดปัจจัยที่ส่งผลกระทบต่อความพึงพอใจของผู้โดยสารและผู้ใช้บริการในท่าอากาศยาน ได้แก่ ระยะเวลาในการรอคิว ความสะอาด พื้นที่นั่งรอและการอำนวยความสะดวก การบอกทิศทางในท่าอากาศยาน บริการร้านอาหาร บริการร้านค้า ความพร้อมใช้งานอินเทอร์เน็ต และการให้บริการของพนักงาน การศึกษานี้ได้อธิบายวิธีการรวบรวมข้อมูลจากผู้โดยสารในท่าอากาศยานผ่านแพลตฟอร์มดิจิตอล การประมวลผล และการอ่านข้อมูลข้อความ เพื่อสำรวจปัจจัยที่มีผลต่อคุณภาพการให้บริการที่ท่าอากาศยาน

จากการศึกษา พบว่า ปัจจัยที่สำคัญที่สุดที่มีผลต่อการจัดอันดับคุณภาพการให้บริการในท่าอากาศยาน คือ ระยะเวลารอคิวและการให้บริการของพนักงาน การศึกษานี้มีจุดมุ่งหมายในการนำข้อมูลที่สนับสนุนการปรับปรุงบริการของท่าอากาศยานในภูมิภาคเอเชียตะวันออกเฉียงใต้และมีความสำคัญในการบริหารจัดการท่าอากาศยาน รวมทั้งนำเสนอประเด็นสำคัญสำหรับการปรับปรุงคุณภาพบริการและประสิทธิภาพในอุตสาหกรรมท่าอากาศยานซึ่งนำไปสู่การเพิ่มจำนวนผู้โดยสารในภูมิภาค

การศึกษานี้มีจุดประสงค์ที่จะช่วยในการทำความเข้าใจความคาดหวังและข้อเสนอแนะของผู้โดยสาร ในขณะเดียวกันสามารถประเมินประสิทธิภาพของท่าอากาศยานในการปรับปรุงประสบการณ์ของผู้โดยสาร ผลลัพธ์ที่ได้จากการศึกษาทำให้สามารถเชื่อมโยงวิธีทางความคิดของผู้โดยสารที่มีต่อบริการที่ท่าอากาศยาน และเป็นแนวทางสำหรับการตัดสินใจโดยมีข้อมูลที่มีประสิทธิภาพและนำไปปรับปรุงกลยุทธ์ในอุตสาหกรรมการบิน

สาขาวิชา วิศวกรรมการจัดการพลังงานและโลจิสติกส์
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ลายมือชื่อนักศึกษา ....
ลายมือชื่ออาจารย์ที่ปรึกษา..................
ลายมือชื่ออาจารย์ที่ปรึกษาร่วม.............

THITINAN PHOLSOOK: A STUDY OF PASSENGER SATISFACTION IN SOUTHEAST ASIA AIRPORTS THROUGH AIRPORT USER-GENERATED CONTENT. THESIS ADVISOR: PROF. VATANAVONGS RATANAVARAHA, Ph.D., 146 PP.

Keyword: Passenger Satisfaction / Airport Service Quality / User-Generated Content / Skytrax / Multiple Regression Analysis / Bayesian Networks / Neural Networks / Text Mining / Sentiment Analysis

As the world adjusts from the COVID-19 pandemic to a new normal, a thorough examination of passenger satisfaction at major airports in Southeast Asia is being carried out. The Airports Council International (ACI) has revealed that the Asia-Pacific region is falling behind other regions in terms of air traffic recovery. Utilizing a multimethod approach comprising multiple regression analysis, Bayesian networks, and neural network analysis the study investigates user-generated content from Skytrax. It considers eight specific attributes of airport customer ratings, including queuing time, cleanliness, seating areas, signages, food services, retail options, Wi-Fi availability, and staff courtesy.

This analysis highlights queuing time and staff courtesy as key factors influencing airport service ratings, offering valuable empirical evidence for enhancing services in the region. It aims to contribute theoretically and provide managerial recommendations to airport authorities for improving service quality and operational efficiency, ultimately aiding in the recovery and growth of air passenger numbers.

The rise of digital platforms has transformed customer review collection but poses challenges in processing and interpreting textual data. This study outlines a methodology using SkyTrax review data, incorporating quantitative sentiment analysis, exploratory data analysis, and statistical modeling to identify factors affecting passenger perceptions. An integrated model, treating airports and passengers as random effects, assesses airports based on sentiment scores.

This method enhances understanding of passenger expectations and evaluates airport performance in enhancing customer experience. The comprehensive approach promises insights into passenger sentiment dynamics, supporting informed decision-making and strategic improvements in the aviation industry.

School of Energy and Logistics Management Engineering
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LIST OF ABBREVIATIONS

ACI	= Airports Council International
ANN	= Artificial neural network
API	= Application Programming Interface
ASQ	= Airport Service Quality
BKK	= Bangkok Suvarnabhumi Airport
BNs	= Bayesian networks
BR	= Building Resources
CART	= Council's Aviation Recovery Task Force
CFA	= Confirmatory Factor Analysis
CFI	= Comparative Fit Index
CGK	= Soekarno-Hatta International Airport
CNN	= Convolutional Neural Networks
COVID-19	= Coronavirus disease 2019
DAG	= Directed acyclic graph
DFs	= Decision factors
DMK	= Mueang International Airport
DPS	= Denpasar International Airport
ED	= Emotion Detection
EFA	= Exploratory Factor Analysis
EWOM	= Electronic word-of-mouth
HAN	= Hanoi Airport
ICAO	= Civil Aviation Organization
KPIs	= Key Performance Indicators
KUL	= Kuala Lumpur International Airport
LSTM	= Long-Short Term Memory
ML	= Machine Learning
ML-SEM	= Maximum likelihood structural equation modeling
MNL	= Manila Airport
MRA	= Multiple regression analysis

LIST OF ABBREVIATIONS (Continued)

NAR	= Non-aviation revenue
NCA	= Necessary condition analysis
NLP	= Natural Language Processing
NNs	= Neural networks
OM	= Opinion Mining
Qu	= Quarter
SA	= Sentiment analysis
SC	= Sentiment classification
SD	= Standard Deviation
SEA	= Southeast Asia
SEE	= Standard Error of Estimate
SEM	= Structural Equation Modeling
SGN	= Ho Chi Minh City Airport
SIN	= Singapore Changi Airport
SVM	= Support Vector Machines
TL	= Transfer Learning
UGC	= User-generated content
VIF	= Variance inflation factor
WoM	= Word-of-mouth

CHAPTER I

INTRODUCTION

1.1 Background

The global aviation industry has been significantly disrupted by the COVID-19 pandemic, with varying recovery rates across different regions and sectors. According to data released by Airports Council International (ACI) in 2023 (ACI, 2023), the Asia-Pacific region experienced the slowest rebound in passenger traffic during the first and second quarters of 2022. This trend was in sharp contrast to other global regions, which began their recovery in the first half of 2021, as shown in Figure 1.1.

The Asia-Pacific region's slow recovery can be defined to a variety of situation, including strict travel restrictions, slower vaccination rollouts, and extended lockdown periods. Collectively, these issues have slowed the recovery of air travel in this region. Conversely, regions such as North America and Europe showed signs of recovery as early as the first half of 2021. This faster rebound is mostly the result of more robust immunization campaigns, less restricted travel rules, and an early rebound in domestic travel demand.

Domestic travel has emerged as the main catalyst for the global recovery in passenger traffic. This shift is largely attributed to the fact that domestic travel encounters fewer issues and restrictions compared to international travel. Projections suggest that global domestic passenger traffic will reach 2019 levels by the end of 2023. This rapid rebound highlight increased demand for intra-country travel, which is supported by a decrease in internal restrictions and a gradual recovery of passenger confidence. In comparison, the recovery of foreign travel has taken substantially longer. This segment of travel continues to face obstacles including as varying entrance and quarantine regulations, discrepancies in pandemic control efforts, and continuing traveler hesitation. Consequently, worldwide international passenger traffic is not likely to fully recover to pre-pandemic levels until the second half of 2024. This extended recovery period underscores the greater complications of international travel, involving integrated travel rules, increased global vaccination rates, and an intentional attempt to restore passenger confidence. Looking ahead, the aviation industry is expected to fully recover in both domestic and international travel domains by 2025, returning to operational and capacity levels achieved in 2019.

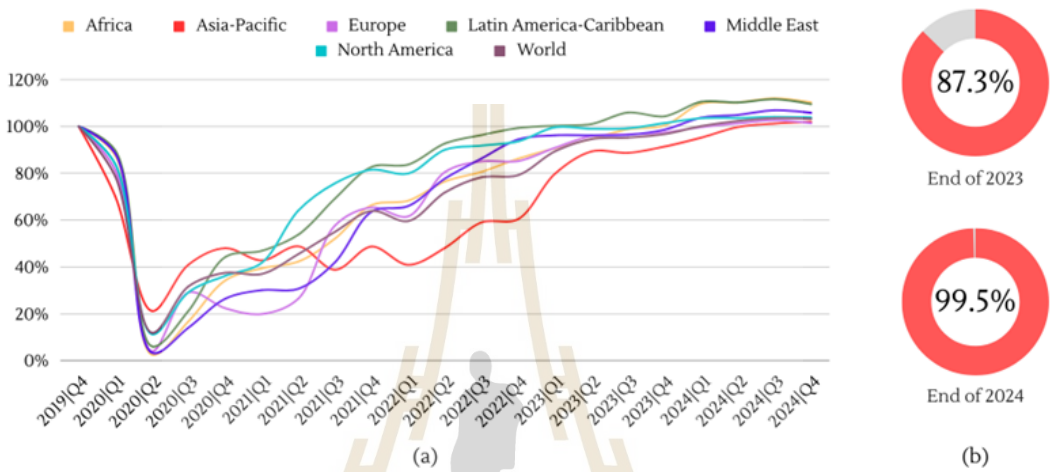


Figure 1.1 Projected passenger traffic compared to the 2019 level (2019 level = 100%): (a) Global quarterly passenger traffic; (b) Passenger traffic in Asia-Pacific region. Source: ACI (2023).

The global aviation sector's recovery path varies significantly across regions and across domestic and international travel sectors. The slower recovery in the Asia-Pacific region compared to the quicker rebound in other areas highlights several challenges that impede recovery efforts. Despite these challenges, the sector is expected to fully recover by 2025, pending positive breakthroughs in vaccine initiatives, policy harmonization, favorable economic conditions, and improved traveler attitude.

Considering the latest information on the impact of COVID-19 on the aviation industry, it is evident that generating non-aviation revenue (NAR) has become crucial to the sector's recovery efforts. Graham (2009) discovered that airports had a major impact on travelers' travel experiences. The commercialization of the airport business has highlighted the need of increasing air service and passenger numbers for airport expansion.

ACI World (2016) states that the most effective method to boost non-aviation revenue (NAR) is by enhancing the customer experience. An analysis of Airport Service Quality (ASQ) data indicated that a 1% growth in passenger numbers correlates with a

0.7% to 1% increase in NAR. Moreover, a 1% expansion in commercial area size results in a 0.2% rise in NAR, and a 1% enhancement in overall passenger satisfaction leads to an average 1.5% increase in NAR (ACI, 2021). With airports adopting a commercial management approach, the importance of customer feedback has significantly increased.

1.2 Airport service quality

Airport management has prioritized the improvement of passenger satisfaction to boost passenger traffic. This goal is pursued by ensuring the seamless and secure completion of all airport operations. The aim is to establish an environment that not only meets but exceeds passenger expectations, thereby enhancing the overall travel experience (Elshafey et al., 2007).

In 2006, the Airports Council International (ACI) introduced the Airport Service Quality (ASQ) program as a worldwide standard for assessing customer perceptions of service quality (ACI, 2022). The ASQ program evaluates 34 attributes across eight categories(Lee & Yu, 2018), providing a consistent way to measure airport performance globally. With nearly 400 airports in 95 countries participating, the ASQ program has become a prominent method for assessing passenger satisfaction.

Improving service quality performance to enhance passenger satisfaction and elevate the airport experience has been a key focus for airport management. This strategy is crucial as excellent service quality and increased passenger satisfaction are associated with positive word-of-mouth (WoM) and a greater likelihood of repeat visits, thereby boosting the potential for generating non-aviation revenue (NAR).

In this new era of normalcy following the COVID-19 pandemic, new expectations concerning personal health and safety have emerged among passengers. In response, new COVID-19-related questions were integrated into the ASQ departure survey by ACI in 2020, addressing the effectiveness of safety and hygiene measures (ACI, 2020b). This measure has played a pivotal role in restoring passengers' confidence in travel and aiding the recovery process.

Moreover, there has been a growing momentum towards the digitalization of operational processes and the adoption of smart airport applications. Technologies such as self-service kiosks, contactless ID verification, mobile applications, and AIpowered queue management have been proven to enhance security, reduce passenger anxiety, and streamline airport operations. Additionally, guidelines on Business Recovery issued by ACI and recommendations from the Aviation Recovery Task Force (CART) of the International Civil Aviation Organization (ICAO) have equipped airports with assessments on aligning their health protocols. These guidelines cover various aspects, including cleaning and disinfection procedures, implementation of physical distancing measures where feasible, staff safety protocols, terminal layout, passenger communication strategies, and amenities for passengers. The guidelines address all passenger zones and processes, encompassing terminal access, check-in areas, security checkpoints, boarding gates, lounges, retail outlets, dining facilities, gate facilities, border security areas, baggage claim zones, and arrival exits (ACI, 2020a).

1.3 User-generated online contents in airport management

In airport management, user-generated online content (UGC) comprises a variety of media forms, including reviews, ratings, social media posts, photos, videos, blogs, vlogs, and forum discussions that passengers create to share their airport experiences. This UGC offers critical insights into customer perceptions and expectations, empowering airport management to optimize services, engage customers, and enhance the overall passenger experience.

The rapid expansion of social media has transformed the global landscape, expanding our knowledge beyond immediate social circles. With travel services being intangible, word-of-mouth marketing has gained significance as clients tend to be wary of new service providers. Online reviews serve as valuable sources of consumer feedback, providing airports with essential data regarding passenger experiences that necessitates thorough analysis. Traditional methods of gathering passenger feedback via survey distribution and collection are time-consuming and costly, often resulting in incomplete surveys that generate noisy data for sentiment analysis. In the realm of airport customer feedback analysis, social media and online platforms outshine traditional surveys.

In recent times, there has been a growing emphasis on sentiment analysis (SA) and opinion mining as significant areas of study. By employing methodologies from Natural Language Processing (NLP), computational linguistics, and text mining, airports can analyze public sentiments and viewpoints on various events, products, and other topics. The advent of electronic word-of-mouth (EWOM) has granted social media a prominent role in global communication. While some view the "social buzz" positively for boosting sales and enhancing marketing efforts, others express concerns that high-volume social media interactions may tarnish reputations. Understanding and predicting passenger behavior, as well as analyzing the impact of EWOM, is indispensable for airports seeking service enhancement and profit generation opportunities.

Machine learning emerges as a crucial tool for analyzing and extracting insights from the vast user-generated online content (UGC) associated with airport management. By leveraging machine learning algorithms, airports can effectively handle user-generated online content within their operational framework. A fundamental application of machine learning involves sentiment analysis and opinion mining in airport management. Through the utilization of techniques rooted in Natural Language Processing (NLP) and machine learning algorithms, airports can analyze user-generated content, gaining a comprehensive understanding of passenger sentiments, opinions, and feedback. This capability enables the assessment of customer satisfaction levels, identification of prominent issues, and proactive implementation of strategies to address concerns.

Crucial utilization of machine learning algorithms is observed in the monitoring and scrutiny of social media platforms to oversee user-generated content relevant to airports. This entails surveillance of mentions, conducting sentiment analysis on posts and comments, trend detection, and feedback categorization. The automation of these processes through machine learning empowers airports to acquire real-time valuable insights, facilitating prompt responses and enhancing customer engagement.

Leveraging historical data, machine learning models can predict forthcoming trends in user-generated content. A detailed examination of patterns and sentiments in past feedback enables airports to anticipate potential issues, forecast passenger behaviors, and proactively introduce service enhancements. This predictive analysis empowers airports to cater to customer demands and uplift the overall passenger experience.

Machine learning plays a significant role in tailoring the customer experience within airports by analyzing user preferences and feedback. This data-centric approach enables airports to customize services, recommend pertinent amenities, and address individual passenger needs more effectively. Personalization anchored in UGC can lead to increased customer satisfaction and loyalty.

Apart from evaluating feedback and sentiments, machine learning algorithms are critical for detecting fraudulent activities and upholding security measures. Monitoring user-generated content for deceptive or malicious behavior, machine learning models assist airports in identifying potential threats, thwarting security breaches, and ensuring a safe travel environment for passengers.

In summary, machine learning emerges as a pivotal asset for airport management in efficiently harnessing user-generated online content. By integrating machine learning algorithms for sentiment analysis, social media monitoring, predictive analysis, personalized customer experiences, and security functions, airports can heighten customer satisfaction, streamline operations, and foster a secure and efficient travel milieu for passengers.

1.4 Research purposes

The utilization of big data and user-generated content in assessing airport service quality, offering diverse and authentic perspectives, has been turned to by researchers on platforms such as Google reviews (e.g., Lee & Yu, 2018; Li et al., 2022; Molaei & Hunter, 2019), TripAdvisor (e.g., Nghiêm-Phú & Suter, 2018; Sezgen et al., 2019), Twitter or recently named as X (e.g., Barakat et al., 2021; Martin-Domingo et al., 2019), Skytrax (refer to Bae & Chi, 2022; Bakır et al., 2022; Bogicevic et al., 2013; Bulatović et al., 2023; Bunchongchit & Wattanacharoensil, 2021; Gitto & Mancuso, 2017; Halpern & Mwesiumo, 2021; Homaid & Moulitsas, 2023; Kiliç & Çadirci, 2022; Wattanacharoensil et al., 2017; Yavuz et al., 2020), and other social media channels (e.g., Arasli et al., 2023) for comprehensive service quality analysis. Recent studies have utilized diverse quantitative content analysis techniques to scrutinize data from a variety of travel platforms, offering valuable insights into different dimensions of airport services.

In this study, a multistage methodology was proposed, incorporating multiple regression analysis (MRA), Bayesian networks (BNs), and neural networks (NNs). The objective was to analyze the service attributes of Skytrax Airport and determine the attribute with the most significant impact on the overall airport rating. Initially, MRA was utilized to test research hypotheses and identify important attributes, which were then integrated into BNs to predict the current total airport rating based on each attribute's presence. Subsequently, NNs were used to identify the key service attribute for enhancing the overall airport rating score. This methodology enables the detection of linear relationships, captures probabilistic dependencies, and is effective in detecting nonlinear patterns. To the best of our knowledge, this study is the first to investigate the critical service attributes of the top ten busiest airports in Southeast Asia (SEA) using the proposed hybrid approach. Furthermore, a systematic literature review by Sadou and Tchouamou Njoya (2023) shed light on the application of artificial intelligence in the aviation industry, highlighting that only a small fraction of air transport studies focus on traveler experience. This research delves into the essential factors of airport services that impact overall airport ratings. The findings presented in this study could aid airport managers and stakeholders in gaining deeper insights into the fundamental attributes of airport services, potentially helping them identify challenges and forecast future trends in airport services.

Furthermore, a diverse and comprehensive evaluation of user-generated online content in airport management within SEA, employing sentiment analysis, has been undertaken in the research objectives. These objectives include understanding passenger sentiments, identifying potential areas for improvement, enhancing the customer experience, predicting passenger behavior, and influencing decision-making processes in airport management throughout the SEA. By leveraging sentiment analysis of user-generated online content, researchers aim to guide strategic decision-making, enhance operational efficiency, refine marketing strategies, and uplift customer engagement initiatives to foster loyalty and heighten levels of passenger satisfaction.

1.5 Scope of research

The research scope focuses on pinpointing the key factors that can notably increase passenger traffic at airports in the Southeast Asia (SEA) region, taking into account the prolonged recovery period for air travel. Specifically, it targets the top ten busiest airports in SEA, as listed by OAG in 2023 (OAG, 2023), are the primary focus of this study, with data sourced from Skytrax's review data. Skytrax, globally renowned for its benchmark airport service quality evaluations, initiated its evaluation program in 1999 based on extensive professional experience.

In this study, data from Skytrax spanning from 2015 to July 2023 was analyzed using R programming. Nine factors were examined, with the total airport rating considered as the potential outcome variable and eight service metrics (queuing time, cleanliness, seating areas, signage, food services, retail shops, Wi-Fi availability, and staff courtesy) acting as predictors. Textual reviews were assessed to validate the feasibility of developing the identified strategic variables.

1.6 Research questions

The research questions outlined based on the research purposes and scope are as follows:

1. Is there a correlation between the dimensions of airport user satisfaction and overall satisfaction?

2. Which Skytrax's ASQs are the most significant in Southeast Asia airports?

3. Is there consistency observed between the results of the MRA-BN-ANN analysis and the text analysis?

These research questions aim to delve into the effectiveness of both quantitative and qualitative analyses in capturing and reflecting the dimensions and attributes of airport user satisfaction derived from Skytrax's user-generated content data. The research seeks to evaluate the harmony and coherence between the two analytical methodologies.

1.7 Research contributions

In the present big data-dominated market, data analytics is a critical tool for airport management and stakeholders to acquire insights into travelers' expectations and preferences. This study explores new ground by using Skytrax as an alternate source of airport-related opinion reviews, with a specific focus on major SEA airports.

This research makes a significant contribution to the understanding of airport service quality by comparing the service attributes outlined in the Airports Council

International's (ACI) Airport Service Quality (ASQ) framework with themes extracted from an alternative data source that reflects passengers' actual experiences.

A key highlight of this study is its utilization of airport users' feedback and evaluations as authentic representations of their airport encounters, offering a novel approach for airport decision-makers and management to assess user experience and service quality. The methodologies presented in this research establish a foundation for future inquiries into the connections between service quality and various aspects of airport performance, such as efficiency and productivity.

The empirical findings from this study offer tangible information that can enhance airport services in the region, advancing theoretical comprehension and offering practical insights for airport management entities and authorities. Consequently, this study serves as a valuable asset for enhancing service quality and operational efficiency in the airport sector, potentially triggering a recovery and surge in air passenger numbers within the region.

1.8 Thesis structure

In this dissertation, the foundational concepts that delineate the study are established in Chapter 1, setting the stage for the ensuing investigation. Chapter 2 conducts a thorough synthesis of the literature review, pinpointing existing deficiencies within current knowledge that warrant attention in this research. Key aspects of airport service quality within the industry are outlined, emphasizing essential factors that shape service strategies. Additionally, this section incorporates relevant theories and literature, including the formulation of hypotheses concerning airport service dimensions.

Progressing to Chapter 3, the focus shifts to data collection and a rigorous evaluation of development trends among prominent SEA (SEA) airports. This chapter introduces the integrating model of Multiple Regression Analysis (MRA), Bayesian Networks (BNs), and Neural Networks (NNs) and text and sentiment analysis methodologies to encapsulate data-driven insights from passengers utilizing SEA airports. By leveraging empirical data and advanced analytical techniques, Chapter 3 aims to uncover intricate patterns and insights in passenger experiences, enriching the understanding of service dynamics in the SEA airport context.

In Chapter 4, the results and insights from preceding chapters are unveiled, culminating in the establishment of a conceptual framework that involves various airport stakeholders in shaping strategic directions. By synthesizing findings from data analysis, literature review, and theoretical foundations, this chapter aims to craft a strategic roadmap that integrates diverse perspectives to enhance airport services and stakeholder engagement effectively.

Concluding the dissertation, Chapter 5 encapsulates the research outcomes, highlighting significant scholarly contributions and discoveries from the comprehensive analysis. Furthermore, it proposes avenues for future research that can build upon the findings of this study. By presenting a comprehensive overview of research findings and suggesting pathways for future exploration, Chapter 5 serves as a platform for continued academic discourse and advancements in the realm of airport service quality and passenger experience analysis.

CHAPTER II

LITERATURE REVIEW

2.1 Service quality in airport industry

2.1.1 Airport service quality

Airports Council International (ACI) World's Airport Service Quality (ASQ) customer experience group, as delineated by ACI (2021), offers a comprehensive, all-encompassing approach to managing the passenger experience at airports through a specialized range of solutions. With proficiency in airport operations, marketing research, customer experience management, and service delivery, ACI supports close to 400 airports globally in delivering outstanding customer experiences. Since its inception in 2006, the ASQ program has been monitoring customer satisfaction levels among airport travelers, providing management with crucial data and research tools to better comprehend passenger preferences and perceptions regarding an airport's offerings and services.

Customer experience management entails strategic planning and responding to customer interactions to meet or surpass their expectations, enhancing customer satisfaction, loyalty, and revenue while concurrently reducing service expenses. Managing passenger experiences at airports is a multifaceted task that involves various stakeholders, including airlines, retailers, government bodies, and more. The effectiveness of the ASQ program is largely attributed to its capability to unite all these stakeholders with a concerted emphasis on customer experience.

The ASQ Departures Survey investigates 34 service elements across 18 segmentation fields, encompassing areas such as access, check-in, passport/ID control, security, wayfinding, food and beverage options, airport facilities, and overall passenger satisfaction. This comprehensive approach ensures that passengers receive superior service, thereby fostering loyalty and encouraging repeat usage of the airport. The program identifies areas requiring investment in financial and human resources and optimizes initiatives to enhance customer satisfaction and boost non-aeronautical revenue.

Similarly, ASQ Arrivals provides an in-depth assessment of the passenger experience upon arrival, examining 37 service elements across seven segmentation fields, including de-boarding, baggage claim, customs, immigration, airport facilities, signage, waiting lines, staff availability, and ambiance. Combining insights from both the Arrivals and Departures surveys furnishes the most holistic view of the entire customer service experience from start to finish. This integration aids in developing branding strategies, setting achievable objectives, and establishing service targets to motivate airport managers and teams. Additionally, service level agreements with key stakeholders are established, monitored, and maintained.

ASQ Commercial provides a distinctive outlook on passenger spending habits and non-spending behaviors concerning duty-free shops, retail outlets, dining establishments, and paid amenities. It evaluates 21 satisfaction Key Performance Indicators (KPIs), six commercial KPIs, and nine passenger profile inquiries, thereby boosting non-aeronautical revenue by prioritizing commercial factors crucial to business strategies. This understanding enables airports to identify opportunities and prioritize initiatives, thereby improving the passenger experience by delivering better customer care even before passenger board their aircraft.

The ASQ scale incorporates 34 attributes grouped into eight distinct airport processes. Many studies on airport service quality have focused, at least partially, on a subset of these 34 attributes (e.g., Bezerra & Gomes, 2015, 2016). However, accessibility to the ACI/ASQ database remains constricted for the wider research community (Martin-Domingo et al., 2019).

Traditionally, studies on ASQ have depended on tailored survey questionnaires to assess passengers' views on different service quality aspects. However, conducting surveys at airports has become more challenging due to cost limitations, security issues, and disruptions to traveler convenience (Martin-Domingo et al., 2019). As a result, modern approaches are being developed that analyze the digital traces travelers leave across online platforms, blogs, niche websites, and social media channels. By incorporating user-generated content, these innovative methodologies provide new ways to address research challenges and complement conventional data analysis techniques.

2.1.2 Key quality attributes of airports management

To enhance the measurement of airport performance, the Airport Service Quality (ASQ) by ACI is widely utilized due to its comprehensive nature, extensive history, and benchmarking capabilities for passenger satisfaction among airports. The ASQ regular audit survey evaluates airport performance based on 34 service aspects across eight main areas: access, check-in, passport control, security, navigation, facilities, environment, and arrival (Lee & Yu, 2018), establishing a global benchmark for performance comparison.

Although the ASQ provides valuable insights, the perception of airport operations by passengers can vary, suggesting that a universal survey may not accurately capture the individual performance of each airport (Yeh & Kuo, 2003). Therefore, developing a specific service quality measurement model tailored to each airport could be necessary to facilitate targeted and effective improvement strategies (Bogicevic et al., 2013; Francis et al., 2003; Yeh & Kuo, 2003).

Airport management must consider both internal and external evaluations when utilizing the ASQ measurement model. Yeh and Kuo (2003) put forth a fuzzy multi-attribute evaluation model based on insights from international travel experts and research conducted by airport stakeholders. Conversely, Fodness and Murray (2007) highlighted the importance of understanding passengers' expectations to effectively monitor and enhance airport service performance. This perspective aligns with the study by Lubbe et al. (2011) that underscores the significance of incorporating air travelers' opinions in assessing service quality.

Various analytical approaches have been employed by researchers to ascertain airport customers' service demands. For instance, Bezerra and Gomes (2015) utilized exploratory factor analysis (EFA) to study travelers' perceptions of ASQ in Brazilian airports and identified seven key service dimensions that significantly influence ASQ. They later conducted confirmatory factor analysis (CFA) in 2016 and refined the significant elements impacting ASQ (Bezerra & Gomes, 2016). Furthermore, Chonsalasin et al. (2021) utilized CFA to explore passenger expectations concerning Thai airports, emphasizing key dimensions like access, check-in, security, and others identified in previous studies.

Di Pietro et al. (2017) employed Bayesian networks to conduct a combined analysis of the perceived and delivered quality of an airport check-in process. This methodology enabled a thorough evaluation of the factors influencing the efficiency of the check-in process. Likewise, Farr et al. (2014) utilized Bayesian networks to explore the factors that contribute to effective wayfinding in airport settings. This approach helped in gaining a deeper insight into the key elements that are essential for ensuring seamless and efficient wayfinding for passengers.

Transitioning to the COVID-19 context, Meidute-Kavaliauskiene et al. (2021) investigated the impact of the pandemic on airline services, particularly focusing on the use of service robots as an alternative to human staff in airports. Their study employing SEM analysis revealed that fear of COVID-19 positively affected perceived trust in the robots, influencing the intention to use them.

Moreover, research by Sun et al. (2021) reviewed the influence of COVID-19 on aviation by categorizing 110 articles published in 2020 into key themes, such as the global air transportation system, passenger-centric flight experience, and long-term aviation impacts. Additionally, studies like that of Tisdall and Zhang (2020) in Australia highlighted the effects of COVID-19 on the general aviation sector, encompassing government policies, business decisions, and mental health considerations.

Fakfare et al. (2021) concentrated on prospective Thai tourists who had visited an international airport in the past 12 months. Due to the COVID-19 pandemic, an on-site survey was deemed impractical, leading to the distribution of an online survey questionnaire link to respondents. In their analysis, they considered 44 quality attributes generated from current literature on air travel. Their focus was on essential dimensions such as airport layout and signage, terminal environment, flight information screens, check-in processes, security procedures, passenger facilities, immigration services, departure halls, baggage handling, and leisure and entertainment amenities.

2.2 Relevant Theories

2.2.1 Multiple regression analysis

Siegel and Wagner (2022) explained that multiple regression is employed to explain or predict a single dependent variable Y using two or more independent variables X. The main goals of multiple regression include: (1) describing and comprehending the connection between variables, (2) predicting or forecasting new observations, and (3) regulating and managing processes.

The intercept, or constant term *a*, provides the predicted (or "fitted") value of *Y* when all *X* variables are zero. Each regression coefficient b_j for the *j*th *X* variable specifies the effect of X_j on *Y* after adjusting for the other *X* variables, indicating how much larger *Y* is expected to be for a unit increase in X_j, with all other *X* variables held constant. Combined, these regression coefficients formulate the prediction equation or regression equation:

$$\text{predicted } Y = a + b_1X_1 + b_2X_2 + \dots + b_kX_k\ .$$

These coefficients ($a, b_1, b_2, \dots, b_k$) are typically calculated using the method of least squares, which aims to minimize the sum of squared prediction errors. Prediction errors or residuals are computed as [*Y* – (Predicted *Y*)].

Two key metrics summarize the quality of a regression analysis. The standard error of estimate S_e provides an approximation of the magnitude of the prediction errors. The coefficient of determination R^2 signifies the proportion of variation in *Y* that is elucidated by the *X* variables.

Inference in multiple regression begins with the *F* test, which assesses whether the *X* variables explain a significant amount of variation in *Y*. If the regression is not significant, further analysis is not warranted. However, if the regression is significant, statistical inference proceeds with t tests for individual regression coefficients. These t tests determine whether each *X* variable has a significant effect on *Y* while holding other *X* variables constant. Confidence intervals and hypothesis tests for individual regression coefficients are based on their respective standard errors, $S_{b1}, S_{b2}, \dots, S_{bk}$, with the critical *t* value having $n - k - 1$ degrees of freedom.

The multiple regression linear model specifies that the observed *Y* is equal to the population relationship plus independent, normally distributed random errors:

$$Y = (\alpha + \beta_1X_1 + \beta_2X_2 + \dots + \beta_kX_k) + \varepsilon$$

$$= (\text{Population relationship}) + \text{Randomness}$$

where ε has a normal distribution with mean zero and constant standard deviation σ, and this randomness is independent across cases. Each population parameter (α, β_1, β_2 + ... + β_k, σ) has a corresponding sample estimator (a, b_1, b_2, ..., b_k, S_e).

F Test Hypotheses:

H_0: $\beta_1 = \beta_2 = ... = \beta_k = 0$

H_1: At least one of $\beta_1, \beta_2, ..., \beta_k \neq 0$

The significance of the *F* test is determined by the p-value computed by statistical software, indicating whether the R^2 value is larger than expected by chance.

Confidence Interval for b_j :

From $b_j - tS_{bj}$ to $b_j + tS_{bj}$

where the critical *t* value is based on $n - k - 1$ degrees of freedom. The hypotheses for the t test of the *j*th regression coefficient are:

H_0: $\beta_j = 0$

H_1: $\beta_j \neq 0$

Assessing Variable Contributions:

Two strategies address the challenge of determining which *X* variables most contribute to the regression. The standardized regression coefficient, b_iS_{Xi} / S_Y represents the expected change in *Y* due to a one standard deviation change in X_i, holding all other *X* variables constant. Alternatively, comparing the absolute values of the correlation coefficients between *Y* and each *X* variable can be used if adjusting for other variables is not desired.

Potential Problems in Multiple Regression:

Multicollinearity: Occurs when explanatory *X* variables are too similar, leading to poorly estimated regression coefficients. It may be addressed by omitting or redefining variables.

Variable Selection: Arises when deciding which X variables to include in the regression. Too many variables waste information, while omitting important ones reduces prediction quality. Solutions include a prioritized list of variables or automated procedures like stepwise regression.

Model Misspecification: Refers to potential mismatches between the application and the multiple regression model. Issues like nonlinearity, unequal variability, or outliers can be identified through data exploration and diagnostic plots.

Diagnostic Plots:

A diagnostic plot (scatterplot of residuals against predicted values) is utilized to detect problems in the data. A cloud of points without tilt suggests that no additional structure is found, and the regression model is performing well.

Dealing with Nonlinearity and Unequal Variability:

Options include variable transformation, introducing a new variable, or using nonlinear regression. Transformations should be applied consistently within groups of variables measured in similar units.

Elasticity and Polynomial Regression:

Elasticity in relation to X_i is the expected percentage change in Y from a 1% increase in X_i, estimated using the logarithmic transformation of both Y and X_i. Polynomial regression can address nonlinearity by including powers of X.

Interaction and Indicator Variables:

Interaction occurs when a change in both variables shifts Y differently from the sum of individual effects, modeled by cross-product terms. Indicator (dummy) variables represent categorical data as X variables, with one less indicator variable than categories. The baseline category is defined by the constant term in the regression output.

2.2.2 Bayesian networks

Within the realm of uncertain domains, Bayesian networks (BNs) serve as probabilistic graphical models, where each node corresponds to a random variable, and the conditional probabilities associated with these variables are represented by the edges. In the theory of Bayesian networks probabilistic graphical models are employed to explore the conditional dependencies among a set of random variables, guided by the principles of Bayes' theorem.

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}.$$

The probability of event A given event B is equal to the probability of event B given event A, multiplied by the probability of event A, divided by the probability of event B.

According to Pearl (1988), Bayesian networks are structured graphical models intended to capture causal probabilistic relationships between variables, often facilitating decision-making processes. These models can exhibit causal probability connections informed by experts or updated with new data through the Bayes' theorem. Variable relationships are graphically depicted using nodes (variable representations) and directed edges (to signify conditional relationships), forming a directed acyclic graph (DAG).

Two predominant approaches are utilized in learning a Bayesian network: (1) Structure Learning: This initial phase involves identifying the optimal DAG that effectively illustrates the causal relationships existing within the dataset, and (2) parameter Learning: Subsequently, the focus shifts towards comprehending the intricate conditional probability distributions inherent in the network.

Key techniques for determining the DAG structure include the DAG search algorithm (Chickering, 2002) and the K2 algorithm (Cooper & Herskovits, 1992). These methods assign prior probabilities to all potential DAG configurations to identify the structure that maximizes the data likelihood given the DAG — known as the Bayesian score P(data | DAG).

Chanpariyavatevong et al. (2021) highlight that Bayesian Networks (BNs) operate as a probabilistic model structured by the Directed Acyclic Graph (DAG), illustrating causal links between factors or variables. The BN, represented as a DAG, encodes probabilistic connections between nodes to facilitate reasoning involving uncertainties (Wipulanusat et al., 2020). The DAG, comprising nodes linked to probability distributions, serves as the BNs model. Bayes' theorem is a central mathematical model within the BN, enabling the updating of belief regarding hypothesis E_i considering event A. Bayes' theorem calculates $P(E_i | A)$ in terms of $P(A | E_i)$, as expressed in the follow Equation.

$$P(E_i|A) = \frac{P(A/E_i) \cdot P(E_i)}{P(A)}$$

The BNs employs Bayes' theorem to estimate unknown $P(E_i | A)$, where the probability of event A hinges on occurrences of events E_i (i = 1, 2, ..., n) for a total of n events.

Post the identification of the optimal DAG structure, the parameter learning process proceeds utilizing the maximum likelihood estimator. It is critically underscored that the integration of prior knowledge concerning causal relationships often holds significance during the parameter learning phase.

2.2.3 Neural networks

Walczak and Cerpa (2003) mentioned that Artificial Neural Networks, often referred to as neural networks or connectionist models, provide a tool for tackling complex issues involving intricate patterns in classification and time-series analysis. The nonparametric nature of neural networks enables the creation of models without the need for pre-existing knowledge about data distribution across the population or potential interactions among variables, as typically required by traditional parametric statistical techniques.

For instance, traditional statistical methods like multiple regression necessitate normal distribution of the error term in the regression equation (with μ = 0) and homoscedasticity. Similarly, discriminant analysis, commonly applied for categorization tasks, mandates that predictor variables follow a multivariate normal distribution. By discarding such assumptions, artificial neural networks streamline the process of devising solutions for domain-specific challenges. Additionally, the capacity of artificial neural networks to construct both linear and nonlinear models enhances their versatility across a diverse array of problem categories.

Drawing insights from research on the brain and nervous system, Artificial Neural Networks (ANNs) are a technology, as shown in Figure 2.1, that mimics biological neural networks while simplifying concepts from biological neural systems. ANNs emulate the electrical behavior of the brain and nervous system, where processing units, called neurodes or perceptrons, connect with other processing units. These neurodes are typically organized in layers or vectors, with outputs from one layer serving as inputs to subsequent layers and potentially to other layers. A neurode can form connections with all or a subset of neurodes in the next layer, mirroring synaptic connections in the brain. The weighted data signals entering a neurode simulate nerve cell excitation and information propagation within the network or brain. The input values to a processing unit, represented as in, undergo multiplication by a connection weight, wn,m, mirroring the reinforcement of neural pathways in the brain. Learning in ANNs is simulated through modifications in connection strengths or weights.

The total of weighted input values to a processing element is aggregated using a vector to scalar function like summation (i.e., $y = \Sigma w_{ij} x_i$), averaging, input maximum, or mode value, resulting in a single input value to the neurode. Subsequently, the processing element applies a transfer function to generate its output (and thus input signals for the subsequent processing layer), transforming the neurode's input value. Typically, this transformation entails the utilization of a sigmoid, hyperbolic-tangent, or other nonlinear function. This iterative process occurs between layers of processing elements until a final output value, o_n, or a vector of values is produced by the neural network.

While ideally, to mirror the human nervous system's asynchronous nature, the processing elements of artificial neural networks should activate in an asynchronous manner based on the weighted input signal, most software and hardware implementations of ANNs opt for a discretized approach. In this approach, each processing element is triggered once for every presentation of a vector of input values to ensure consistency.

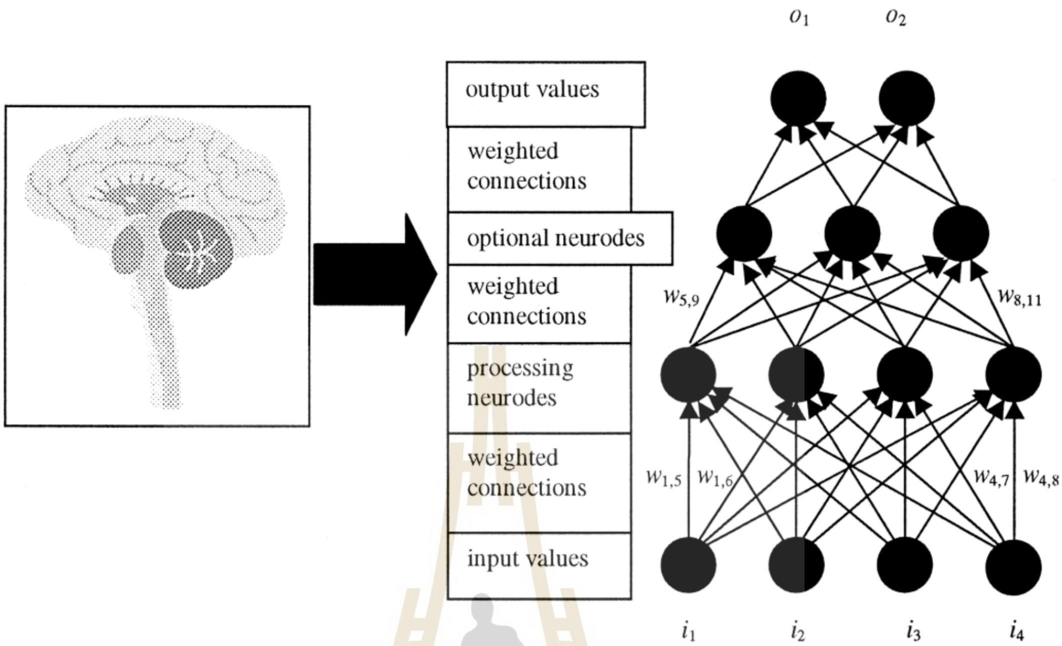


Figure 2.1 Sample artificial neural network architecture. Source: Walczak and Cerpa (2003).

Neural networks utilize different learning algorithms, which are primarily categorized based on the input type: binary-valued (0s and 1s) or continuous-valued input. These categories are further subdivided into supervised learning and unsupervised learning. In supervised learning algorithms, the distinction between the desired and actual output is employed to adjust weights for the ANNs. Some supervised algorithms receive feedback on output correctness to refine weights for more accurate results. Examples of supervised learning algorithms include the binary Hopfield network and the continuous backpropagation method. On the other hand, unsupervised learning algorithms rely solely on input stimuli, allowing the network to self-organize and develop hidden processing elements that respond uniquely to different input stimuli, without depending on output correctness information. Examples of unsupervised learning algorithms include the binary ART I and the continuous Kohonen algorithms.

Despite often being perceived as black boxes with an ability to decipher intricate data patterns, neural network applications necessitate extensive knowledge engineering and the integration of substantial domain expertise into the artificial neural networks. Successful development of artificial neural networks demands a profound comprehension of the design processes involved. Creating artificial neural networks (ANNs) involves making several critical decisions, such as selecting input values, establishing the sizes of training and testing datasets, opting for a learning algorithm, defining the network's architecture or topology, and choosing transformation functions. These decisions are often interconnected; for example, the architecture and learning algorithm of ANNs influence the type of input values (binary or continuous). As a result, following a systematic methodology or a clearly defined sequence of steps is essential in ANN design. The key steps include:

1. Determining the data to utilize.
2. Identifying input variables.
3. Segmenting data into training and test sets.
4. Defining the network architecture.
5. Selecting a learning algorithm.
6. Converting variables into network inputs.
7. Training the network iteratively until the ANNs error falls below an acceptable threshold.
8. Testing the network on a hold-out sample to validate the generalization of the ANNs.

In the design of artificial neural networks (ANNs), a comprehensive knowledge acquisition process plays a crucial role. Initially, selecting the appropriate input vector for the ANNs involves capturing all the essential decision criteria used by domain experts to address the specific domain problem intended for modeling by the ANNs, while also removing any correlated variables. Subsequently, choosing a suitable learning method presents a significant challenge, with the optimal method selected based on an evaluation of the constraints imposed by the available training examples for the ANNs training process.

The next step involves determining the architecture of the hidden layers, which requires a thorough examination of how domain experts cluster input variables or create heuristic rules to derive an output value from the input variables. This set of clustering and decision heuristics, known as decision factors (DFs), establishes the minimum number of hidden units needed for an ANNs to accurately represent the problem space within the domain.

Utilizing knowledge-based design heuristics enables an artificial neural network (ANNs) designer to create concise ANNs that efficiently tackles specific domain complexities. While the idea of future automated techniques for optimizing the configuration of hidden layers in ANNs shows potential, current methodologies advocate for minimal-size ANNs configurations to attain optimal results within a shorter training period.

Furthermore, a novel concept known as the time-series recency effect has been discovered, consistently demonstrating efficacy in different currency exchange time series ANN models. This effect suggests that constructing the model using more recent data closer in time to the out-of-sample values enhances forecasting accuracy.

2.2.4 Sentiment analysis

Sentiment analysis, also known as opinion mining, involves attributing an opinion or emotional classification to textual content (Medhat et al., 2014; Stine, 2019). Typically, this classification signifies polarity, indicating whether the text conveys a positive or negative sentiment. The prevalent approach to sentiment analysis operates on the premise that a document's text conveys an assessment or viewpoint regarding a particular entity, often reflecting a customer's opinion articulated in a product review. Within this framework, emphasis is placed on developing a classifier that anticipates polarity based on textual input. Sentiment Analysis can be considered a classification process as illustrated in Figure 2.2.

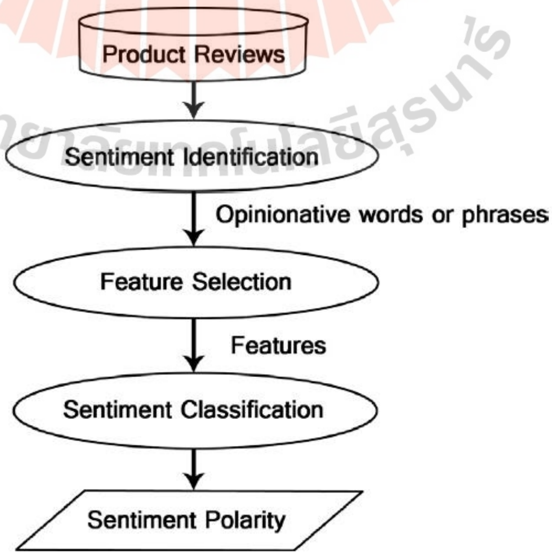


Figure 2.2 Sample sentiment analysis process. Source: Medhat et al. (2014).

2.2.4.1 Level of sentiment analysis

Sentiment analysis (SA) consists of three main levels of classification: document-level, sentence-level, and aspect-level SA. Document-level SA involves categorizing an opinion document based on its expression of positive or negative sentiment. At this level, the entire document is considered the primary unit of information, focusing on a singular topic. On the other hand, sentence-level SA aims to analyze sentiment on a sentence-by-sentence basis. The initial step is to differentiate between subjective and objective sentences. For subjective sentences, the analysis proceeds to identify whether they convey positive or negative opinions. (Medhat et al., 2014; Wankhade et al., 2022)

Medhat et al. (2014) stated that classifying text at either the document or sentence level may lack the depth required to capture opinions on all aspects of an entity, essential in various applications. To achieve this requisite level of detail, a shift to the aspect level is necessary. Aspect-level sentiment analysis (SA) is designed to categorize sentiment concerning the aspects of entities under consideration. The initial phase involves the identification of entities and their corresponding aspects.

In the study by Medhat et al. (2014), a comprehensive investigation of a diverse range of sentiment analysis (SA) fields is conducted. These articles have been published recently and are categorized based on the focus of the research—depicting the algorithms and data utilized. The authors delve into the intricacies of Feature Selection (FS) techniques in detail, outlining their relevance along with the associated articles and original references. Similarly, the Sentiment Classification (SC) techniques are elaborated on in Figure 2.3. The survey serves as a valuable resource for emerging researchers in the domain of SA by encapsulating prominent SA techniques and applications within a single research paper. Notably, this survey introduces a refined categorization of various SA techniques, a distinctive feature not commonly found in other surveys. Moreover, the inquiry delves into emerging trends in sentiment analysis that have captured the interest of researchers, including Emotion Detection (ED), Building Resources (BR), and Transfer Learning (TL). Emotion detection seeks to extract and scrutinize emotions within sentences, spanning from overt to implicit expressions. Transfer learning or cross-domain classification involves analyzing data within one domain and leveraging the findings to enhance performance in another domain. Additionally, Building Resources focuses on developing lexicons and datasets with annotated opinion expressions based on polarity, occasionally integrating dictionaries to expand the analysis.

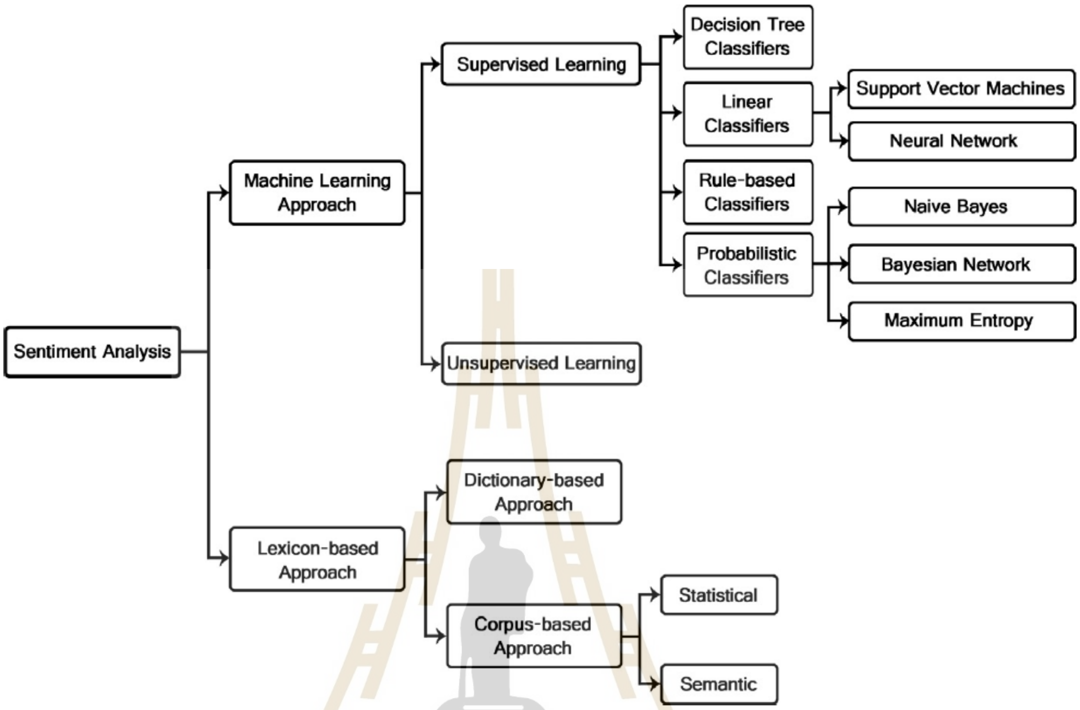


Figure 2.3 Sentiment classification techniques. Source: Medhat et al. (2014)

2.2.4.2 Sentiment classification techniques

Sentiment classification methodologies can be broadly classified into three primary strategies: the machine learning approach, lexicon-based approach, and hybrid approach. The Machine Learning Approach (ML) employs well-known machine learning algorithms and integrates linguistic characteristics. Conversely, the Lexicon-based Approach relies on a sentiment lexicon containing precompiled sentiment terms. This approach is further divided into the dictionary-based approach and corpus-based approach, which utilize statistical or semantic techniques to determine sentiment polarity. The Hybrid Approach combines elements of both machine learning and lexicon-based approaches and is commonly utilized in sentiment classification techniques, with sentiment lexicons often playing a significant role in these methods. These various approaches and the popular algorithms for Sentiment Classification (SC) are highlighted in Figure 2.3, as previously mentioned.

In addition, text classification techniques that utilize the Machine Learning Approach can be broadly categorized into supervised and unsupervised learning methods. Supervised methods rely on a substantial amount of labeled training documents, whereas unsupervised methods are employed in situations where acquiring labeled training documents is difficult.

In the lexicon-based approach, text analysis relies on the identification of an opinion lexicon, a crucial component in evaluating text sentiment. This approach comprises two main methods. Firstly, the dictionary-based approach involves pinpointing opinion seed words and then expanding the search in a dictionary for related synonyms and antonyms. Secondly, the corpus-based approach starts with a seed list of opinion words and proceeds to discover additional opinion words within a large corpus to assist in discerning context-specific sentiments. This step may involve the application of statistical or semantic methods. Detailed insights into the algorithms and relevant literature regarding both approaches are provided in the following sections.

1. Machine learning approach

The machine learning approach leverages well-known machine learning algorithms to address sentiment analysis (SA) as a standard text classification challenge, utilizing syntactic and/or linguistic features. The classification model correlates the features within the given record to one of the class labels. Subsequently, for an unidentified instance, the model is employed to predict a class label. The classification task can be categorized into hard classification, where only one label is assigned to an instance, and soft classification, which assigns probabilistic values of labels to instances.

Supervised learning methods depend on labeled training data and include a range of classifiers, such as Probabilistic classifiers (e.g., Naive Bayes Classifier, Bayesian Network, Maximum Entropy Classifier), Linear classifiers (including Support Vector Machines, Neural Networks, Decision Tree classifiers, and Rule-based classifiers). In contrast, unsupervised learning, although creating labeled training data can be challenging in text classification, collecting unlabeled data is typically more straightforward, granting unsupervised methods a distinct advantage.

Meta classifiers, as discussed by Lane et al. (2012) and , address the challenge of identifying documents expressing positive or negative sentiment within media analysis. Key challenges they encountered include handling the imbalance in positive and negative sample distributions, monitoring document transformations over time, and devising effective training and evaluation procedures for the models. Their work involved three datasets provided by a media-analysis company, focusing on two classifications: detecting favorability presence and distinguishing positive versus negative favorability. Various features extracted from raw text were used to create the datasets. Several classifiers, such as SVM, K-nearest neighbor, Naive Bayes, Bayesian Network, Decision Tree, Rule learner, among others, were evaluated to determine the optimal choice. The study revealed that balancing the class distribution in the training data could enhance performance, although the efficacy of Naive Bayes was shown to be impacted negatively by such balancing efforts.

2. Lexicon-based approach

Opinion words are pivotal in sentiment analysis tasks, with positive words conveying favorable sentiments and negative words reflecting unfavorable ones. Furthermore, opinion phrases and idioms, together known as an opinion lexicon, play a key role in sentiment analysis endeavors. The creation or collection of opinion word lists commonly follows three main approaches. The manual approach, despite being labor-intensive, is frequently used as a final validation step alongside automated methods to reduce potential errors from automated processes. The following sections present and discuss the two automated approaches for compiling or acquiring opinion words.

3. Dictionary-based approach

The dictionary-based approach advocated by Hu and Liu (2004) involves initially gathering a small set of opinion words manually, known for their orientations. This set is then expanded by identifying synonyms and antonyms in established corpora like WordNet or thesaurus. The process iterates until no new words are found, with a final manual review conducted to rectify any errors.

One drawback of the dictionary-based method is the difficulty in pinpointing domain-specific and context-specific opinion words. Qiu et al. (2010) applied this method in contextual advertising analysis, suggesting tactics to improve ad relevance and user experience. Through the utilization of syntactic parsing and sentiment dictionaries, they introduced a rule-based framework to tackle topic word extraction and identify consumer attitudes in advertising keyword extraction, specifically examining web forums from automotiveforums.com. Their research showcased the effectiveness of their approach in fine-tuning advertising keyword extraction and ad selection.

4. Corpus-based approach

The Corpus-based approach offers a solution to discovering opinion words tailored to specific contexts. This technique relies on identifying syntactic or collocational patterns alongside a seed list of opinion words within a large corpus to extract additional opinion words. An exemplar of such method was demonstrated by Hatzivassiloglou and McKeown (1997). Initiating with a seed list of opinion adjectives, they incorporated linguistic constraints, particularly involving connectors like AND, OR, BUT, and EITHER-OR. For instance, the conjunction AND typically implies that conjoined adjectives share the same orientation, known as sentiment consistency. Adversative expressions like but and however indicate shifts in opinions. To discern the orientation of conjoined adjectives, a learning process is applied to a vast corpus. This leads to the creation of a graph representing relationships between adjectives, subsequently subjected to clustering to form positive and negative word sets.

The Conditional Random Fields (CRFs) method was harnessed by Jiao and Zhou (2011) for sentiment polarity discrimination through a multi-string pattern matching algorithm in Chinese online reviews. They developed emotional dictionaries and analyzed online reviews from various sectors. Meanwhile, Xu et al. (2011) utilized a two-level CRF model to extract comparative relations between products from customer reviews, aiming to facilitate decision-making in enterprise risk management. Their approach involved mobile customer reviews from diverse platforms and demonstrated superior accuracy in comparative relation extraction, enhancing risk management outcomes.

Cruz et al. (2013) introduced a taxonomy-based technique for extracting feature-level opinions and slotting them within a feature taxonomy model. Focused on domain-specific Opinion Mining (OM), they leveraged resources derived from annotated documents across headphones, hotels, and cars reviews from epinions.com. Their domain-specific approach underscored the significance of domain-specificity in enhancing opinion extraction accuracy compared to generic techniques.

While the corpus-based approach may not be as comprehensive as the dictionary-based method due to the challenge of compiling an exhaustive corpus covering all English words, it excels in pinpointing domain and context-specific opinion words and their orientations using domain-specific corpora. The corpus-based approach can be implemented with statistical or semantic techniques.

Document-level sentiment analysis involves evaluating an entire document to assign a single sentiment to its content. While utilized less frequently, this method can categorize book chapters or pages as positive, negative, or neutral. Both supervised and unsupervised learning methods aid in document categorization, with challenges emerging in cross-domain and cross-language sentiment analysis due to the necessity of maintaining domain-specific sensitivity for accuracy.

At the sentence level, individual sentences are assessed for sentiment, particularly beneficial in documents with mixed sentiments. Subjective classification aligns closely with this method, where each sentence's sentiment is determined independently using methodologies similar to those employed at the document level, supported by enriched training data and computational resources. Sentence-level sentiment analysis allows for both standalone analysis of each sentence and generating an overall sentiment for the document.

Phrase-level sentiment analysis involves examining and classifying sentiments conveyed by words or phrases, particularly helpful for analyzing product reviews that convey various aspects within sentences. Recent research has emphasized the importance of phrase-level sentiment analysis.

Sentiment analysis at the aspect level involves scrutinizing specific aspects within sentences, requiring the identification and categorization of individual aspects to determine an aggregate sentiment for the sentence. This detailed approach highlights the importance of analyzing various aspects mentioned in shaping a comprehensive sentiment assessment.

The evolution of sentiment analysis has catered to diverse sectors such as healthcare, tourism, finance, and electoral politics. Platforms like Skytrax and Trip Advisor have become essential tools for travelers, influencing their travel decisions based on shared experiences. This thesis focuses on analyzing sentiments expressed in publicly available airport reviews to unravel consumer perceptions and preferences shaping their travel decisions and experiences.

2.3 Relevant literature

2.3.1 Airport service quality

According to a 2021 study by the Airports Council International (ACI), boosting non-aviation revenue (NAR) is closely linked to enhancing the customer experience. The research found a notable correlation: a 1% increase in passenger numbers corresponds to a 0.7% to 1% rise in NAR. Furthermore, a 1% improvement in overall passenger satisfaction leads to an average 1.5% increase in NAR. This highlights the direct influence of passenger satisfaction on revenue generation in the aviation sector (ACI, 2021).

Previous investigations into airport service quality have largely concentrated on the multifaceted concept of passenger satisfaction. Enhancing this satisfaction is a central aim for airport management, promoting greater competitiveness and improved operational efficiency. Research by Wattanacharoensil et al. (2015) demonstrates a connection between airport's aeronautical and non-aeronautical performance with passenger experiences. Non-aviation revenue is increasingly recognized as a crucial driver of economic growth within the aviation sector.

Airport service quality (ASQ) is vital for travelers, greatly impacting their experiences at airports. ASQ, a globally recognized assessment tool created by the ACI, serves as a standard for measuring passenger satisfaction during their airport journeys. This highlights the industry's commitment to meeting and exceeding passenger expectations.

To accurately measure airport service levels and passenger satisfaction, a comprehensive approach that includes both internal and external evaluations is necessary. According to Fodness and Murray (2007), systematically analyzing passenger expectations is crucial for prioritizing improvements in key service areas. Supporting this view, research by Lubbe et al. (2011) emphasizes the importance of integrating air travelers' perspectives into service evaluations.

Researchers such as Bezerra and Gomes (2020) employed structural equation modeling (SEM) to examine the interconnections among factors that impact passenger satisfaction, providing insights into passenger expectations, airport service quality (ASQ), switching costs, and loyalty dynamics. Isa et al. (2020) studied the klia2 terminal at Kuala Lumpur International Airport, identifying eight dimensions affecting overall satisfaction through PLS-SEM analysis. Bulatović et al. (2023) used ordinal regression and maximum likelihood structural equation modeling (ML-SEM) to evaluate the effectiveness of the Skytrax evaluation system, highlighting facility comfort, wayfinding and signage, and restaurant outlets as key indicators of airport service quality.

In airport management, hybrid methodologies have gained traction. Bakır et al. (2022) analyzed online airport reviews in Europe using multiple regression analysis (MRA) and necessary condition analysis (NCA), identifying airport operators as significant influencers of passenger experiences. Additionally, Pholsook et al. (2023) conducted a thorough three-stage analysis to determine the essential dimensions of airport service quality, emphasizing the importance of airport facilities, wayfinding, and security as vital components for overall passenger satisfaction.

2.3.2 User-generated content of airport services

Considering the pandemic, the "new normal" has developed, and alternative channels for capturing customer feedback have become increasingly essential in this data-driven era. Two prominent methods are:

(1) Creating online questionnaires: digital platforms enable the creation of online questionnaires, allowing airports to gather direct feedback from travelers. This approach provides a structured method to collect specific insights into different facets of the airport experience.

(2) Scraping data from user-generated content (UGC): this involves extracting data from social media platforms and review websites, such as Google Maps (Lee & Yu, 2018; Li et al., 2022; Molaei & Hunter, 2019), TripAdvisor (Nghiêm-Phú & Suter, 2018; Sezgen et al., 2019), Twitter (Barakat et al., 2021; Martin-Domingo et al., 2019), Skytrax (Bae & Chi, 2022; Bakır et al., 2022; Bogicevic et al., 2013; Bulatović et al., 2023; Bunchongchit & Wattanacharoensil, 2021; Gitto & Mancuso, 2017; Halpern & Mwesiumo, 2021; Homaid & Moulitsas, 2023; Kiliç & Çadirci, 2022; Wattanacharoensil et al., 2017; Yavuz et al., 2020), and airports' social media channels (Arasli et al.,

2023). Recently, Abouseada et al. (2023) conducted quantitative analysis of data extracted from the Skytrax, TripAdvisor, Traveler, and Flight Report platforms. Scraping data from these platforms allows airports to analyze real-time, unfiltered feedback from passengers.

UGC has become an alternative data source for evaluating service levels in the age of data analytics and machine learning. Numerous studies (see Barakat et al., 2021; Bogicevic et al., 2013; Bunchongchit & Wattanacharoensil, 2021; Gitto & Mancuso, 2017; Lee & Yu, 2018; Martin-Domingo et al., 2019; Nghiêm-Phú & Suter, 2018; Wattanacharoensil et al., 2017) highlight the potential of leveraging UGC for this purpose. The rise of online platforms has amplified passengers' voices, providing a powerful channel for expressing opinions and satisfaction levels concerning airports. While customer reviews offer valuable insights for airport improvement, the sheer volume of daily reviews poses a challenge for effective management. Data mining and analytics have emerged as promising solutions, allowing airports to efficiently analyze large datasets from review and rating websites.

Skytrax is a well-regarded platform in the aviation industry, known for aggregating passenger reviews and comments, providing a rich source of data for comprehensive airport management research. The integration of alternative feedback channels and the utilization of user-generated content (UGC), particularly from platforms like Skytrax, have emerged as significant trends in airport management research. This approach helps airports remain attuned to passenger sentiments, facilitating continuous improvement and adaptation to changing customer expectations and experiences.

Despite the heightened focus on passenger satisfaction and the adoption of advanced analytical models, there are notable gaps in the existing body of knowledge. Many studies focus on individual models or a limited set of variables, potentially missing the complex interplay among various factors. Although UGC data is increasingly acknowledged for its value, more research is needed to explore its intricacies. Issues such as sentiment analysis, topic modeling, and the impact of cultural and demographic factors on feedback require deeper investigation.

The literature on airport service quality (ASQ) largely relies on individual analysis methods, with a distinct lack of studies exploring the integration of various techniques. Extensive secondary data sources, particularly when combined with advanced methods such as multiple regression analysis (MRA), Bayesian networks (BNs), and neural networks (NNs), have not been thoroughly examined. This is especially true concerning the analysis of airport passenger satisfaction using organic Skytrax UGC data. The limited research using these advanced methods highlights the need for further investigation to understand both the challenges and benefits of their integration and assess their practical applicability in airport management.

Recognizing the critical role of passenger satisfaction in effective airport management, scholars and industry experts are increasingly interested in gaining a deeper understanding of and enhancing passenger satisfaction levels. This study aims to address these knowledge gaps by employing an innovative approach that integrates MRA and BNs. Additionally, the study plans to use NNs to identify the most influential attributes affecting overall evaluations.

2.3.3 Sentiment analysis of airport services

In the era of data science, the integration of machine learning (ML) and natural language processing (NLP) techniques to analyze reviews is considered standard practice, especially when dealing with large volumes of unstructured web data available for research. Business intelligence solutions for managing such vast amounts of web data include utilizing data mining and ML approaches (Gitto & Mancuso, 2017). Some studies have applied ML methods to the aviation domain, particularly focusing on airports and airline passenger services. Past research using ML approaches on reviews aims to enhance and extract valuable insights to aid enterprises (Bunchongchit & Wattanacharoensil, 2021). Big data and public reviews from platforms like Skytrax, Google Review, Twitter, and TripAdvisor have also been utilized in recent research concerning airport service quality, although the number of studies remains limited.

Sentiment analysis, a popular text mining method, concentrates on extracting both positive and negative opinions, emotions, and evaluations from extensive textual data collections. Early efforts in text-mining web evaluations within airport management focused on evaluating airport service levels (Bogicevic et al., 2013). By employing data mining techniques, researchers generated tag clouds, word networks, and word tree visualizations based on content analysis of 1,095 reviews posted on Skytrax between 2010 and 2013. Such analysis offers consumer researchers more objective ratings of qualitative consumer evaluations, assisting in operational management decision-making.

Researchers have explored various methods to assess airport service quality, with Gitto and Mancuso (2017) utilizing sentiment analysis on Skytrax airport reviews at five main European airports. By leveraging open-source programs like KNIME and Semantria, the aim was to gauge passenger perceptions of service quality. Sentiment analysis, which draws insights from textual data, helps in summarizing consumer satisfaction. Data mining and machine learning complement traditional technologies for processing extensive web data, particularly sentiment analysis, which aims to discern customer sentiments based on their writings.

In further investigation, the comparison between user-generated web data, such as Google reviews, and established metrics like ASQ ratings for evaluating airport service quality was explored (Lee & Yu, 2018). By utilizing user-generated internet content as an alternative data source, this study applied topic modeling and sentiment analysis techniques based on reviews gathered from Google Maps. The study's research process, depicted in Figure 2.4, involved four distinct steps. Through a comparative analysis between user-generated content and industry-standard ratings, the study aimed to uncover insights that complement existing metrics for assessing airport service quality. By leveraging sentiment analysis and topic modeling techniques on a substantial dataset of Google reviews, the researchers aimed to develop complementary strategies for evaluating passenger perceptions. Their findings underscored the value of Google reviews in creating comprehensive indicators for assessing airport service quality alongside traditional survey methods.

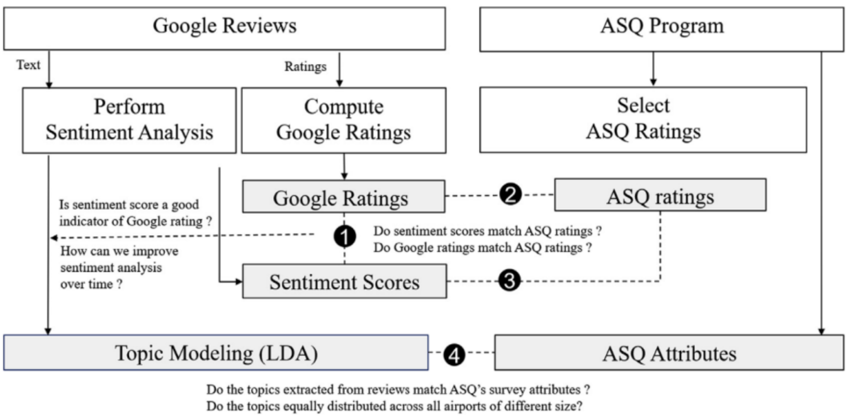


Figure 2.4 Lee and Yu's text analytic framework. Source: Lee and Yu (2018)

Additionally, studies like those by Nghiêm-Phú and Suter (2018) and Martin-Domingo et al. (2019) utilized sentiment analysis on reviews from platforms like TripAdvisor and Twitter to understand traveler evaluations and identify service attributes affecting passenger perceptions. Leveraging tools like Theysay and Twinword, researchers extracted insights to improve airport services based on sentiment analysis results.

More recent research, like that of Barakat et al. (2021), delves into deep neural network architectures to predict sentiment from social media data, specifically tweets, to assess airport service quality more effectively. By utilizing advanced techniques such as Convolutional Neural Networks (CNN) and Long-Short Term Memory (LSTM) models, researchers aim to improve sentiment prediction accuracy.

In summary, sentiment analysis and related techniques play a crucial role in analyzing customer feedback, uncovering valuable insights, and enhancing decision-making processes in various domains, including airport management. These analytical methods enable researchers to understand and quantify sentiments, emotions, and opinions expressed in textual data, providing deeper insights into customer perceptions and preferences.

Natural Language was employed to conduct sentiment analysis by feeding it the title and comment texts for evaluation. This API encompasses a range of NLP services, such as entity analysis, content classification, and the sentiment analysis utilized within this study. The researchers treated this API similar to a black box, as depicted in Figure 2.5, utilizing it as a tool for processing the text and deriving sentiment insights without deep knowledge of its internal functioning.

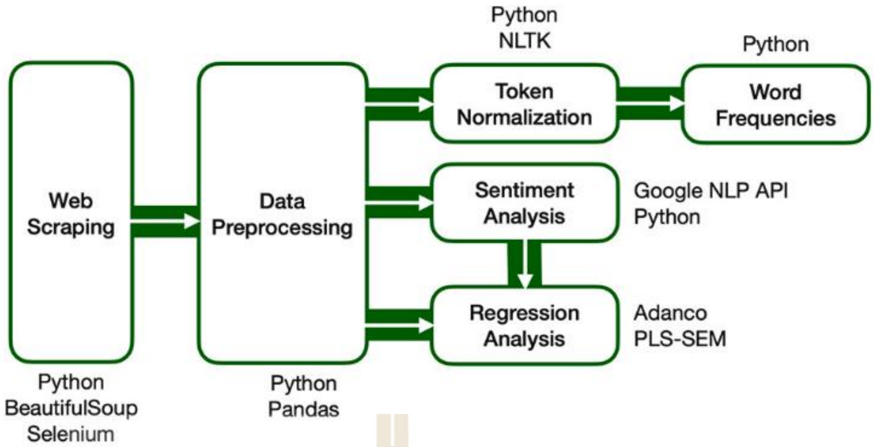


Figure 2.5 Steps of the text analytics and tools used in each step. Source: Bunchongchit and Wattanacharoensil (2021)

2.4 Hypothesis development

Derived from secondary data extracted from the Skytrax online review platform (Skytrax, 2023b), eight distinct attributes are identified as contributing to the evaluation of Skytrax airport service levels. The dimensions identified are as follows:

(1) Queuing Time: This dimension pertains to the duration that passengers spend in queues, specifically the time allocated to waiting in lines at the airport.

(2) Cleanliness: This attribute refers to the overall tidiness and straightforwardness of the terminal environment, reflecting the general condition and maintenance of cleanliness within the airport.

(3) Seating Areas: This dimension involves the accessibility and convenience of seating options available within the terminal, addressing the adequacy and comfort of places for passengers to sit.

(4) Signage: This attribute encompasses the existence and quality of well-designed, informative signs within the terminal, focusing on aspects such as clarity, usefulness, and overall quality.

(5) Food Services: This dimension relates to the quality and diversity of food and beverage options offered to passengers at the airport, encompassing both the range and the standard of culinary provisions.

(6) Retail Options: This attribute revolves around the shopping opportunities available to passengers within the airport, addressing the variety and accessibility of retail outlets.

(7) Wi-Fi Availability: This dimension pertains to the quality and availability of internet services within the airport, reflecting the capacity and reliability of connectivity provided to passengers.

(8) Staff Courtesy: This attribute concerns the behavior and assistance rendered by airport staff, encompassing their politeness, helpfulness, and overall demeanor in interactions with passengers.

These dimensions collectively form a comprehensive framework for evaluating the efficacy of airport service levels as reported on the Skytrax platform, underscoring critical areas of passenger experience and satisfaction. Further research into these attributes can yield insights into the operational strengths and areas for improvement within airport service management.

Airport terminals are dynamic environments where passengers engage significantly in boarding and check-in procedures (Bezerra & Gomes, 2016). Throughout these processes, queues frequently arise, hindering access to services and causing time inefficiencies (Aniyeri & Nadar, 2018; Stolletz, 2011). A reduction in queuing time is paramount for airport operators, as prolonged waiting negatively affects the service rate and overall passenger satisfaction (Yavuz et al., 2020). Halpern and Mwesiumo (2021) suggested that service disruptions related to staff interactions and queuing have a more significant negative impact on airport user satisfaction compared to issues related to shopping and internet services.

Kiliç and Çadirci (2022) applied text mining techniques to analyze Skytrax data regarding airport experiences, highlighting predominantly positive sentiments expressed towards airports. However, slightly negative sentiments were associated with areas such as baggage claims, queues, employee services, and human interactions. Schultz et al. (2021) underscored the detrimental effects of operational issues, particularly in the check-in process, leading to substantial passenger queues and bottlenecks at security checkpoints.

Pandey (2016) conducted an evaluation of service quality at major Thai airports, pinpointing areas for enhancement such as check-in wait times, security inspection delays, speed of baggage delivery, and wait times for passport/ID inspections. The cleanliness of airport terminals has been a persistent concern for passengers, influencing their tolerance for any shortcomings (Halpern & Mwesiumo, 2021). Studies indicate that terminal cleanliness has a positive impact on passengers' emotions and overall satisfaction (Allen et al., 2021; Bogicevic et al., 2013; Nghiêm-Phú & Suter, 2018; Paramonovs & Ijevleva, 2015; Yavuz et al., 2020). Passengers who arrive early prioritize cleanliness, whereas foreign travelers place greater emphasis on the clarity of information displays (Bellizzi et al., 2018). Lee and Yu (2018) discovered that smaller airports tend to prioritize convenient transportation, cleanliness, and staff friendliness, while larger airports concentrate on customs inspection processes and ambiance.

Lopez-Valpuesta and Casas-Albala (2023) emphasized the importance of cleanliness and comfort as critical dimensions in airport facilities, particularly in times of health emergencies. The availability of seating areas in terminals significantly impacts customer satisfaction across diverse customer groups (Wakefield & Blodgett, 1996; Yavuz et al., 2020; Zheng, 2014). The spacing between seats not only affects mobility but also plays a role in shaping service quality (Bogicevic et al., 2013; Wakefield & Blodgett, 1996; Zheng, 2014).

Airports have transformed into complex environments, presenting challenges for efficient service utilization (Bezerra & Gomes, 2016). Terminal signage is crucial in preventing confusion and ensuring passengers do not miss their flights (Fewings, 2001; Jianxin et al., 2014). Well-designed signage contributes to an overall higher service quality (Fewings, 2001). Jianxin et al. (2014) focused on enhancing the effectiveness of pedestrian guiding signs (PGSs), while Das and Choudhury (2022) underscored the significance of visual signage and wayfinding measures in enhancing passenger satisfaction. Farr et al. (2014) investigated the intricacies of wayfinding influenced by both human behavior and environmental factors. Pholsook et al. (2023) identified airport facilities, wayfinding, and security as critical elements that impact passenger satisfaction.

Non-aeronautical activities, particularly retail and food services, play a significant role in boosting airport profitability (Cao et al., 2023; Del Chiappa et al., 2016; Martin-Domingo et al., 2019). Studies suggest that a wider range of food and beverage options has a positive impact on service quality and passenger satisfaction (D'Alonzo et al., 2021). However, high retail prices at airports, often due to increased concession fees, can have a detrimental effect on customer satisfaction (Del Chiappa et al., 2016). Providing reasonably priced offerings is essential for enhancing customer satisfaction (Han et al., 2012). Freitas et al. (2021) identified various factors influencing passengers' perceptions of food and beverage services.

Retail shopping is a favored pastime for airport passengers, offering entertainment value and contributing to non-aeronautical revenue streams. (Bezerra & Gomes, 2016). Shopping facilities significantly predict overall satisfaction (Bogicevic et al., 2013; Cao et al., 2023; Gitto & Mancuso, 2017). Han et al. (2018) emphasized that satisfied customers demonstrate higher loyalty levels. Molaei and Hunter (2019) stressed the significance of enhancing shopping and relaxation amenities to ensure well-rounded passenger satisfaction.

The internet has become fundamental at airports, with passengers considering it essential for tasks and leisure (Bogicevic et al., 2013; Jiang & Zhang, 2016; Lee & Yu, 2018; Lubbe et al., 2011; Martin-Domingo et al., 2019; Nghiêm-Phú & Suter, 2018). Wi-Fi hotspots significantly impact airport service quality (ASQ) (Lubbe et al., 2011). Passengers expect courteous and competent operators for a positive airport experience (Antwi, Fan, Ihnatushchenko, et al., 2020; Bakır et al., 2022; Pandey, 2016; Paramonovs & Ijevleva, 2015). Staff orientation toward passenger satisfaction influences service perceptions significantly (D'Alonzo et al., 2021; Fodness & Murray, 2007; Halpern & Mwesiumo, 2021; Sezgen et al., 2019). The courtesy displayed by airport operators positively influences service perceptions (Mirghafoori et al., 2018; Paramonovs & Ijevleva, 2015). Employee resources affect check-in queuing processes and passenger arrival (Stolletz, 2011).

To conclude, the comprehensive passenger journey at airports is influenced by a range of factors such as wait times, hygiene, seating provisions, signage quality, dining options, shopping choices, internet accessibility, and staff demeanor. Addressing these elements is crucial for improving service excellence and enhancing the overall airport experience. Based on existing research, eight hypotheses have been developed as outlined below.

H1. Queuing time correlates significantly with the total airport rating.
H2. Cleanliness correlates significantly with the total airport rating.
H3. Seating areas correlate significantly with the total airport rating.
H4. Signage correlates significantly with the total airport rating.
H5. Food services correlate significantly with the total airport rating.
H6. Retail options correlate significantly with the total airport rating.
H7. Wi-Fi availability correlates significantly with the total airport rating.
H8. Staff courtesy correlates significantly with the total airport rating.

The above eight hypotheses were constructed to depict the influence of the eight attributes of airport services on the total rating. This relationship was assessed through the application of multiple regression analysis (MRA), as illustrated in Figure 2.6.

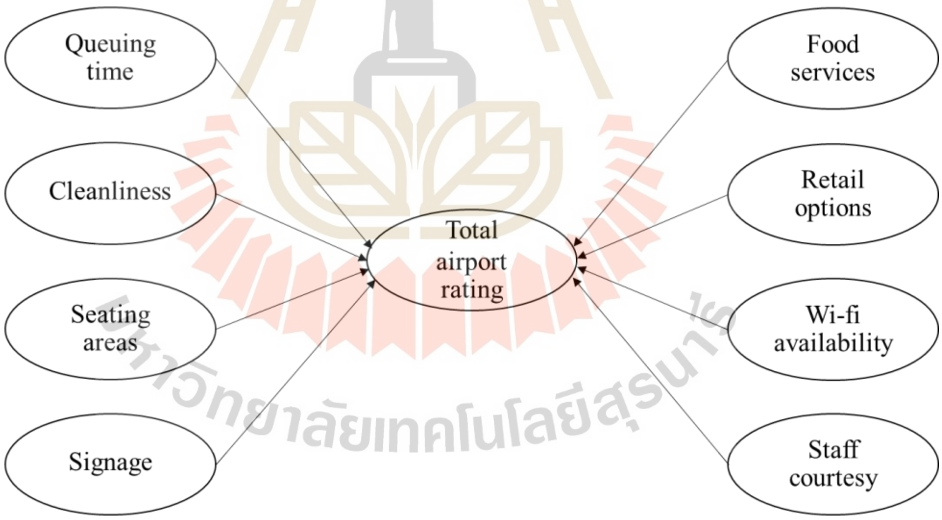


Figure 2.6 The model of airport service.

2.5 Summary

The literature identifies a critical gap in the holistic strategic planning of airport service systems, emphasizing the integration of multiple service dimensions to enhance non-aviation revenue (NAR). Previous research has predominantly focused on airport passenger satisfaction, a crucial aspect of airport management that enhances competitiveness and operational efficiency. The Airport Service Quality (ASQ) program by ACI serves as a benchmark for measuring passenger satisfaction, underscoring the industry's commitment to exceeding passenger expectations.

Studies advocate for comprehensive evaluations of service levels and passenger satisfaction through both internal and external assessments. Systematic analysis of passenger expectations and incorporation of air travelers' perspectives are critical. Advanced methodologies such as Structural Equation Modeling (SEM) and sentiment analysis have been employed to explore factors influencing satisfaction. User-generated content (UGC) from platforms like Google Maps, TripAdvisor, and Skytrax provides valuable real-time insights, pertinent especially in the current "new normal" post-pandemic landscape.

However, there exists a notable gap in the integration of advanced analytical techniques—such as Multiple Regression Analysis (MRA), Bayesian Networks (BNs), and Neural Networks (NNs)—with extensive UGC data. Addressing this gap could yield deeper insights into passenger satisfaction and inform more effective airport management strategies.

Transitioning to SEA, where airports are pivotal to economic and tourism growth, the need for a holistic approach is evident. SEA airports face unique challenges and opportunities due to rapid passenger growth and varying service expectations. Research should focus on the key dimensions of service quality, including queuing time, cleanliness, seating areas, signage, food services, retail options, Wi-Fi availability, and staff courtesy, and apply advanced analytical methods tailored to the region's specific context.

In conclusion, bridging the research gap requires a holistic strategic planning framework that integrates multiple service dimensions, advanced analytical techniques, and user-generated content, tailored to the SEA context. This comprehensive approach is essential for improving airport service quality, driving economic growth, and enhancing the overall passenger experience in the region.

CHAPTER III

RESEARCH METHODOLOGY

3.1 Data

This study focuses specifically on the top ten busiest airports in Southeast Asia (SEA), recognized as key revenue drivers in the regional aviation industry. Using data from OAG Aviation Worldwide Limited (OAG, 2024), as of January 2024, as depicted in Figure 3.1, these airports are highlighted for their significant importance. The list includes three airports in Indonesia, two in Thailand, two in Vietnam, one in Singapore, one in Malaysia, and one in the Philippines: Bangkok Suvarnabhumi Airport (BKK, Thailand), Soekarno-Hatta International Airport (CGK, Indonesia), Don Mueang International Airport (DMK, Thailand), Denpasar International Airport (DPS, Indonesia), Hanoi Airport (HAN, Vietnam), Kuala Lumpur International Airport (KUL, Malaysia), Manila Airport (MNL, Philippines), Ho Chi Minh City Airport (SGN, Vietnam), Singapore Changi Airport (SIN), and Sultan Hasanuddin International Airport (UPG, Indonesia). A thorough analysis of these airports is essential for comprehensively understanding and strategically addressing the intricacies of passenger traffic in the SEA aviation landscape.

The user-generated data selected for this study is sourced from the Skytrax online review platform (Skytrax, 2023b). Skytrax, well-known for its worldwide aviation assessments, launched the World Airline and Airport Star rating program in 1999. This program uses online passenger reviews to evaluate and rank airlines and airports based on factors like product quality and service standards (Skytrax, 2023a). The decision to utilize Skytrax data in this research is justified by the requirement for passengers to authenticate their identities before reviews are published, helping mitigate potential bias when passengers voluntarily share feedback (Wattanacharoensil et al., 2017). Additionally, Skytrax aggregates data from airports globally, providing a highly representative dataset. Punel et al. (2019) underscored Skytrax's reliability as a well-established and reputable measure of passenger satisfaction in the aviation industry.

The air transport research field has increasingly relied on Skytrax as a valuable data source due to its comprehensive and reliable nature (e.g., Bae & Chi, 2022; Bulatović et al., 2023; Bunchongchit & Wattanacharoensil, 2021; Halpern & Mwesiumo, 2021; Homaid & Moulitsas, 2023; Shadiyar et al., 2020). Skytrax is commonly utilized in academic literature as a means to capture online word-of-mouth feedback due to the depth and quality of the data it offers (Chatterjee & Mandal, 2020).

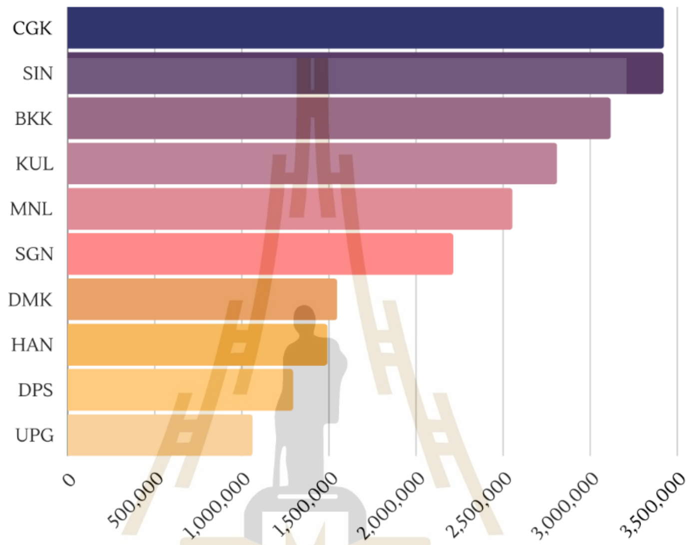


Figure 3.1 Top ten busiest airports in Southeast Asia in January 2024. Source: OAG (2024)

The analysis presented in Figure 3.1 sheds light on the distribution of seat capacities in Southeast Asia (SEA) airports as of January 2024. Here is a breakdown of the key findings from the analysis:

Highest Seat Capacity: Jakarta Soekarno-Hatta Airport (CGK) emerges as the leader with 3,066,153 seats, reaffirming its status as a major aviation hub in Indonesia. This substantial seat capacity underscores the airport's pivotal role in regional air traffic.

Significant Capacity: Singapore Changi Airport (SIN) and Kuala Lumpur International Airport (KUL) closely follow CGK in seat capacity. SIN, known for its premier international gateway status, boasts a seat capacity of 3,027,143, aligning with its global reputation. KUL also demonstrates significant capacity, further solidifying its position as a key aviation hub in the region.

Moderate Capacity: Airports in Bangkok (BKK and DMK) exhibit substantial seat capacities, emphasizing Thailand's prominent position in regional air travel. The moderate capacity of these airports highlights their importance in managing passenger traffic efficiently.

Lowest Capacity: Sultan Hasanuddin International Airport (UPG) shows the smallest seat capacity among the airports analyzed, with 953,791 seats. This lower capacity hints at a more regional focus for UPG compared to other major SEA airports.

Skytrax Data Availability and Service Quality: Nine out of the ten airports in the analysis have Skytrax data available, indicating their recognition for service quality assessment. The absence of Skytrax data for Sultan Hasanuddin International Airport (UPG) suggests a more localized operational scope and potentially less international exposure.

Regional Insights: The analysis offers insights into the aviation landscape of various SEA countries. Indonesia stands out with three airports in the list, showcasing its extensive domestic and international connectivity. Thailand's dual airport strategy in Bangkok reflects the city's efforts to manage high passenger volumes effectively. Vietnam's major urban centers are supported by robust aviation infrastructure, as evidenced by the presence of both Ho Chi Minh City Airport (SGN) and Hanoi Airport (HAN) in the analysis. Additionally, Malaysia, the Philippines, and Singapore each have a major airport serving as a crucial entry point and hub in their respective countries.

Overall, the analysis underscores the diverse range of capacities and service standards across SEA airports, highlighting the strategic planning and infrastructure investments aimed at efficiently managing air traffic and providing high-quality services to passengers in the region.

3.1.1 Data collection

The study leveraged secondary data sourced from user-generated feedback collected via the Skytrax online review platform (Skytrax, 2023b). This data was harvested using the rvest package in the R programming language, focusing on a pre-selected range of airport reviews. An algorithm was developed to sequentially navigate through each airport's review section to gather the relevant data from the webpages. Prior to initiating the automated collection, a manual review of each airport's webpage was conducted to ascertain the total number of pages, as the volume of reviews varied across different airports. Given that each review page contains a set number of evaluations, it was possible to approximate the aggregate count of reviews by multiplying the page count. The compilation of historical reviews accessible on the Skytrax website commenced once the preconditions were satisfied for the streamlined list of airports. Authors who willing to submit the review can provide their information in https://www.airlinequality.com/write-a-review/?type=airport as the following fields and these will be publicly shown as in Figure 3.2.

1. Author's name
2. Trip verified (Denotes reviews where users have provided evidence of travel by submitting a copy of their e-ticket or boarding pass)
3. Author's email address
4. Author's country name
5. Airport name
6. Airport visiting date.
7. Travel purpose (departure, arrival, departure & arrival, or transit)
8. Review writing (between 150 - 3500 characters)
9. Overall rating (ranging from 1 to 10)
10. Terminal signs & directions rating (ranging from 1 to 5)
11. Queuing times rating (ranging from 1 to 5)
12. Terminal cleanliness rating (ranging from 1 to 5)
13. Terminal seating rating (ranging from 1 to 5)
14. Food & beverages rating (ranging from 1 to 5)
15. Airport shopping rating (ranging from 1 to 5)
16. Airport staff rating (ranging from 1 to 5)
17. Airport Wi-fi service rating (ranging from 1 to 5)
18. Author’s recommendation (yes or no)
19. Traveler type (Solo Leisure, Business, Family Leisure, or Couple Leisure)
20. Photos of author’s visit to the airport (optional)

Figure 3.2 presents a sample structure of a review posted by a traveler on January 2nd, 2023. The traveler had a business flight passing through Jakarta Soekarno-Hatta airport. This review is marked as verified, signifying the traveler has submitted evidence of their journey to Skytrax. Reviews that lack verification do not feature a checkmark. The review includes a variety of information, such as the date of visit, the traveler type, service ratings of the airport, and a recommendation status regarding the airport experience.

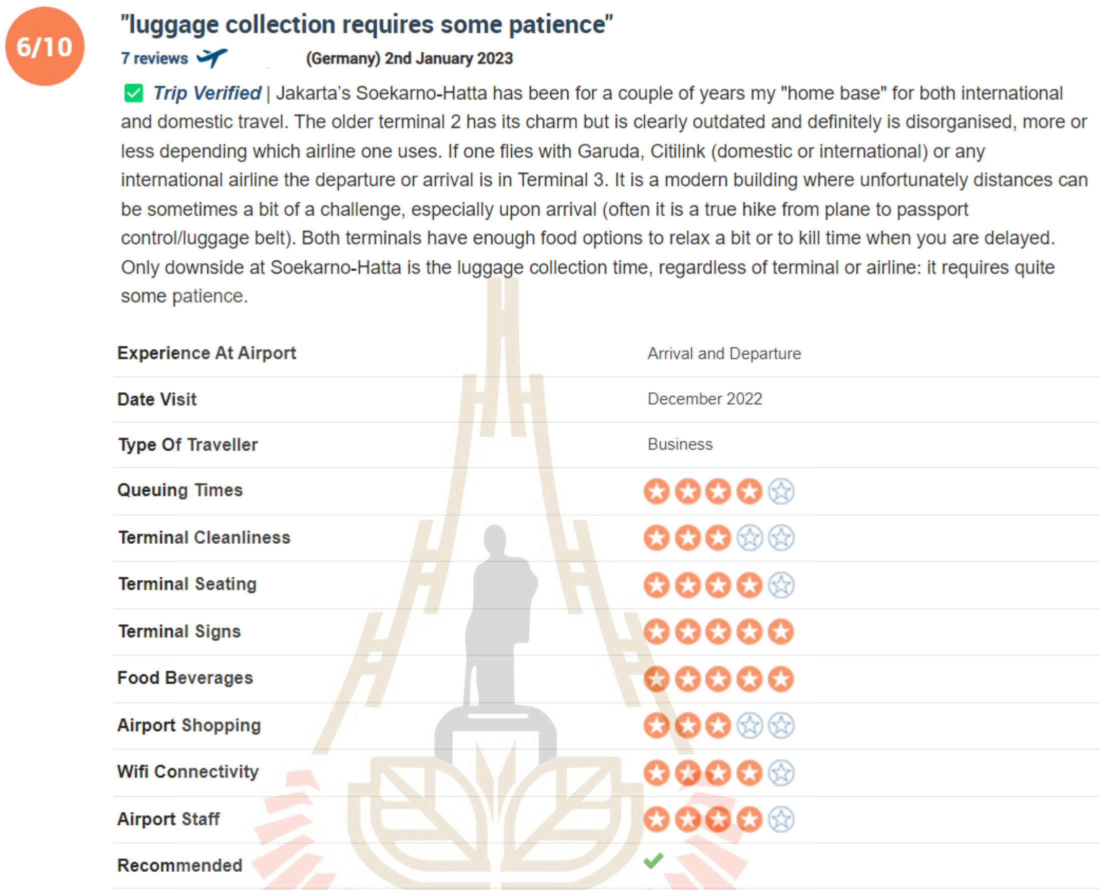


Figure 3.2 A screenshot of Skytrax reviewed by a passenger who arrives to and departs from Jakarta Soekarno-Hatta Airport. Screenshot available from https://www.airlinequality.com/airport-reviews/jakarta-airport/.

The dataset included ratings for airport services across eight unique attributes as well as an overall airport rating. It is important to note that the user-generated content (UGC) data examined in this study were willingly contributed by airport passengers. However, it should be noted that the Skytrax online review platform offers data for solely the nine busiest airports in Southeast Asia (SEA), omitting the tenth airport. As a result, this research is based solely on UGC data from the region's leading nine airports.

The original dataset comprised 2490 passenger reviews and travel details for nine airports in Southeast Asia (SEA). Data collection from the website was conducted using R on July 14, 2023, resulting in 1016 valid cases. These cases included a mix of quantitative and qualitative feedback from 1016 passengers, covering the period from 2015 to July 2023.

The initial stage of gathering airport passenger reviews on Skytrax involved capturing demographic details from respondents. This demographic information included various characteristics like the passenger's name, country of residence, airport visited, date of visit, and purpose of the trip. Subsequently, passengers had the opportunity to share their experiences, write reviews, and rate eight distinct aspects of airport services: queuing time, cleanliness, seating areas, signage, food services, retail options, Wi-Fi availability, and staff courtesy. Skytrax's airport star ratings, considered a globally recognized benchmark for airport service quality, are determined based on extensive industry experience and specialized knowledge of airport operations (Skytrax, 2024). These star ratings, derived from customer feedback throughout their airport journey, range from one to five. A 5-star rating indicates service excellence meeting or exceeding global standards. A 4-star rating signifies good quality though not the highest. A 3-star rating reflects average service standards, indicating some inconsistencies or weaknesses. A 2-star rating is assigned for below-par amenities or facilities, falling short of passengers' typical expectations. Lastly, a 1-star rating signifies an unacceptable level of service. Additionally, passengers were asked to rate their overall experiences on a scale of one to ten, serving as a general satisfaction metric. Furthermore, passengers indicated their willingness to recommend the airport, providing a binary response—either 'yes' or 'no'.

3.1.2 Demographic information

The dataset consists of reviews for nine Asian airports collected from 2015 to July 2023, resulting in 1016 valid reviews. The demographic profile of the content reviewers is presented in Table 3.1, reflecting a diverse range of passenger backgrounds. The table provides a comprehensive overview of the passenger demographics. The primary category, “Passenger Characteristics”, encapsulates various aspects of passenger demographics. “Category” and “Subcategory” further refine these characteristics into more specific segments. For instance, the category “Passenger Experience” is divided into subcategories such as “Arrival and Departure” and “Departure Only”. This pattern is mirrored in “Passenger Type” and “Passenger by Continent”, each of which is further subdivided into more specific classifications. The “Frequency” and “Percentage” columns present the actual data. The frequency denotes the number of respondents in each subcategory, while the percentage represents the proportion of total respondents in each category calculated as a percentage of the total number of respondents.

Table 3.1 Demographic information (n = 1016).

Passenger Characteristics	Category	Subcategory	Frequency	Percentage
Passenger Experience	Arrival and Departure		408	40.16%
	Departure Only		362	35.63%
	Transit		146	14.37%
	Arrival Only		100	9.84%
Passenger Type	Solo Trip		357	35.14%
	Business Trip		238	23.43%
	Family Trip		224	22.05%
	Couple Trip		197	19.39%
Passenger by Continent	Asia	Southeast Asia	452	44.49%
		East Asia	56	5.51%
		South Asia	27	2.66%
		West Asia	21	2.07%
	Oceania	Australia and New Zealand	154	15.16%
	Europe	Northern Europe	132	12.99%
		Western Europe	55	5.41%
		Southern Europe	9	0.89%
		Eastern Europe	8	0.79%
	North America	North America	89	8.76%
		Central America	1	0.10%
	South America	South America	2	0.20%
	Africa	Southern Africa	1	0.10%
	Nonidentified	Nonidentified	9	0.89%

The demographic analysis conducted provides valuable insights into the diverse traveler profiles utilizing the airport, shedding light on their behaviors and origins. Here is a breakdown of the key findings from the analysis:

Passenger Experience:

Most Common Category: A significant proportion of passengers (40.16%) engage in both arrival and departure processes, indicating a balanced mix of inbound and outbound travelers.

Departure Only: Following closely, 35.63% of passengers were solely departing from the airport, emphasizing a considerable number of outbound journeys.

Transit and Arrival Only: Lower frequencies were observed for transit passengers (14.37%) and those who solely arrived at the airport (9.84%), reflecting the varied nature of passenger movements.

Passenger Type:

Predominant Type: Solo trips accounted for the highest percentage (35.14%), indicating a substantial presence of individual travelers.

Business and Family Trips: Business trips (23.43%) and family trips (22.05%) were also prevalent, showcasing diverse travel purposes.

Couple Trips: Representing 19.39% of the demographic, couple trips constituted a significant portion of the traveler profile.

Passenger by Continent:

Asia: Southeast Asia emerged as the primary source of passengers, with 44.49% (452 passengers), highlighting the high travel activity within this subcontinent.

Oceania: Australia and New Zealand were well-represented, with 15.16% (154 passengers) of the total demographic, indicating robust travel links from the region.

Europe: Northern Europe accounted for a notable segment, with 12.99% (132 passengers), followed by Western Europe (5.41%), Southern Europe (0.89%), and Eastern Europe (0.79%), showcasing varied travel patterns within the continent.

North America: North America contributed 8.76% (89 passengers) to the passenger profile, signifying significant travel ties with the region.

Other Regions: Central America, South America, Southern Africa, and non-identified regions, though with lower representation, further illustrate the diverse continental origins of passengers using the airport.

3.2 Integrating Multiple Regression Analysis (MRA), Bayesian Networks (BNs), and Neural Networks (NNs)

The integration of Multiple Regression Analysis (MRA), Bayesian Networks (BNs), and Neural Networks (NNs) in research or application development presents a robust approach to tackling complex problems with precision. By leveraging the strengths of these diverse methodologies, this integration aims to enhance understanding, predict outcomes, and facilitate decision-making processes. The structured framework for the conjoint application of MRA, BNs, and NNs encompasses problem definition, analysis, and iterative model refinement.

The initial phase of this methodology involves a clear delineation of the research problems, or the phenomena targeted for modeling. This stage considers prediction, classification, decision-making, or exploratory analysis of variable relationships. MRA is utilized to reveal linear relationships among variables, helping identify significant predictors and establish a fundamental model for baseline comparisons. Subsequently, after identifying relevant variables through MRA, constructing a BNs provides a graphical representation of their probabilistic relationships and conditional dependencies, unveiling complex interplays and independences among variables. NNs are then employed to delve into intricate, nonlinear relationships between variables that may not be fully captured by MRA or BNs. The architectural design of NNs is guided by significant predictors from MRA and insights from the BNs model, ensuring a methodical and focused approach.

In the field of evaluating airport services, Skytrax utilizes eight criteria: queuing time, cleanliness, seating areas, signage, food services, retail options, Wi-Fi availability, and staff courtesy. Survey participants evaluate each criterion using a five-point scale, enabling them to provide feedback spanning from 1 (lowest rating) to 5 (highest rating). The overall rating summarizes the overall traveler satisfaction level, ranging from 1 (lowest rating) to 10 (highest rating).

This systematic approach not only amalgamates the strengths of MRA, BNs, and NNs but also aligns them seamlessly to address complex problems systematically, enabling researchers to navigate intricate relationships, predict outcomes, and enhance decision-making processes effectively.

3.2.1 Multiple regression analysis

The first phase of this study involved assessing the proposed relationships utilizing multiple regression analysis (MRA). MRA is a statistical technique that utilizes multiple independent variables to forecast the outcome of a dependent variable. MRA constructs a model illustrating the connection between service attributes and airports' overall ratings, under the premise of a linear relationship between the input variables and the output (Mooi & Sarstedt, 2019).

3.2.2 Bayesian networks

The next methodology employed in this study involves the utilization of Bayesian networks (BNs), developed based on a validated Multiple Regression Analysis (MRA) model. These BNs are designed to forecast and pinpoint improvements in the overall rating of airport services. BNs are a type of graphical model that autonomously learns from data, is grounded in probability theory, and enables scenario analysis for enhanced predictions and decision-making (Wipulanusat et al., 2020). However, when BNs are used in isolation, their accuracy is contingent solely on expert knowledge, which presents a limitation (Zhou et al., 2014). Consequently, the integration of MRA and BNs analyses not only enhances reliability but also delivers operational advantages to airports.

3.2.3 Neural networks

The third methodology employed in this study focuses on identifying essential airport service attributes that necessitate improvement, utilizing neural networks (NNs) derived from the Multiple Regression Analysis (MRA) model. Neural networks, also known as simulated neural networks (SNNs) or artificial neural networks (ANNs), constitute a subset of machine learning. The transportation sector has witnessed a multitude of neural network applications, leveraging their advanced pattern recognition and data processing capabilities to enhance various facets of transportation systems (Chen et al., 2022; Zou et al., 2022). NNs analyze the most critical factors, and enhancements in these key areas can result in an elevation of the overall airport star rating. NNs, by nature, are nonlinear, enabling them to capture intricate relationships and patterns within data. When dealing with the intricacies of human decision-making processes, they outperform traditional models in terms of predictive accuracy (Kalinic et al., 2019; Leong et al., 2015).

3.3 Text mining and sentiment analysis

Sentiment analysis, known as opinion mining and emotion assessment, is a method employed to assess the positivity or negativity within a dataset, offering a valuable tool for efficiently extracting insights from extensive text datasets. Fang and Zhan (2015) underscore the significance of sentiment analysis in categorizing viewpoints and emphasizing critical facts through the scrutiny of customer emotions via natural language processing, text evaluation, and statistical methods to enhance business efficacy.

The technological advancements in sentiment analysis have enabled the extraction of customer sentiments from various sources such as social media, reviews, and business interactions, serving as essential information for engineers and business leaders across contemporary industries. With the evolution of deep learning methods, sentiment analysis has become a prominent tool for advanced algorithmic applications.

A key strength of sentiment analysis lies in its ability to evaluate user opinions on products or services, aiding decision-making processes like airline selections via the analysis of online feedback or micro-blogging platforms. Recognizable emotions such as anger, disgust, and displeasure, identified by Kiritchenko, Zhu, and Mohammad (2014), are evident in written text, reflecting the sentiments expressed by the authors.

Despite its advantages, a significant challenge in sentiment analysis lies in the time-intensive nature of annotating training sets. Efforts to address this challenge, such as utilizing automatic tagging with emojis or hashtags, provide substantial benefits for organizations utilizing classification models.

Prominent review platforms like Consumer Reports, Amazon, and Yelp play a crucial role in consolidating customer feedback across diverse industries, with sentiment analysis playing a pivotal role in evaluating evaluative aspects of textual data, refining customer interaction models, identifying satisfaction levels, and adjusting response strategies based on user sentiment.

Text mining, which involves extracting meaningful information and insights from unstructured text data, leverages natural language processing (NLP), machine learning, and statistical techniques to analyze large volumes of unstructured textual data encompassing emails, social media posts, customer reviews, and articles.

The study incorporated R programming, an open-source software, for text mining and sentiment analysis, emphasizing the use of tidy data principles to simplify and enhance data management, notably when working with text data. Hadley Wickham's concept of tidy data emphasizes a specific structure where each variable corresponds to a column, each observation aligns with a row, and each type of observational unit is represented in a separate table.

The tidy text format entails organizing data into a tabular format where each row contains a single token, representing a meaningful text unit like a word for subsequent analysis. This structured approach contrasts traditional methods of storing text data such as strings or document-term matrices. In tidy text mining, tokens are typically stored as individual words or can encompass n-grams, sentences, or paragraphs.

Embracing tidy data principles allows analysts to efficiently manipulate text data utilizing a standardized set of tools like dplyr, tidyr, ggplot2, and broom. This framework facilitates smooth transitions across various packages, offering natural extensions to different text analyses and exploratory tasks.

The tidytext package supports the maintenance of tidy text data throughout the analysis and provides functions for converting data into a tidy format when necessary. This flexibility enables users to leverage tidy tools for data processing, convert data into document-term matrices for machine learning tasks, and then reconvert the data into a tidy format for interpretation and visualization using tools like ggplot2 (Silge & Robinson, 2024).

The structured organization of text data in a standardized format enables the utilization of standard tidy tools such as dplyr, tidyr, and ggplot2 for text manipulation, processing, and visualization, enhancing the analytical capabilities, as depicted in Figure 3.3.

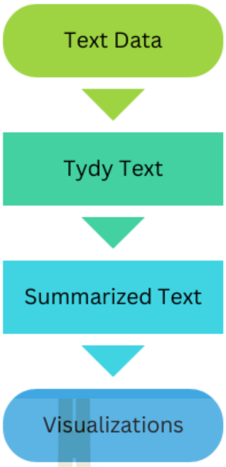


Figure 3.3 A flowchart of a typical text analysis using tidy data principles.

Employing robust methodologies for text data analysis in academic research is crucial. The steps being followed are part of a larger text mining and Natural Language Processing (NLP) methodology. This methodology involves:

1. Text Cleaning: Standardizing the text data by removing noise and irrelevant information.

2. Stop Words Removal: Filtering out words that do not contribute meaningfully to the analysis, tailored to the research context.

3. Tokenization: Breaking down the text into smaller units (tokens), such as words, for easier analysis.

4. Frequency Analysis: Quantifying the occurrence of each word to identify trends, patterns, or topics of interest.

Sentiment analysis using R is an approach for analyzing attitudes, opinions, and emotions expressed in text data. There are several libraries in R that can be used for sentiment analysis, such as 'tm', 'qdap', 'sentimentr', and 'textblob'. These libraries provide functions to tokenize text data into individual words or n-grams, after that preprocess the text data by removing punctuation, stopwords, and performing stemming or lemmatization. Use sentiment analysis functions to analyze sentiment polarity for each text document. Visualize the sentiment analysis results using plots or summary statistics.

3.3.1 Data preprocessing

The preprocessing steps for text data before sentiment analysis in R encompass several critical tasks to ensure the accuracy and relevance of the analysis.

Removing Punctuation and Stopwords: Punctuation removal and stopwords elimination are fundamental processes in text preprocessing. The 'tm' package in R can facilitate the removal of both punctuation and stopwords, which are common, non-informative words like 'a', 'the', and 'is'. By excluding these stopwords, the focus remains on the significant terms in the text data without noise from frequent but less meaningful words.

Stemming or Lemmatization: Stemming or lemmatization aids in reducing words to their base or root forms, enabling consistency and simplifying the analysis process. This task can be executed using the 'textstem' package in R, ensuring unified representations of similar words for improved analysis accuracy.

Custom Stopwords for Domain-Specific Text Analysis: In the context of Southeast Asian (SEA) airport analysis, customizing the stopwords list to exclude region-specific terms or names of airports enhances the relevance of the analysis. This tailored list merges general English stopwords with industry-specific terms, ensuring that both domain-specific and common language words are excluded from the analysis, thus refining the dataset for a focused sentiment analysis.

Once the text data is formatted into a one-word-per-row structure, manipulation using tidy tools like 'dplyr' becomes feasible. The next step often involves removing stopwords – ubiquitous but non-informative words like 'the', 'of', and 'to' – to streamline the analysis. This can be accomplished by leveraging the 'anti_join()' function with the default English stopwords provided by the 'tidytext' package in R to eliminate irrelevant common words from the text data effectively.

The tokenization process, which breaks down the text into individual words, coupled with the removal of stopwords, is a crucial preliminary step before examining word frequencies. Two distinct analyses were conducted in this research:

In the first analysis, tokenization was performed with the removal of default stopwords only.

In the second analysis, both default and custom stopwords tailored to the SEA airport context were eliminated to refine the text dataset further for sentiment analysis.

By systematically implementing these preprocessing tasks, the text data is optimized for sentiment analysis in R. This meticulous approach ensures that irrelevant information is filtered out, allowing for a focused and accurate analysis of the textual content related to SEA airports.

3.3.2 Tokenization

Tokenization in text processing is the process of converting a text into smaller units, called tokens, which can typically be words, characters, or subwords, byusingvarious packages, such as 'tm', 'textTinyR', or 'tokenizers'. The tokenizers package offers more advanced options and functionalities, such as n-grams tokenization, skip n-grams, whitespace tokenization, etc.

tokenize your text data into words or n-grams before proceeding with preprocessing steps like removing punctuation, stopwords, stemming, or lemmatization. Here's how you can tokenize text data into words or n-grams using the 'tm' package.

Tokenize into words: to tokenize text data into individual words.

Tokenize into N-Grams: to tokenize text data into n-grams (sequences of 'n' words).

By tokenizing text data into words or n-grams, you can prepare your text for further preprocessing steps like removing punctuation, stopwords, stemming, or lemmatization. These tokenization steps are essential for text analysis tasks like sentiment analysis.

3.3.3 Sentiment analysis

Sentiment analysis, or opinion mining, stands at the forefront of natural language processing techniques, serving as a sophisticated method to discern the emotional undertones and opinions conveyed within textual data. In this analytical domain, text is meticulously dissected to extract subjective components, including emotions, attitudes, and perspectives articulated by the author. Leveraging sentiment analysis algorithms allows for the categorization of text into sentiments such as positive, negative, or neutral, thereby offering profound insights into the emotional subtleties present across diverse textual forms like social media posts or customer reviews. This computational approach enables organizations to decipher customer feedback, gauge public sentiment, evaluate brand perception, and devise data-informed strategies based on the sentimental context conveyed within written content (Silge & Robinson, 2024).

The structured analysis facilitated by sentiment analysis provides a systematic approach to recognize and classify sentiment embedded within written communication, illuminating the emotional dimensions intrinsic to textual exchanges. The array of text mining tools utilized to programmatically approach the emotional content of text.

Diverse methodologies and lexicons are employed to evaluate the opinions or emotions portrayed in text data. The 'tidytext' package within the sentiment analysis domain offers access to multiple sentiment lexicons, with three prominent general-purpose lexicons developed by renowned researchers. These lexicons, including AFINN by Finn Årup Nielsen, Bing curated by Bing Liu and collaborators, and NRC by Saif Mohammad and Peter Turney, predominantly focus on single words and assign scores indicating positive/negative sentiments and underlying emotions such as joy, anger, sadness, and more.

The NRC lexicon delineates words into binary categories ("yes"/"no") denoting positive, negative sentiments, and a range of emotions like anger, anticipation, disgust, fear, joy, sadness, surprise, and trust. Conversely, the Bing lexicon categorizes words binary into positive or negative classifications. The AFINN lexicon assigns scores between -5 and 5 to words, with negatives expressing negative sentiment and positives representing positive sentiment.

The NRC Word-Emotion Association Lexicon acts as a comprehensive Word-Emotion and Word-Sentiment Association Lexicon, featuring sentiments like negative, positive, and emotions spanning anger, anticipation, disgust, fear, joy, sadness, surprise, and trust.

Moreover, specialized sentiment lexicons tailored for specific content areas are available. These dictionary-driven methodologies, including the aforementioned lexicons, ascertain the overall sentiment of text by summing individual sentiment scores assigned to each word in the text. It is paramount to acknowledge that such lexicon-based methods may overlook qualifying terms preceding a word, evident in phrases like "no good" or "not true", due to their sole reliance on unigrams.

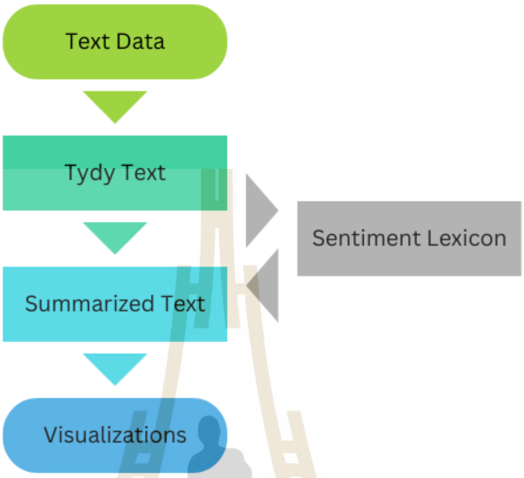


Figure 3.4 A flowchart of a typical text analysis that uses tidytext for sentiment analysis.

Sentiment analysis, which is a component of natural language processing, facilitates the categorization of text data into sentiment categories such as positive, negative, or neutral. When applied to the passenger feedback dataset, sentiment analysis allows for a deeper exploration of travelers' experiences and perceptions, providing insights into the underlying sentiments conveyed in their feedback. This analytical approach aims to uncover actionable insights that can inform airport operations, drive service enhancements, and improve overall customer satisfaction strategies.

Through sentiment analysis, positive aspects identification: detection of positive sentiment in passenger feedback sheds light on areas that passengers find satisfying and commendable at airports. This insight helps in highlighting strengths and successful components of the airport experience that contribute to positive passenger perceptions.

Negative feedback revelation: analysis of negative sentiment exposes areas of concern, dissatisfaction, or potential shortcomings that passengers may have encountered at the airport. This critical feedback presents essential input for identifying improvement areas and effectively addressing passenger pain points.

Neutral sentiments comprehension: examination of neutral sentiment provides a nuanced perspective on aspects that do not strongly evoke either positive or negative responses from passengers. Understanding neutral feedback aids in discerning areas that passengers find acceptable but may require further attention or enhancement.

By integrating sentiment analysis with existing tokenization methods, the depth of the analysis can be enhanced, revealing the underlying sentiments expressed by passengers. This comprehensive approach enables airport authorities to customize services, address feedback proactively, and ultimately elevate the overall passenger experience.

When approaching a text, human readers utilize their understanding of the emotional intent of words to infer whether a section of text is positive, negative, or characterized by more nuanced emotions such as surprise or disgust. This emotional content can also be approached programmatically using the tools of text mining.

Sentiment Lexicons and Tools

Several methods and lexicons exist for evaluating the opinion or emotion in text. The tidytext package provides access to several sentiment lexicons, notably:

1. AFINN by Finn Årup Nielsen. AFINN Lexicon: Assigns words a score ranging between -5 and 5, with negative scores indicating negative sentiment and positive scores indicating positive sentiment.

2. Bing by Bing Liu and collaborators. Bing Lexicon: Categorizes words into binary positive and negative categories.

3. NRC by Saif Mohammad and Peter Turney. NRC Lexicon: Categorizes words in a binary fashion ("yes"/"no") into categories of positive, negative, anger, anticipation, disgust, fear, joy, sadness, surprise, and trust.

All three lexicons are based on unigrams, i.e., single words, and contain many English words assigned scores for positive/negative sentiment and potentially emotions like joy, anger, sadness, etc.

Lexicon-Based Sentiment Calculation

Dictionary-based methods, such as those discussed, determine the total sentiment of a piece of text by summing the individual sentiment scores for each word. Importantly, these methods do not account for qualifiers before words, such as “no good” or “not true,” as they are based solely on unigrams.

These lexicon-based methods are useful for programmatically approaching the emotional content of text, but limitations remain in their inability to consider contextual qualifiers.

In the domain of sentiment analysis, different levels of analysis, including Document Level, Sentence Level, Phrase Level, and Aspect Level, have been scrutinized (Wankhade et al., 2022). Document-level sentiment analysis involves assessing the sentiment of an entire document and assigning a single polarity to the entire content, commonly used for classifying chapters or pages of a book as positive, negative, or neutral. Various supervised and unsupervised learning techniques can be applied for this purpose, although challenges arise in cross-domain and cross-language sentiment analysis. Domain-specific sentiment analysis proves effective by incorporating a domain-sensitive feature vector with a limited set of domain-specific words, achieving impressive accuracy in domain-specific tasks.

In sentiment analysis, the 'tidytext' package offers access to multiple sentiment lexicons, including AFINN by Finn Årup Nielsen, Bing developed by Bing Liu and collaborators, and NRC by Saif Mohammad and Peter Turney. These lexicons primarily focus on single words, using unigrams to assign scores indicating positive or negative sentiment and underlying emotions like joy, anger, and sadness.

3.3.3.1 AFINN Lexicon

The AFINN Lexicon, devised by Finn Årup Nielsen, stands as a prominent sentiment analysis tool widely employed in research endeavors. This lexicon, composed of English words, assigns sentiment scores to each word, ranging from -5 (indicating highly negative sentiment) to +5 (reflecting profoundly positive sentiment).

Researchers utilize the AFINN lexicon in sentiment analysis tasks to assess the emotional nuances within textual data by evaluating the sentiment polarity associated with individual words present in the text. By leveraging the lexicon's sentiment scores, text can be classified into positive, negative, or neutral categories based on the emotional tones encapsulated in the words. The straightforward scoring system of the AFINN lexicon makes it a valuable resource for extracting sentiment from text, providing deep insights into the emotional expressions contained in written content for a myriad of research and analytical purposes.

3.3.3.2 Bing Lexicon

The Bing Lexicon, established by Bing Liu and a team of collaborators, serves as a fundamental sentiment analysis tool that categorizes English words into binary sentiment classifications – positive or negative. Diverging from lexicons that incorporate nuanced sentiment scores, the Bing lexicon streamlines sentiment evaluation by distinguishing words strictly into positive or negative categories without nuanced sentiment intensity gradations. In sentiment analysis tasks, the Bing lexicon simplifies text assessment by categorizing words solely as positive or negative, eliminating the need for specific sentiment intensity ratings. This lexicon plays a pivotal role in sentiment analysis applications by facilitating text classification based on the identification of positive or negative words, offering a simplistic yet effective approach to interpret sentiment within textual data for diverse research and analytical endeavors.

3.3.3.3 NRC Lexicon

Developed by Saif Mohammad and Peter Turney, the NRC (National Research Council) Lexicon emerges as a sophisticated sentiment analysis resource, offering an intricate categorization of English words based on sentiment and emotion. Distinguished from simplistic positive-negative classifications, this lexicon delves into a comprehensive range of sentiment categories, encompassing binary distinctions like positive and negative, alongside a diverse spectrum of emotions such as anger, anticipation, disgust, fear, joy, sadness, surprise, and trust. By embracing a holistic approach to sentiments and emotions associated with individual words, the NRC Lexicon provides a nuanced and detailed foundation for sentiment analysis. Its inclusive classification scheme enables a profound exploration of the diverse emotional nuances embedded within textual content, rendering it a valuable asset for sentiment analysis applications across various research and analytical domains.

CHAPTER IV

RESULTS AND DISCUSSION

4.1 General description

The statistical distribution summarized in Table 4.1 involves various airport service dimensions, as evaluated by 1016 participants. The scores range from a minimum of 1 to a maximum of 10 for the overall score, and up to 5 for specific service criteria. Criteria are presented with their minimum (Min), first quartile (1st Qu.), median, mean, third quartile (3rd Qu.), and maximum (Max) values.

Table 4.1 Statistical Distribution of Airport Service Dimension.

Dimension	Min	Max	Median	Mean	SD
Overall Score	1	10	4	4.90	3.284
Queue	1	5	3	2.76	1.555
Cleanliness	1	5	3	3.33	1.414
Seating	1	5	3	2.96	1.490
Signage	1	5	4	3.29	1.426
Food & Beverage	1	5	3	2.91	1.497
Shopping	1	5	3	2.92	1.472
Wi-Fi	1	5	3	3.053	1.487
Staff Courtesy	1	5	3	2.91	1.557

The data on the overall score indicates significant variability in overall passenger satisfaction, with scores ranging from 1 to 10 and a mean score of approximately 4.90. Queuing experiences at airports are frequently found to be suboptimal, as suggested by the mean score of 2.76. Cleanliness typically receives moderate feedback, evidenced by a mean score of 3.33. Seating arrangements are often rated below average, as indicated by the mean score of 2.96, while signage is generally perceived somewhat positively, with a mean score of 3.29. Food and beverage options receive moderate satisfaction, reflected by a mean score of 2.91, highlighting room for improvement. Shopping facilities are considered satisfactory but not exceptional, as suggested by the mean score of 2.92. Wi-Fi availability is rated moderately, with a mean score of 3.05. Staff courtesy is often perceived as satisfactory but with significant room for improvement, as shown by the mean score of 2.91.

The data suggests that while certain aspects of airport services, such as overall scores, cleanliness, and signage, are relatively well-regarded, other areas, including queuing, seating, and staff courtesy, reflect room for significant enhancement. Strategic efforts focused on these lower-scoring areas could potentially elevate overall passenger experience and satisfaction at airports.

The table above showcases the minimum, 1st quartile, median, mean, 3rd quartile, and maximum values for various criteria related to airport performance, including overall score, queue, cleanliness, seating, signage, food and beverage, shopping amenities, Wi-Fi availability, and staff service.

A comprehensive analysis of airport service quality dimensions across the top nine busiest SEA airports is presented. Key criteria, including overall score, queue management, cleanliness, seating comfort, signage visibility, food and beverage offerings, shopping amenities, Wi-Fi availability, and staff service, have been meticulously evaluated.

Upon analysis, a varied spectrum of scores emerges for each dimension, reflecting diverse service quality levels at these busy airports. Notably, cleanliness and signage visibility exhibit higher mean scores, indicating relatively commendable standards in these aspects. Conversely, queuing management and staff service showcase slightly lower mean scores, implying potential areas for enhancement in operational efficiency and customer service delivery.

The dataset also reveals the spread of scores around the median for each service quality dimension, shedding light on the consistency or variability in service provision among the top nine busiest SEA airports. This detailed statistical scrutiny serves as a robust foundation for identifying nuanced strengths and weaknesses, guiding targeted strategies to elevate overall service quality and passenger experience within the bustling aviation hubs of the region.

By delving into the intricacies of airport service quality at these prominent airports, stakeholders can leverage these insights to benchmark performance, drive continuous improvement initiatives, and align service delivery with industry best practices to meet the evolving needs and expectations of passengers in the dynamic aviation landscape of SEA.

Table 4.2 presents a comparative analysis of airport performance metrics based on overall scores. Each airport is gauged using essential statistical indicators, including the minimum, median, maximum, mean, and standard deviation of overall scores. This comprehensive examination offers insights into the variation and central tendencies of performance levels across the airports. The data underscores the diverse range of scores among different airports, from the lowest to the highest values, while also shedding light on the average performance and the level of dispersion around the mean score.

Table 4.2 Comparative Analysis of Airport Performance Metrics.

Airport Name	Min Overall Score	Median Overall Score	Max Overall Score	Mean Overall Score	SD of Overall Score
BKK	1	4	10	4.22	2.84
CGK	1	5	10	4.95	3.18
DMK	1	3	10	4.21	3.15
DPS	1	3	10	3.89	2.85
HAN	1	8	10	8.12	1.89
KUL	1	3	10	4.34	3.01
MNL	1	2	10	3.09	2.45
SGN	1	3	9	3.80	2.85
SIN	1	9	10	7.89	2.77

At the country level, Singapore and Indonesia exhibit higher mean and median scores, indicating superior airport performance. Specifically, Singapore (represented by Changi Airport) achieves a mean score of 7.89, with a median score of 9, reflective of consistently high service standards.

At the airport level analysis, Singapore Changi Airport (SIN) and Hanoi Noi Bai Airport (HAN) exhibit remarkably high median and mean scores (SIN: mean = 7.89, median = 9; HAN: mean = 8.12, median = 8), representing excellent service standards. Conversely, Soekarno-Hatta (CGK) and Suvarnabhumi Airport (BKK) demonstrate wider ranges of overall scores (CGK: min = 1, max = 10, SD = 3.18; BKK: min = 1, max = 10, SD = 2.84), indicating potential irregularities in service quality. Manila Ninoy Aquino Airport (MNL) records the lowest mean score (3.09) among all listed airports, signifying the necessity for significant service quality enhancements.

The analysis of performance metrics at both the country and airport levels provides valuable insights into airport operations. The comparison reveals notable disparities in service quality, with airports like Changi and Noi Bai establishing high benchmarks, while others, such as Ninoy Aquino, signaling areas that require improvement. Leveraging these insights enables stakeholders to make informed decisions and implement targeted quality enhancement initiatives to enhance overall airport performance in the aviation industry.

According to the dataset presents in Table 4.3, a comprehensive comparative analysis of airport performance metrics across various SEA countries. Key statistical indicators, including the minimum, median, maximum, mean, and standard deviation of overall scores, have been calculated for airports within Indonesia, Malaysia, Philippines, Singapore, Thailand, and Vietnam.

Table 4.3 Comparative Analysis of Country Performance Metrics

Country	Min Overall Score	Median Overall Score	Max Overall Score	Mean Overall Score	SD of Overall Score
Indonesia	1	4	10	4.44	3.06
Malaysia	1	3	10	4.34	3.01
Philippines	1	2	10	3.09	2.45
Singapore	1	9	10	7.89	2.77
Thailand	1	3	10	4.22	2.91
Vietnam	1	7	10	6.12	3.21

This analysis reveals significant variations in airport performance metrics among the countries, reflecting diverse levels of service quality and customer satisfaction. Countries such as Singapore and Indonesia demonstrate higher median and mean overall scores, suggesting potentially superior airport experiences compared to others. Conversely, countries like the Philippines exhibit lower median and mean scores, indicating areas for improvement in airport service delivery.

The standard deviation values further emphasize the dispersion of overall scores around the mean, providing insights into the consistency or variability of airport performance within each country. This detailed statistical analysis is crucial for benchmarking airport quality, identifying areas for enhancement, and informing strategic decisions to elevate the overall aviation standards in the region.

Such an examination of airport performance metrics across SEA countries lays the groundwork for further in-depth investigations and policy considerations aimed at optimizing airport operations and enhancing passenger experiences in the aviation industry.

4.1.1 Descriptive statistics

In the study involving 1016 participants, Table 4.4 presents descriptive statistics and Pearson correlations for service attributes, offering insights into the relationships among various elements of the service experience. The attributes, ranging from queuing time and cleanliness to staff courtesy and overall satisfaction, are evaluated based on mean scores and standard deviations. The Pearson correlation coefficients, denoted by ** for statistical significance at the 0.001 level, illuminate the strength and direction of associations between pairs of attributes.

Passenger evaluations of service attributes, ranging from 2.76 to 3.33 on a 1 to 5 scale, indicate varying levels of satisfaction, neutrality, and dissatisfaction. The average overall satisfaction score of 4.90 suggests a largely indifferent passenger perception across the rated attributes. Notably, 'staff courtesy' and 'queuing time' exhibit the strongest positive correlation with airport rating scores, underscoring their influential roles.

The attributes demonstrate moderate positive relationships, notably 'cleanliness,' 'seating areas,' and 'signage,' with statistically significant correlations at the 0.001 level. For instance, Queuing Time reveals a mean of 2.76 and a standard deviation of 1.555, with robust positive correlations with Cleanliness (0.804) and Staff Courtesy (0.805). Cleanliness, scoring an average of 3.33 and a standard deviation of 1.414, displays significant associations with Queuing Time (0.804) and Seating Areas (0.759). Seating Areas, with an average rating of 2.96 and a standard deviation of 1.490, show significant positive correlations with Cleanliness (0.759) and Signage (0.791), both statistically significant at the 0.001 level.

Signage, with an average of 3.29 and a standard deviation of 1.426, exhibits significant positive relationships with Cleanliness (0.766), Seating Areas (0.791), and Food Services (0.742), all statistically significant at the 0.001 level. Retail Options, with a mean of 2.92 and a standard deviation of 1.472, shows significant associations with Seating Areas (0.742) and Signage (0.708). Wi-Fi Availability, averaging at 3.05 with a standard deviation of 1.487, demonstrates moderate positive correlations with

Queuing Time (0.665) and moderate negative correlations with Cleanliness (0.632), both significant at the 0.001 level.

Strong positive correlations are evident in Staff Courtesy, with an average of 2.91 and a standard deviation of 1.557, showing notable associations with Queuing Time (0.805), Cleanliness (0.705), and Seating Areas (0.673), all statistically significant at the 0.001 level.

The data presented in Table 4.4 indicate strong positive correlations between the total score and factors such as queuing time, cleanliness, seating areas, signage, food services, retail options, and staff courtesy. These correlations suggest that enhancements in these areas are likely to lead to a higher total rating.

4.1.2 Results of the multiple regression analysis

Multiple regression analysis (MRA), a potent statistical method, has been utilized effectively in the literature for comprehensive analysis of online reviews, as evidenced by Chatterjee and Mandal (2020). However, it is crucial to ensure that certain prerequisites are satisfied before initiating MRA. According to Pallant (2020), the $N > 50 + 8k$ rule was applied in this research. This is a rule of thumb for determining the minimum sample size needed for MRA. Here, N represents the total sample size and k denotes the number of independent variables in the model. In this study, with a sample size of 1016, the sample size surpassed the threshold set by the rule, ensuring that the sample size was adequate for the MRA. The research also confirmed the absence of collinearity risk among the independent variables, as depicted in Table 4.5, using the variance inflation factor (VIF), as recommended by Mooi and Sarstedt (2019). The variance inflation factor (VIF) is used to ensure that there is no chance of collinearity between the independent variables. The VIF measures the extent to which an estimated regression coefficient's variance increases due to multicollinearity. A VIF greater than five indicates a significant level of multicollinearity. However, in this research, all the VIFs fell below this threshold, indicating the absence of multicollinearity. The research thus validates the absence of collinearity risk among the independent variables, ensuring the robustness and validity of the MRA model.

Table 4.4 Summary statistics and correlations (n = 1016).

Attributes	Mean	SD[1]	Overall	Queuing Time	Cleanliness	Seating Areas	Signage	Food Services	Retail Options	Wi-Fi Availability	Staff Courtesy
Total rating	4.90	3.284	1								
Queuing time	2.76	1.555	0.804 **	1							
Cleanliness	3.33	1.414	0.759 **	0.661 **	1						
Seating areas	2.96	1.490	0.769 **	0.659 **	0.791 **	1					
Signage	3.29	1.426	0.766 **	0.651 **	0.720 **	0.742 **	1				
Food services	2.91	1.497	0.761 **	0.625 **	0.717 **	0.767 **	0.714 **	1			
Retail options	2.92	1.472	0.763 **	0.633 **	0.712 **	0.742 **	0.708 **	0.846 **	1		
Wi-Fi availability	3.05	1.487	0.665 **	0.610 **	0.632 **	0.620 **	0.622 **	0.616 **	0.606 **	1	
Staff courtesy	2.91	1.557	0.805**	0.705 **	0.682 **	0.673 **	0.682 **	0.667 **	0.666 **	0.619 **	1

[1]standard deviation, **significant at the 0.001 level.

The significance of the F test in Table 4.5 indicates a highly significant relationship ($p < 0.001$) between attributes and the total score in this model. Moreover, the proposed model accounts for a substantial proportion of the variance in the total score, as demonstrated by the R-squared value of 0.830. This finding suggests that the model explains 83.0% of the variance, which is a notable degree of explanatory power in consumer behavior research. The Durbin–Watson statistics, with a value of 1.895, fall within the range of 1.5 to 2.5, confirming that the model errors are free from autocorrelation (Mooi & Sarstedt, 2019).

As further illustrated in Table 4.5, 'queuing time' (β is 0.298, $p < 0.001$) emerges as the most potent predictive service attribute, closely trailed by 'staff courtesy' (β is 0.252, $p < 0.001$), validating hypotheses H1 and H8. Furthermore, the effects of 'signage' (β is 0.125, $p < 0.001$), 'retail option' (β is 0.109, $p < 0.001$), 'food services' (β is 0.091, $p < 0.05$), 'seating area' (β is 0.084, $p < 0.05$), and 'cleanliness' (β is 0.072, $p < 0.05$) on the total rating are statistically significant, leading to hypotheses H4, H6, H5, H3, and H2, respectively, according to the research model. However, 'Wi-Fi availability' is found to exert no influence on the total rating, resulting in the rejection of hypothesis H7 (β is 0.029, $p < 0.120$).

These results indicate the importance of various service attributes in influencing passengers' perceptions of airport services, providing valuable insights for optimizing service quality and overall passenger experience.

Table 4.5 Summary of MRA results.

Hypothesis Path	B	Standard Error	β	*t* Value	Decision	VIF
Constant	−1.930	0.118	-	−16.363 **	-	-
H1: Queuing time → Total airport rating	0.630	0.043	0.298	14.591 **	Supported	2.476
H2: Cleanliness → Total airport rating	0.167	0.055	0.072	3.017 *	Supported	3.380
H3: Seating areas → Total airport rating	0.185	0.056	0.084	3.319 *	Supported	3.800
H4: Signage → Total airport rating	0.288	0.052	0.125	5.581 **	Supported	2.972
H5: Food services → Total airport rating	0.199	0.059	0.091	3.356 *	Supported	4.327
H6: Retail options → Total airport rating	0.244	0.058	0.109	4.175 **	Supported	4.069
H7: Wi-Fi availability → Total airport rating	0.064	0.041	0.029	1.558	Not Supported	2.070
H8: Staff courtesy → Total airport rating	0.532	0.045	0.252	11.785 **	Supported	2.719

Total airport rating: dependent variable; B: unstandardized coefficient; β: standardized coefficient.
$R^2 = 0.830$, SEE = 1.395, F = 614.862, Sig. of F = 0.000, Dubin–Watson = 1.895, * $p < 0.05$, ** $p < 0.001$.

4.1.3 Results of the Bayesian networks

Bayesian networks (BNs) are instrumental in decision-making scenarios involving uncertainty, serving as sophisticated probabilistic graphical models. In this study, BNs were harnessed to refine and further quantify the correlations delineated through Multiple Regression Analysis (MRA). The MRA analysis identified seven crucial influencing factors—queuing time, cleanliness, seating areas, signage, food services, retail options, and staff courtesy—that significantly impact the total airport rating. Utilizing the outcomes derived from the BNs analysis played a pivotal role in the determination of the overall airport service rating, enabling a more nuanced understanding of the interplay between variables and their influence on the final customer satisfaction metrics.

To enhance the learning process and facilitate a structured analysis, the dataset underwent a crucial data discretization step. Aligning with established best practices, the service variables were segmented into distinct low, medium, and high states. Notably, the airport service variables, gauged on a 5-point scale, were discretized into differentiated intervals to ensure a coherent analysis based on varying attribute states. Similarly, the overall airport service, rated on a 10-point scale, was stratified into distinct segments, reflecting the different satisfaction levels experienced by passengers.

For an efficient learning process, it is essential to discretize the data first. Typically, the data are segmented into three states: low, medium, and high (Häger & Andersen, 2010). Considering that the independent variables in this study are measured on a 5-point scale, the airport service variables are divided into three equal states: [1, 1.6] for low, [1.6, 3.3] for medium, and [3.3, 5] for high. For overall airport service, which is gauged on a 10-point scale, the dependent variables are segmented into three equal states: [1, 3.3] as low, [3.3, 6.6] as medium, and [6.6, 10] as high.

As illustrated in Figure 4.1, the Bayesian networks of service factors comprise eight nodes and seven links connecting these nodes. The parent node symbolizes seven significant attributes, while the child node signifies the total score. Figure 4.1 illustrates that each node is associated with varying probabilities, denoted as percentages, across three states: high, medium, and low. Below each node, the two figures represent the mean and standard deviation, respectively. The BNs serve as a crucial tool for assessing the influence of attributes on the total score for airport services. The outcomes of the BNs represent the current state of the total score. Specifically, 33.8% of the travelers expressed high satisfaction, while 33.0% and 33.3% express medium and low satisfaction, respectively. The mean of the total service score was computed to be 4.98, with a standard deviation of 2.9.

Subsequently, neural networks (NNs) were employed in the final analysis stage to discern the service variables that predominantly impacted the total rating score, shedding light on areas warranting potential service quality enhancements and optimization strategies. The integration of these analytical methodologies, spanning from Bayesian networks to neural networks, underscored a comprehensive approach towards understanding and improving the overall airport service quality based on customer feedback and satisfaction metrics.

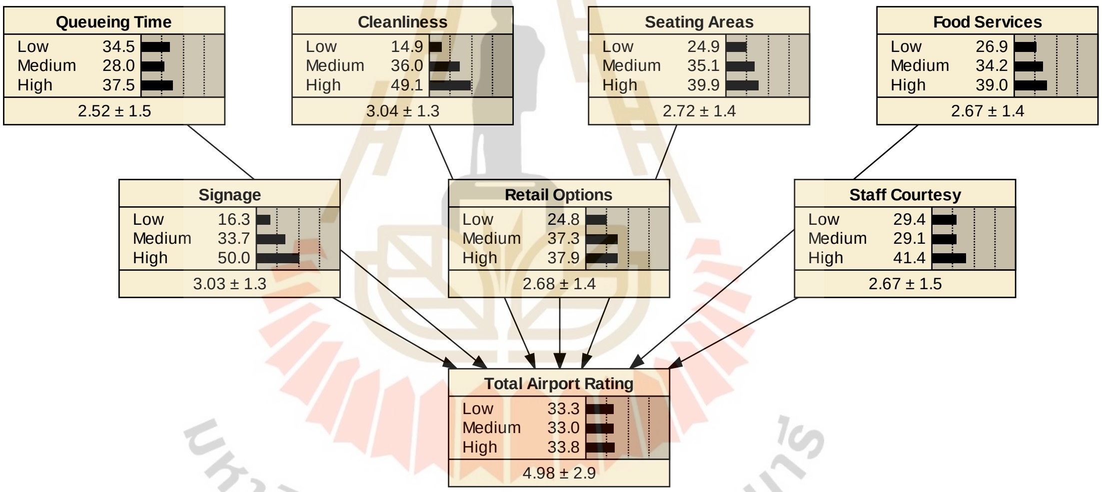


Figure 4.1 BNs results for the Skytrax total rating score.

4.1.4 Results of the neural networks

The research leveraged neural networks (NNs), particularly a multilayer perceptron (MLP), to delve into the intricate and nonlinear relationships between service attributes and the holistic measurement of airport satisfaction. By incorporating variables such as queuing time, cleanliness, seating areas, signage, food services, retail options, and staff courtesy as inputs to the NNs model, the study sought to capture the nuanced interplay within these factors. The MLP training algorithm, dividing the dataset into training (70%) and validation (30%) sets, aimed to optimize the neural network's performance in discerning patterns and interactions. Through the utilization of a classification matrix for accuracy evaluation, the study efficiently gauged the NNs' predictive capabilities across training and testing phases. The results showcased an accuracy rate of 81.7% during the training phase and a correctness rate of 79.4% in the testing phase, affirming the efficacy and robustness of the constructed NNs in forecasting overall satisfaction levels with a high degree of precision.

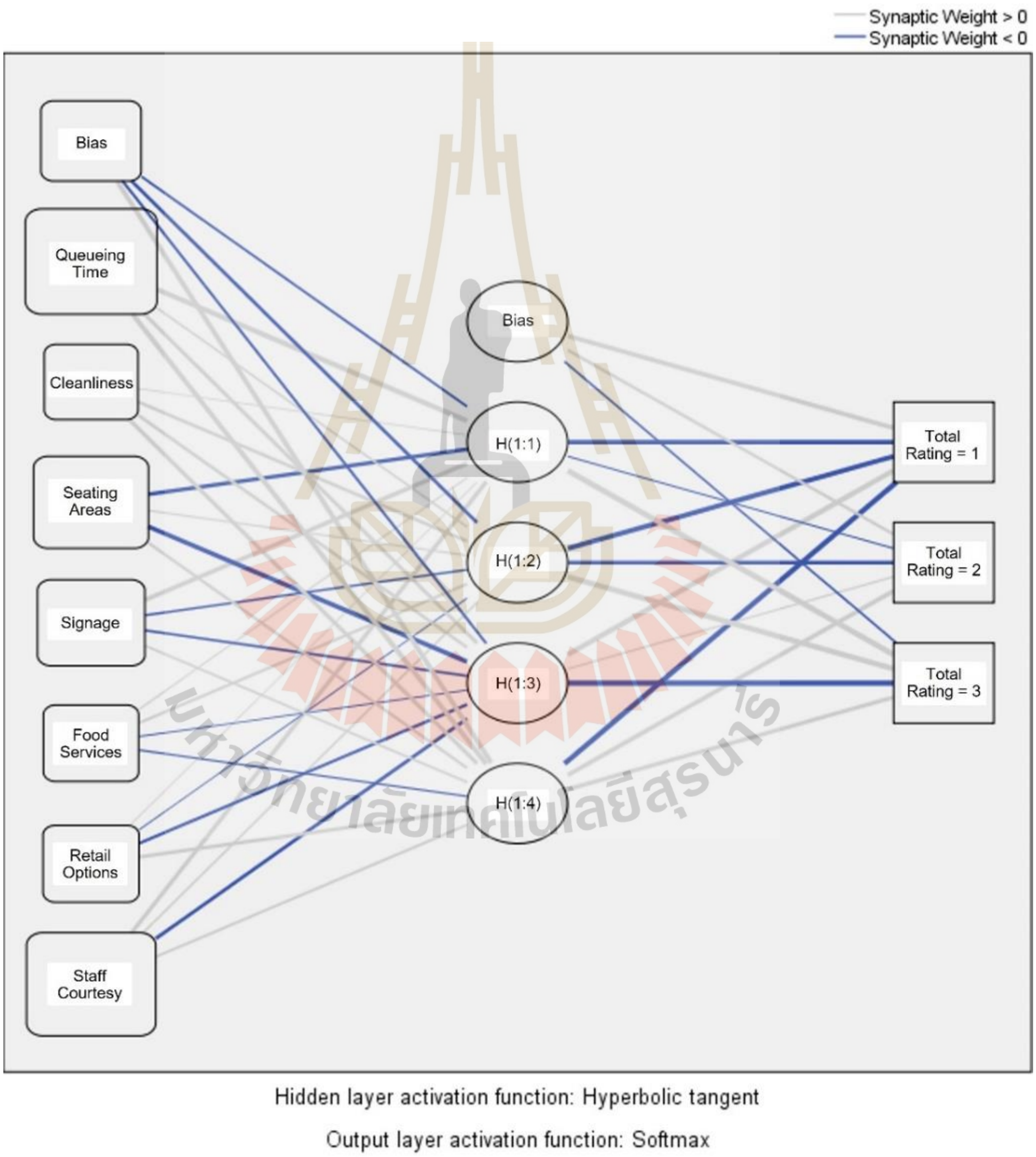


Figure 4.2 Neural network model.

The model was trained using the Multi-Layer Perceptron (MLP) training algorithm, with 70% of the samples allocated for training and the remaining 30% reserved for validation purposes. Subsequently, post the development of Neural Networks (NNs), an evaluation of their accuracy was conducted. Utilizing a classification matrix, the performance of the NNs in the classification test was assessed. The classification matrix, structured with columns representing the expected values from the NNs and rows indicating the observed values corresponding to overall satisfaction levels, played a crucial role in this assessment. By employing a tabulation method to document agreements and discrepancies between the expected and observed values, an accurate percentage was calculated. These accuracy assessments based on percentages allowed for the evaluation of the NNs' predictive capacity during both the training and testing phases. The data derived from the classification matrix, exhibited in Table 4.6 to test the resilience and efficiency of the NNs, indicated that during the training phase, an accuracy rate of 81.7% was achieved, while in the testing phase, a correctness rate of 79.4% was observed. These outcomes indicate a high level of accuracy in the constructed NNs.

By dissecting the empirical data through neural network analysis, the study uncovered significant insights into the complex dynamics underlying airport service attribute interactions and customer satisfaction metrics. The neural network's ability to navigate intricate and nonlinear relationships proved instrumental in elucidating the impact of variables such as queuing time, cleanliness, and staff courtesy on the overarching airport experience. The integration of a multilayer perceptron model enabled a comprehensive examination of these attributes, leading to a nuanced understanding of customer preferences and behaviors within airport settings. Moreover, the classification matrix's systematic evaluation approach provided a quantitative measure of the NNs' accuracy, validating their reliability in predicting satisfaction levels across diverse service categories. Overall, the study's findings underscore the value of neural network analysis in uncovering hidden patterns and informing strategic decision-making processes within the realm of service quality assessment and enhancement.

Table 4.6 Classification matrix for evaluating robustness.

Sample	Observation	Prediction			
		Low	Medium	High	Percent Accuracy
Training	Low	302	23	9	90.4%
	Medium	44	42	24	38.2%
	High	3	26	232	88.9%
	Overall Percent	49.5%	12.9%	37.6%	81.7%
Testing	Low	121	7	2	93.1%
	Medium	26	10	21	17.5%
	High	3	5	116	93.5%
	Overall Percent	48.2%	7.1%	44.7%	79.4%

The sensitivity analysis conducted in the study aimed to gauge the mean predictive relevance of various variables, ultimately shedding light on their relative importance. By calculating the normalized importance of each variable, derived from dividing its importance by the maximum importance value, Table 4.7 provides a concise summary of the significance attributed to different airport service attributes. The neural network (NN) model unveiled crucial insights, indicating that queuing time and staff courtesy emerge as the most influential variables in amplifying overall satisfaction levels. Following these pivotal areas, seating areas, signage, retail options, food services, and cleanliness play consequential roles in shaping customer perceptions and satisfaction within airport environments. Notably, the data underscores the paramount importance of efficient queuing processes and courteous staff interactions, suggesting that these factors bear significant weight in influencing customer satisfaction. This thorough examination of service attribute importance not only delineates key factors contributing to customer experience but also underlines the value of prioritizing these aspects in service quality enhancement efforts within airport settings.

Table 4.7 Importance of airport service attributes (independent variables).

Attribute	Importance	Normalized Importance
Queuing time	0.220	100.0%
Staff courtesy	0.211	96.0%
Seating areas	0.161	73.4%
Signage	0.135	61.3%
Retail options	0.095	43.1%
Food services	0.092	42.0%
Cleanliness	0.087	39.6%

The pivotal role of service quality at airports in shaping passenger experience and satisfaction is underscored in this study, which emphasizes the significance of understanding the relative importance of various service attributes for effective resource allocation and prioritization of improvements.

An analysis of key airport service attributes yielded insights into passenger satisfaction levels, highlighting the following key findings: Queuing Time emerged as the most crucial attribute, with a normalized importance of 100.0%, indicating its paramount role in enhancing passenger satisfaction through efficient queue management. Staff Courtesy ranked second in importance, with a normalized importance of 96.0%, underscoring the impact of courteous and helpful staff interactions on passengers' airport experiences. Seating Areas and Signage were classified as moderate importance attributes, emphasizing the importance of comfortable seating and effective signage in enhancing passenger comfort and reducing stress.

Lower importance attributes such as Retail Options, Food Services, and Cleanliness were identified, suggesting that while these elements are important, they are less critical compared to queuing time and staff courtesy.

Implications drawn from the analysis include the necessity for airports to prioritize operational efficiency by focusing on reducing queuing times and enhancing staff training in customer service. Emphasis is also placed on the importance of improving seating areas and ensuring clear signage to maintain passenger comfort and streamline navigation through the airport.

The study recommends directing investments towards improving queuing times and staff courtesy as primary focus areas, with secondary attention given to retail options, food services, and cleanliness. Overall, the analysis underscores queuing time and staff courtesy as pivotal factors influencing passenger satisfaction, necessitating strategic efforts by airport management to enhance the overall passenger experience.

4.2 Text mining and sentiment analysis of airport UGC

User-generated content (UGC) of SEA airports was analyzed using text mining and sentiment analysis to derive insights into passenger experiences. Data were collected from Skytrax. Preprocessing involved tokenization, normalization, removal of stop words, and lemmatization.

Sentiment analysis classified the text into positive, negative, and neutral categories, with optional aspect-based sentiment analysis identifying specific aspects of the airport experience, such as "cleanliness," "staff behavior," and "security check."

A comparative analysis of word frequency was conducted using default and custom stop words. A frequency table was created for both scenarios. Visualizations, such as bar charts and word clouds, highlighted differences in word prevalence.

Findings revealed that default stop words retained generic terms, providing less-specific insights. Custom stop words enhanced relevance, surfacing terms such as "delayed," "check-in," "staff," and "security," which were more indicative of airport experiences. Positive sentiment was associated with words like "friendly," "clean," "efficient," and "comfortable," while negative sentiment frequently included "delays," "crowded," "rude," and "long lines."

The analysis demonstrated that the use of custom stop words facilitated the identification of specific issues and positive aspects, offering targeted insights for improving passenger experiences.

4.2.1 Comparative analysis of word frequency using default and custom stop words

A common task in text mining involves examining word frequencies. The following analysis, illustrated in Figure 4.3 presents the top ten words found in passenger reviews of the nine busiest SEA (SEA) airports, based on UGC data from Skytrax.

In text data analysis, the selection of stop words is crucial for deriving meaningful insights. Default stop words typically encompass common words that are generally uninformative for the analysis (e.g., "the," "and"). However, in specialized contexts, such as the study of SEA airports, domain-specific terms may require exclusion to uncover deeper insights.

This study conducted a comparative analysis of word frequencies using two approaches: one utilizing only default stop words and another employing a combination of default and custom stop words tailored to the context of SEA airports. The inclusion of custom stop words, specific to the airport domain, aimed to filter out non-informative yet frequently occurring terms (such as "airport," "flight," and the names of the airports), thus allowing for more accurate identification of meaningful patterns and insights within the UGC.

By adopting this tailored approach, it was hypothesized that a more precise understanding of passenger experiences and sentiments could be achieved, facilitating targeted recommendations for airport management and service improvements. The results underscored the significance of customizing stop word lists in domain-specific text mining tasks to enhance the relevance and granularity of the derived insights.

```
# A tibble: 5,918 × 2
   word            n
   <chr>       <int>
 1 airport      1803
 2 terminal      743
 3 staff         549
 4 immigration   529
 5 security      421
 6 time          400
 7 flight        324
 8 check         321
 9 food          311
10 gate          298
# ℹ 5,908 more rows
```

(a)

```
# A tibble: 5,883 × 2
   word            n
   <chr>       <int>
 1 terminal      743
 2 staff         549
 3 immigration   529
 4 security      421
 5 time          400
 6 flight        324
 7 check         321
 8 food          311
 9 gate          298
10 passengers    257
# ℹ 5,873 more rows
```

(b)

Figure 4.3 Word Frequency after Using Stop Words. (a) after using default stop words and (b) after using custom with default stop words.

```
#Custom stop words
custom <- tibble(word = c("airport","cgk","sin","kul","bkk","mnl","sgn","han","dmk","dps",
                          "jakarta","soekarno-hatta","soekarno","hatta",
                          "changi","kuala","lumpur", "klia",
                          "bangkok","suvarnabhumi","manila","ninoy","aquino",
                          "ho","chi","minh","hanoi","bangkok","don","mueang","muang",
                          "denpasar-bali","denpasar","bali","denpasar","ngurah","rai",
                          "indonesia","singapore","malaysia","thailand","philippines","vietnam"),
                 lexicon = "custom")
```

Figure 4.4 R script for creating combination of custom stop words and default stop words.

The custom stop words were integrated with a predefined set of standard stop words, such as those provided by the tidytext package. This combined approach aimed to improve the analysis by filtering out both commonly uninformative words and domain-specific terms that might obscure deeper insights into passenger sentiments and experiences.

In text mining, the inclusion of custom stop words is considered essential for contextual precision. While standard stop words (e.g., "the," "and") remove general noise from the data, they often fail to address domain-specific jargon. For the context of SEA airports, terms frequently mentioned in passenger reviews, such as "airport," "flight," or specific airport names, were identified as custom stop words. These terms, although common in UGC, add little analytical value and could potentially distort the outcome of frequency analysis.

By combining custom stop words with a standard set, a clearer picture of passenger concerns and highlights was obtained. This methodology allowed for a more nuanced understanding of the data, as the removal of irrelevant but frequent terms brought to light more salient issues and aspects of passenger experiences.

The enhanced filtering process facilitated by this combined stop word list underscored the importance of adapting text mining techniques to specific research contexts. The resulting analysis provided more actionable insights, aiding airport management in making informed decisions to improve passenger satisfaction and overall service quality. Thus, the study demonstrated the efficacy of a tailored stop word strategy in refining the granularity of text mining outcomes within specialized domains.

A comparative analysis revealed significant differences in the insights derived from using default versus combined stop words. In the first analysis, which only removed default stop words, terms like "airport," "terminal," and "flight" dominated the text. Although these terms reflected the core subject matter, they overshadowed more nuanced insights related to specific operational or experiential aspects.

In the second analysis, depicted as Figure 4.3 (b), both default and custom stop words were utilized after the creation of custom stop words as illustrated in Figure 4.4. This approach led to the highlighting of less obvious but potentially significant terms. By filtering out words like "airport" and "flight," logistical and service-related terms such as "passengers" were brought to the forefront in the analysis. This shift enabled the prominence of specific challenges and areas of interest like passenger experience, security, and staffing—crucial for operational improvement and policymaking.

The importance of tailoring stop words to the research context was underscored by these findings. By filtering out ubiquitous terms, underlying patterns and issues requiring attention were uncovered. For instance, understanding the frequency and context of terms like "passengers" and "security" can assist in improving airport operations, enhancing traveler experiences, and informing policy and management decisions.

The study demonstrated that combining custom stop words with default stop words offers a more focused and insightful understanding of text data. While removing default stop words is necessary for an initial broad analysis, incorporating custom stop words specific to the research context reveals deeper layers of information, leading to more actionable findings. This methodology is essential for conducting thorough and context-aware text data analysis in academic research.

Integrating a customized list of stop words specific to SEA airports with standard stop words enhances the quality and relevance of text analysis. This approach ensures that the analysis centers on actionable data, resulting in better-informed decisions and insights.

Ultimately, keyword frequency analysis, after excluding common and uninformative terms, reveals critical aspects of passenger experiences at airports. Focusing on cleaned keywords provides stakeholders with clearer insights into passenger concerns and satisfaction. Understanding passenger feedback can thus help airport management identify key areas for operational improvement and enhance passenger satisfaction. The cleaned dataset, which ranked the top twenty keywords by frequency, as illustrated in Figure 4.5, highlighted important themes in passenger feedback.

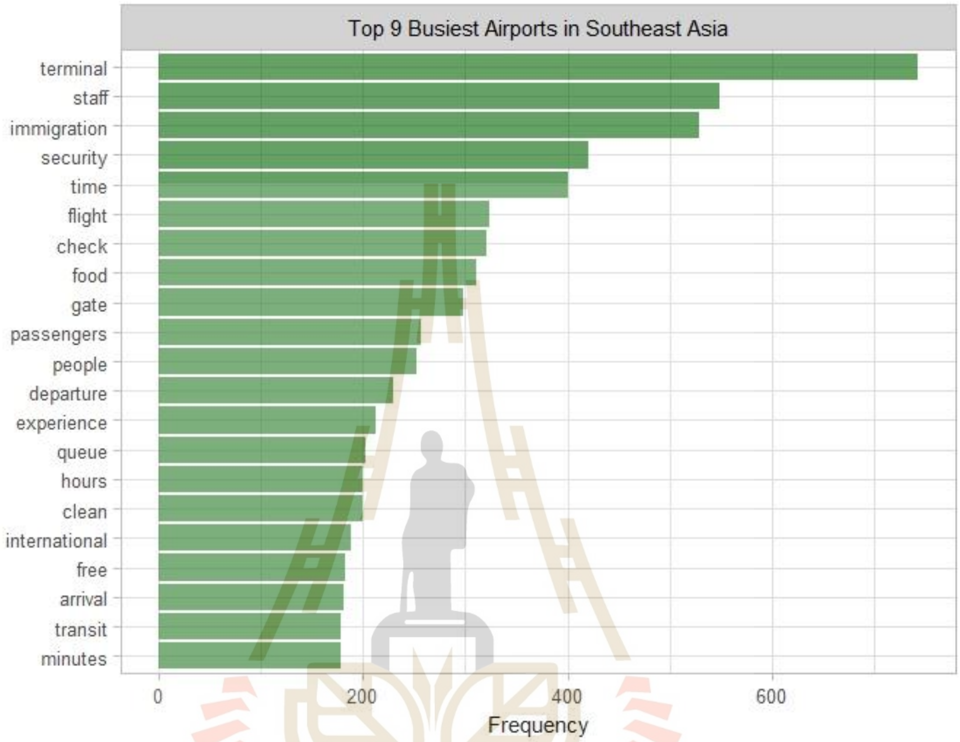


Figure 4.5 Top twenty keywords by frequency after removing custom stop words and default stop words.

The data indicate key themes and areas of concern or interest as expressed by passengers. The following, top ten occurring words are explained.

Terminal (743 occurrences): The term "terminal" emerges as the most frequently mentioned word, indicating that passengers frequently discuss various aspects of the airport terminals. This could encompass terminal facilities, layout, cleanliness, and overall convenience.

Staff (549 occurrences): The significant frequency of the word "staff" suggests that interactions with airport personnel are a major concern for passengers. This term likely reflects comments on staff behavior, helpfulness, and efficiency.

Immigration (529 occurrences): The term "immigration" is a prominent topic of discussion, highlighting the importance of the immigration process in passengers' airport experiences. This could relate to the speed of processing, the behavior of immigration officers, and the overall efficiency of the immigration checkpoints.

Security (421 occurrences): The frequent mention of "security" underscores its critical role in the airport experience. Passengers likely refer to the security screening procedures, the perceived safety of the airport, and the efficiency of security staff.

Time (400 occurrences): The word "time" appears frequently, indicating that time-related issues are a major consideration for passengers. This may include references to waiting times at various checkpoints, delays, and the overall time efficiency of airport processes.

Flight (324 occurrences): The term "flight" is commonly mentioned, reflecting those discussions about flight experiences, such as delays, cancellations, and the boarding process, are prevalent in passenger reviews.

Check (321 occurrences): The frequent mention of "check" relates to check-in processes, document checks, and baggage checks. This suggests that these procedures are significant points of interaction and potential stress for passengers.

Food (311 occurrences): The term "food" indicates that passengers also discuss the availability, quality, and variety of food options at the airports. This reflects the broader concern with amenities and comfort during the airport experience.

Gate (298 occurrences): The frequent mention of "gate" signifies its importance in the passenger journey. Discussions likely revolve around gate locations, ease of access, and boarding procedures.

Passengers (257 occurrences): The term "passengers" itself being frequently mentioned suggests a focus on the overall passenger experience, possibly including references to crowding, fellow travelers, and the general atmosphere at the airports.

The frequency of these keywords reveals critical aspects of passenger experiences at SEA airports. High mentions of "terminal," "staff," and "immigration" suggest that administrative efficiency and staff interactions are primary concerns. The emphasis on "security" and "time" points to the importance of safety and timeliness in passenger satisfaction. Discussions about "food" and "gate" further indicate that amenities and logistical factors are vital.

Understanding these keyword frequencies allows airport management to prioritize areas for improvement. Enhanced staff training, more efficient check-in and security processes, better time management strategies, and improved food services can address the most frequently voiced passenger concerns. These insights can thereby guide strategic decisions, aiming to enhance overall passenger satisfaction and operational efficiency at SEA airports.

Figure 4.6 offers a detailed frequency analysis of keywords associated with specific aspects of passenger experiences at nine of the busiest Southeast Asian (SEA) airports, based on user-generated content. The table below summarizes the top mentions per airport, revealing the predominant concerns or areas of interest as voiced by passengers.

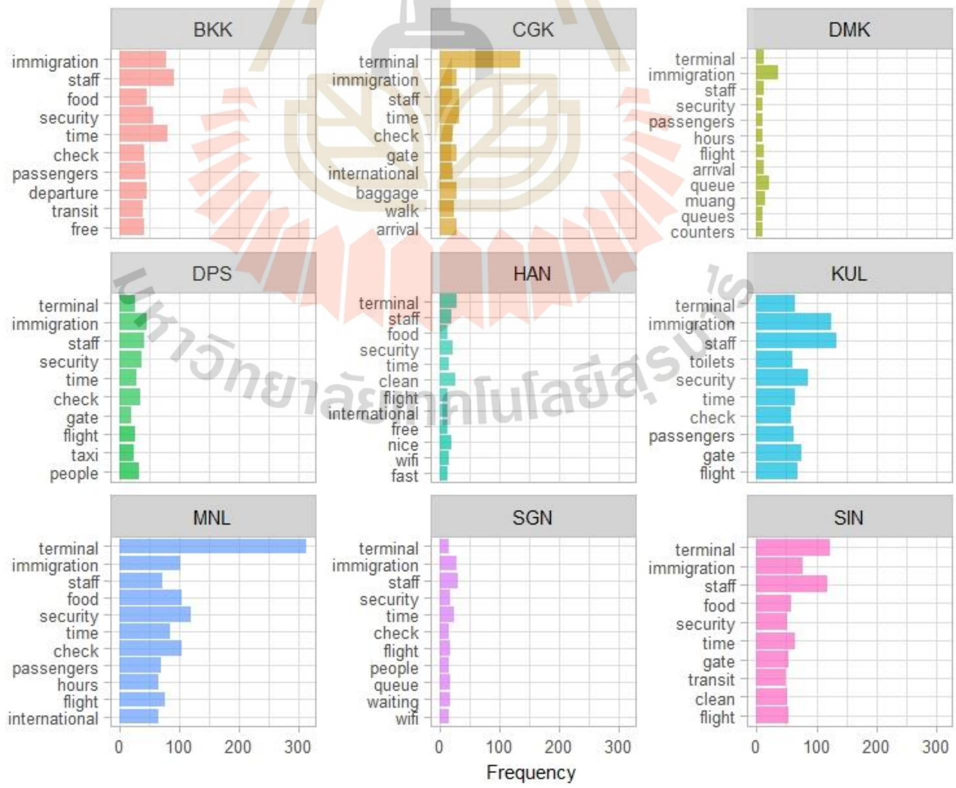


Figure 4.6 Top ten keywords by frequency of top nine busiest SEA airport after removing custom stop words and default stop words.

Insights into the most frequently mentioned terms at each airport are provided below to offer valuable perspectives on passenger feedback and concerns:

1. Suvarnabhumi Airport, Bangkok (BKK)

Departure, Passengers, Check, Free, and Transit were prominent terms, emphasizing departures-related feedback, passenger experiences, check-in processes, complimentary services, and transit experiences, respectively.

2. Soekarno-Hatta International Airport, Jakarta (CGK)

Terminal ranked highest with significant discussions on terminal amenities, followed by Staff and Time, which highlighted staff interactions and time efficiency. Baggage and Gate also received notable mentions regarding baggage handling and gate procedures.

3. Don Mueang International Airport, Bangkok (DMK)

Immigration stood out as a significant area of feedback, followed by Queue and Flight, reflecting concerns over queuing and flight experiences. Staff and Terminal were also mentioned in connection to staff behavior and terminal facilities.

4. Ngurah Rai International Airport, Bali (DPS)

Immigration was a primary concern, alongside Staff and Security, addressing staff quality and security protocols. Check and Time were also noted, indicating issues with check-in processes and time efficiency.

5. Noi Bai International Airport, Hanoi (HAN)

Terminal discussions were emphasized, with noteworthy mentions of Clean and Security, reflecting feedback on cleanliness and security standards. Staff and Wifi were also noted in the context of staff conduct and available WiFi services.

6. Kuala Lumpur International Airport (KUL)

The focus was on Staff and Immigration, highlighting staff quality and immigration processes. Security and Gate were critical areas, with Flight and Terminal also receiving frequent mentions regarding security, gate operations, flight experiences, and terminal facilities.

7. Ninoy Aquino International Airport, Manila (MNL)

Terminal and Security discussions were prevalent, indicating concerns with terminal facilities and security. Check and Food were commonly discussed, followed by Immigration and Time, noting feedback on check-in processes, food services, immigration procedures, and time management.

8. Tan Son Nhat International Airport, Ho Chi Minh City (SGN)

Staff and Immigration mentions centered on staff efficiency and immigration experiences. Time and Security highlighted time-related concerns and security procedures. Flight and Queue were significant for flight experiences and queuing feedback.

9. Changi Airport, Singapore (SIN)

Terminal and Staff were focal points, stressing terminal facilities and staff interactions. Immigration and Time were key areas concerning immigration processes and time management. Food and Flight were main topics linked to food services and flight experiences.

The analysis sheds light on prevalent themes and issues voiced by passengers across varied airports, guiding airport authorities to address specific areas for enhancement and improve overall passenger experiences at SEA airports.

The frequency analysis unveils varied priorities and concerns among passengers at each airport. Terminal facilities, staff interactions, security protocols, and immigration processes recurrently surface across multiple airports, indicating their universal impact on passenger satisfaction.

The emphasis on terminal amenities noted in airports like MNL, CGK, and SIN underscores the significance of physical infrastructure and amenities in enhancing passenger experience. Notable mentions of staff interactions in KUL, SIN, and BKK emphasize the pivotal role of customer service in determining airport satisfaction.

Security and immigration emerge as pivotal operational domains drawing substantial passenger feedback, suggesting ongoing efforts are crucial to enhance efficiency and ensure traveler comfort. Furthermore, time-related issues featured across airports stress the need to minimize delays and enhance process efficiency.

By addressing these identified areas, airport management can prioritize enhancements in terminal facilities, staff training, security measures, and immigration processes, thereby elevating passenger experiences and satisfaction levels. The insights gleaned from the frequency analysis of passenger reviews can inform strategic decisions and policy formulations to pursue operational excellence and elevate traveler comfort.

Consistent themes impacting passenger satisfaction across all airports include terminal facilities, staff interactions, security protocols, and immigration processes, indicating universal concerns.

Enhancing operational efficiency and reducing delays is crucial, as emphasized by the frequent mentions of time, underscoring the need for improved efficiency.

Critical elements influencing the passenger experience include staff performance and behavior, advocating for enhanced training and customer service initiatives.

Targeted improvements in these areas hold the potential to significantly boost overall passenger satisfaction, elevate operational performance, and establish higher standards across SEA airports.

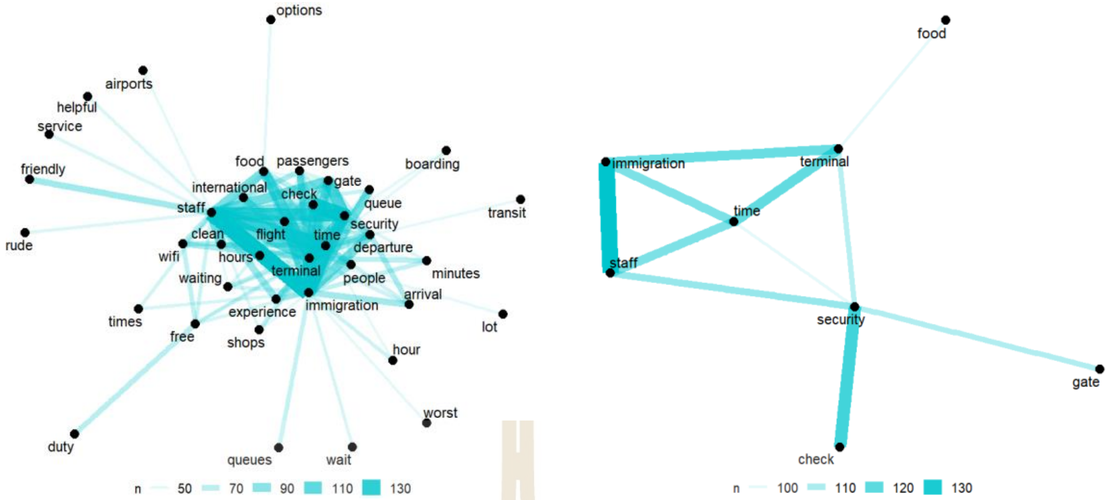
4.2.2 Word cloud visualization and word pairs analysis

The word cloud visualization is created to represent the frequency importance of words in the context of the top nine busiest SEA airports. Each word's size in the word cloud corresponds to its frequency in the dataset, where larger words reflect higher frequency occurrences. Additionally, a word pairs analysis using pairwise_count() from the widyr package is conducted to determine how often pairs of words occur together in the dataset. This analysis helps uncover word co-occurrences and correlations. This approach provides insights into the relationships between words and their co-occurrence patterns, which can offer valuable information on common themes and associations within the dataset. Word co-ocurrences and correlations, using pairwise_count() from the widyr package to count how many times each pair of words occurs together in a field.

In the analysis conducted utilizing pairwise_count() from the tidyr package, a comprehensive overview of word pairs and their co-occurrence frequency is provided. According to Figure 4.8, particularly noteworthy pairs include "immigration" and "staff," observed together 134 times, followed by "security" and "check" with 124 occurrences. Notable pair occurrences include "terminal" and "time" (119 times), "terminal" and "immigration" (118 times), and "time" and "staff" (115 times) within the dataset, which encompasses a total of 531,371 word-pairs.

The word cloud prominently features words like "terminal," "staff," "immigration," "security," and "time" due to their high frequencies in the dataset. Other significant terms such as "flight," "check," "food," "gate," and "passengers" are also displayed prominently, reflecting their substantial presence in the text data. Less common terms like "people," "departure," "experience," and "queue" may appear slightly smaller but remain noticeable, indicating their frequency relative to the dominant terms. Infrequent terms such as "worsened," "worthwhile," "đá," and others are represented in a comparatively smaller size within the word cloud, reflecting their lower occurrence in the dataset.

Figure 4.7 Word cloud of the top nine busiest SEA airports.



(a) (b)

Figure 4.8 Word pairs of the top nine busiest SEA airports. (a) Word pairs by frequency occur more than and equal to 50 occurrences. (b) Word pairs by frequency occur more than and equal to 100 occurrences.

Word cloud visualization and word pairs analysis by airport

The word cloud visualization will showcase the frequencies of various words in the dataset, with each word's size reflecting its frequency. The dataset's focus on multiple airports will be mirrored in the word cloud, highlighting prevalent terms such as "terminal," "staff," "immigration," "security," "time," "flight," "check," "food," "gate," and "passengers."

Insights from the word cloud may reveal distinct patterns. For instance, airports like MNL and SIN may exhibit heightened frequencies of terms like "terminal," "security," and "immigration," indicating core operational elements at these sites. Conversely, specific airports like KUL might display increased frequencies for terms such as "staff," "immigration," and "security," underscoring key operational domains unique to those locations. Additionally, word pair analysis conducted utilizing pairwise_count() can offer valuable insights on co-occurrence frequencies, with significant pairs providing deeper context to the prevalent terms.

Word pair analysis could elucidate key associations. For instance, "immigration" and "staff" appearing together frequently suggests a notable relationship, possibly signaling interactions between staff and immigration processes. Another noteworthy pair like "security" and "check" may indicate a focus on security checks and procedures.

The dataset's large number of word pairs, totaling 531,371, allows for comprehensive exploration of these associations.

By visually representing word frequencies and word pairs related to various airports in a word cloud and through detailed analysis, visualization aids in identifying prevalent themes and understanding crucial aspects of airport operations and services. This integrated approach provides a comprehensive view of the most significant terms and associations within the dataset, promoting a deeper understanding of passenger feedback and priorities for each airport location.

1. Bangkok Suvarnabhumi Airport (BKK)

The dataset on passenger reviews at Bangkok Suvarnabhumi Airport (BKK) identifies prevalent themes through the frequency of mentioned words. Key topics include staff interactions, time-related matters, immigration procedures, security measures, food services, departure experiences, passenger interactions, check-in procedures, complimentary services, and transit experiences.

Insights from the BKK airport dataset reveal notable word pairings, with occurrences of 10 or more indicating significant relationships. Noteworthy pairs include "time" and "staff" (29 occurrences) and "security" with "time" (25 occurrences). Additional pairings, such as "immigration" with "staff" (24 occurrences) and "security" with "staff" (23 occurrences), shed light on essential connections. Associations like "immigration" with "queues," "passengers," and "departure" occurred 18, 18, and 17 times, respectively.

High-frequency terms at BKK airport highlight important traveler concerns, with a notable focus on "staff" (92 mentions) and "time" (80 mentions) reflecting customer service and operational efficiency. Additionally, mentions of "immigration" (79), "security" (57), "check" (42), and "passport" (31) underscore the significance of immigration and security procedures. Terms like "food" (47), "departure" (45), and "passengers" (43) indicate considerations regarding dining options, departure processes, and passenger volume. "Free" (41) and "transit" (39) suggest attention to amenities and transit ease.

Prominent mentions of "queue" (32) and "queues" (29) underscore waiting time challenges, pointing to areas requiring efficiency improvements. Less common terms like "wire," "wishing," and "xray," each mentioned once, hint at niche or minor concerns in the traveler experience.

The forthcoming word cloud will visually represent word frequencies at BKK airport, with varying sizes reflecting word frequencies. Essential operational aspects, such as "staff," "time," "immigration," "security," "food," "departure," "passengers," "check," "free," "transit," "gate," "flight," "experience," and "Thai," are anticipated to be prominently featured.

Observations and interpretations showcased in the word cloud can highlight significant operational areas and services at BKK airport through terms like "staff," "time," "immigration," and "security." While terms like "food," "experience," and "Thai" may suggest service elements and cultural nuances, less frequent terms like "wire," "woes," "yelling," and "zones" may also be integrated, though appearing smaller due to lower frequencies.

The visual presentation of key themes and operational nuances specific to BKK airport in the word cloud aids in comprehensively understanding the dataset and critical aspects associated with Bangkok Suvarnabhumi Airport.

Figure 4.9 Word cloud of BKK airport.

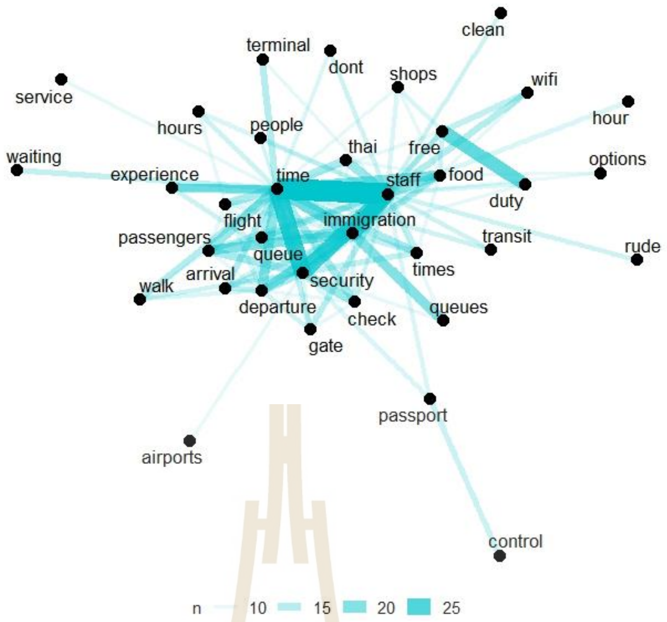


Figure 4.10 Word pairs of BKK airport.

Figure 4.10 presents co-occurrence data for various items at BKK airport, demonstrating significant relationships between these items. Noteworthy pairings include occurrences such as "time" with "staff" appearing 29 times, "security" paired with "time" 25 times, and "immigration" with "staff" noted 24 times. Additionally, pairs like "security" with "staff" (23 occurrences) and "duty" with "free" (21 occurrences) are also highlighted. Other substantial associations encompass "immigration" with "time" observed 20 times, "food" with "time" 18 times, and "immigration" with "queues," "passengers," and "departure" each occurring 18, 18, and 17 times, respectively.

Through this result, crucial insights into the co-occurrence relationships and frequencies among different items at BKK airport are unveiled, providing a deeper understanding of the interconnected themes and interactions within the dataset.

2. Soekarno-Hatta International Airport (CGK)

Insights into traveler experiences at Soekarno-Hatta International Airport (CGK) are provided by the dataset through word frequency analysis, showcasing predominant themes and notable word pairings that have frequencies meeting or exceeding the 10-occurrence threshold. Various critical aspects of the passenger journey are underscored, with a primary focus on airport infrastructure emphasized by the frequency of the term "terminal", mentioned 135 times. Concerns related to customer service and efficiency are highlighted by the frequencies of "staff" and "time," each mentioned 33 times.

Other significant pairings, such as "terminal" associated with "time" occurring 21 times, followed by combinations like "terminal" with "immigration" and "food," occurring 15 and 14 times respectively, provide valuable insights into passenger sentiments. Navigational and check-in processes for international flights are indicated by terms like "walk," "check," and "international," mentioned 23, 22, and 22 times, respectively. Issues involving parking and ground transportation are reflected in terms like "lot," "minutes," and "taxi," each mentioned 21 times.

Moreover, key areas for improvement at CGK, including terminal infrastructure, staff interaction, process efficiency, baggage handling, and security, are identified. The word cloud visualization aims to represent the frequencies of different words at CGK airport visually, with the size of each word indicating its frequency in the dataset. Essential airport-related terms such as "terminal," "staff," and "time" signify core operational elements and services at CGK airport, while less frequent terms suggest niche or less critical topics. Visual representation through a word cloud aids in quickly comprehending the significant terms associated with CGK airport, facilitating the identification of key elements and themes relevant to the airport context.

Figure 4.11 Word cloud of CGK airport.

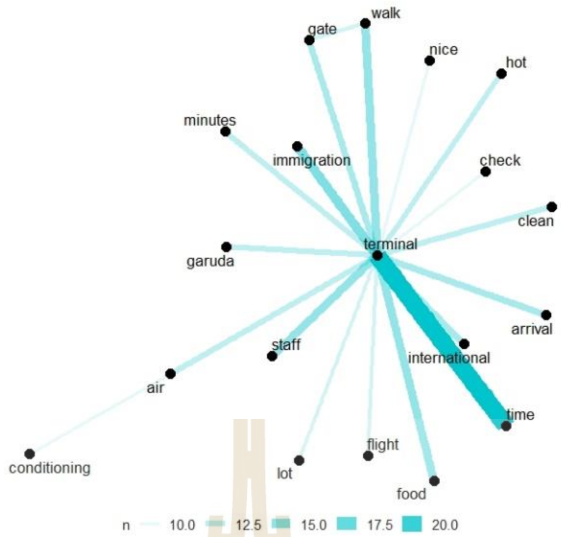


Figure 4.12 Word pairs of CGK airport.

In Figure 4.12 provided, key associations at CGK airport are outlined, with frequencies listed for word pairings that meet or exceed the 10-occurrence threshold. The dataset indicates that the term "terminal" emerges prominently, mentioned in various pairings such as "terminal" with "time" occurring 21 times, followed by associations like "terminal" with "immigration" and "food," each recorded at 15 and 14 occurrences, respectively. Noteworthy combinations include "terminal" paired with "walk" and "staff," each appearing 14 times.

Furthermore, the dataset reveals other significant associations like "international terminal" with 13 occurrences, along with pairings such as "terminal" with "arrival" and "gate," each noted 13 times. Additional frequent pairings include "terminal" with terms like "Garuda," "hot," "air," "minutes," and "clean," each detailed 12 times. Associations like "walk" and "gate," "terminal" and "lot," as well as "terminal" paired with "flight," each had 11 occurrences. Moreover, terms like "air" with "conditioning," and "terminal" with "check" and "nice" were each mentioned 10 times within the dataset.

The dataset provides valuable insights into the interconnectedness of terms related to different aspects of CGK airport, shedding light on prevalent word pairings and their frequencies for further analysis and interpretation in the context of passenger experiences and operational factors at the airport.

3. Don Mueang International Airport (DMK)

Based on the dataset analysis of Don Mueang International Airport (DMK), key themes have been identified through the frequent mention of specific words. Common topics include discussions on immigration processes, queuing experiences, flight feedback, arrivals, staff interactions, terminal facilities, hours of operation, multiple queues, check-in counters, and passenger interactions.

"Immigration" emerged as the most mentioned term (35 occurrences), emphasizing the significance of immigration processes and queue management at DMK. "Queue" followed with 20 mentions. Frequent terms such as "flight," "arrival," "staff," and "terminal" highlight essential aspects of the travel experience. Operational considerations are indicated by "hours" and "queues." Less frequently mentioned aspects include "counters," "security," and "passengers," reflecting operational procedures and security measures. Niche topics such as "wailing," "waived," and "walkway" appear less critical to the broader traveler experience but are nonetheless present in the dataset.

The analysis underscores the need for improvements in immigration efficiency, queuing practices, staff performance, and overall traveler experience at DMK airport. A word cloud visualization will be employed to display the frequencies of different words, with the size of each word indicating its frequency in the dataset. Terms such as "immigration," "queue," "flight," "arrival," "staff," "terminal," "hours," "passengers," "security," and "experience" will be prominently featured. Less frequent terms, including "visited," "wary," "water," and "zone," will appear smaller due to their lower occurrence.

The word cloud serves as an effective visual tool for identifying significant terms and thematic focus areas relevant to DMK airport, providing a quick overview of key elements and topics within the dataset. This visualization aids in communicating the emphasis and importance of specific keywords associated with Don Mueang International Airport.

Figure 4.13 Word cloud of DMK airport.

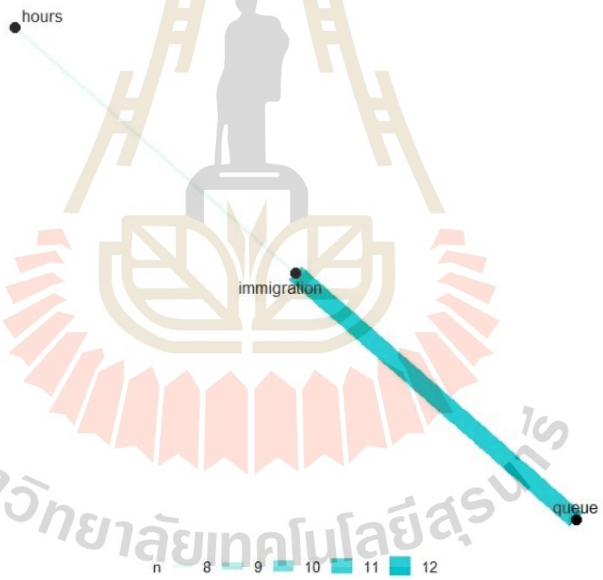


Figure 4.14 Word pairs of DMK airport.

Figure 4.14. presents various associations between terms, with frequencies listed for specific word pairings that meet or exceed the 5-occurrence threshold. Notable associations include "immigration" with "queue" occurring 12 times, followed by pairings like "immigration" with "hours" noted 8 times, and "queues" with "immigration" appearing 7 times. Additionally, terms like "immigration" with "times" and "arrival" with "immigration" each occurred 7 times and 6 times, respectively.

Further insights from the dataset include combinations such as "arrival" with "queue" and "times" with "queue," each documented 6 times. Moreover, associations like "immigration" with "worst" and "visa" were recorded 6 times each, while "hour" coupled with "immigration" had 5 occurrences.

These findings from the dataset offer valuable information on common word pairings related to immigration processes, queues, wait times, and arrival experiences at DMK airport. The identified associations can provide a basis for exploring passenger perceptions, operational efficiencies, and potential areas for improvement within the immigration and arrival procedures at the airport.

4. Denpasar International Airport (DPS)

The analysis of passenger reviews for Denpasar International Airport (DPS) reveals key topics based on the most frequently mentioned words. Predominant themes include discussions on immigration processes, staff interactions, security measures, check-in procedures, passenger experiences, time management, flight experiences, terminal facilities, taxi services, and gate operations.

Word pairings meeting or exceeding the 10-occurrence threshold were examined. "Security" with "check" and "immigration" with "people" were each observed 13 times. Pairings such as "security" with "gate" and "immigration" with "time" were noted 12 times. Further associations included "immigration" with "flight" and "staff," "security" with "staff," and "people" with "staff," each occurring 11 times. The pairings "time" with "departure" and "immigration" with "wait" and "departure" were observed 11 and 10 times, respectively. A total of 12 significant word pairs meeting the frequency criteria were identified, providing valuable insights into co-occurrence patterns within the DPS airport dataset.

A word cloud visualization was utilized to represent word frequency data associated with DPS airport. Key terms such as "immigration," "staff," "security," "check," "people," "time," "flight," "terminal," "taxi," "gate," "departure," and "hours" are emphasized proportionally to their frequency.

Prominent terms like "staff," "immigration," and "security" indicate critical operational areas and services at DPS airport, suggesting significant traveler focus and potential discussion points regarding service quality and operational efficiency. Terms such as "time," "flight," "terminal," and "taxi" point towards time management, flight operations, terminal facilities, and ground transportation services, indicating essential elements of the airport experience.

Less frequent terms such as "wife," "worried," "x-ray," and "yelled" will appear smaller in the word cloud, reflecting their lower frequency. Although these terms are less prominent, their inclusion provides a comprehensive view of the varied topics and experiences expressed in the dataset.

The word cloud visualization offers a compelling and informative snapshot of textual data specific to DPS airport. Significant themes, operational aspects, and key terms associated with Denpasar International Airport are effectively captured, facilitating a quick and engaging overview for further analysis and interpretation.

The dataset for DPS airport reveals significant associations between terms, highlighting frequent pairings such as "security" with "check" and "immigration" with "people," each occurring 13 times. Additionally, terms like "security" with "gate" and "immigration" with "time" are noted 12 times. Other notable associations within the dataset include "immigration" paired with "flight" and "staff," and "security" with "staff," each mentioned 11 times. The pairing of "people" with "staff" and "time" with "departure" are also observed 11 times. Moreover, associations like "immigration" with "wait" are recorded 10 times.

Figure 4.15 Word cloud of DPS airport.

These findings provide insights into word pairings related to security checks, immigration procedures, staff interactions, and passenger experiences at DPS airport. Understanding the frequencies of these associations can aid in identifying areas for enhancing security protocols, immigration processes, staff training, and overall operational efficiency at the airport.

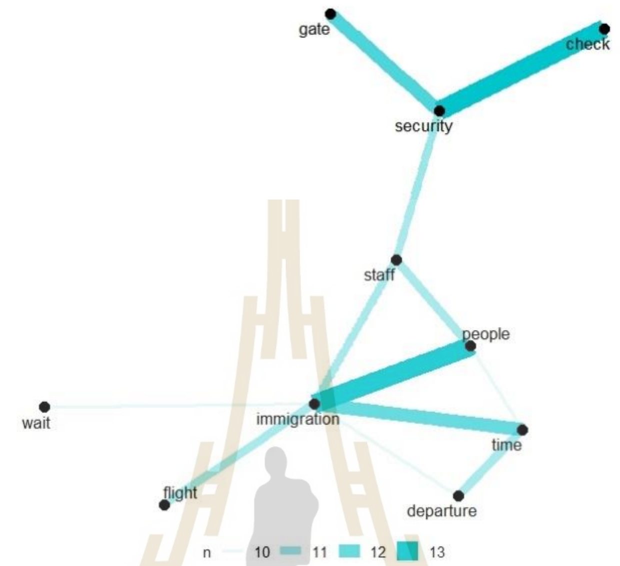


Figure 4.16 Word pairs of DPS airport.

5. Hanoi Airport (HAN)

The analysis conducted for Hanoi Airport (HAN) extracted a total of 649 words from passenger reviews. Key terms identified include "terminal" (27 mentions), "clean" (26 mentions), "security" (21 mentions), "nice" (20 mentions), "staff" (19 mentions), "time" (15 mentions), "wifi" (14 mentions), "fast" (13 mentions), "flight" (13 mentions), and "food" (13 mentions).

Word pairings meeting or exceeding the 6-occurrence threshold were examined. Notable pairings include "clean" with "nice" (12 mentions), "clean" with "staff" (11 mentions), and "security" with "clean" (9 mentions). Additional associations include "staff" with "nice" and "international terminal" (8 mentions each), and "Noi" paired with "Bai" (7 mentions). Other relevant pairings include "clean" with "time," "staff" with "friendly," and "clean" with "terminal" (7 mentions each), as well as "clean" with "food" (6 mentions).

A word cloud visualization will portray the frequency distribution of terms related to HAN airport. Prominently featured terms include "terminal," "clean," "security," "nice," "staff," "time," "wifi," "fast," "flight," "food," "free," "international," "immigration," "check-in," "terminals," "friendly," "gate," "hours," "Noi," and "shopping." Significant terms such as "terminal," "clean," "security," and "nice" highlight critical aspects of airport infrastructure, cleanliness standards, security measures, and overall service quality. Terms like "time," "wifi," "fast," and "flight" suggest concerns related to operational efficiency, connectivity services, and flight-related experiences.

Less frequent terms like "welcoming," "world-class," "worst," and "zone" will appear smaller, reflecting their lower frequency but providing a comprehensive overview of diverse topics and sentiments.

This visual representation serves as an effective tool to capture key themes and top terms associated with Hanoi Airport, offering an informative snapshot of textual data specific to HAN. Significant associations between terms, such as "clean" with "nice" (12 mentions) and "clean" with "staff" (11 mentions), indicate prevalent themes of cleanliness and staff behavior. Further associations like "security" with "clean" (9 mentions) and "staff" with "nice" (8 mentions) provide additional insights into passenger experiences.

Figure 4.17 Word cloud of HAN airport.

The dataset concerning HAN airport highlights significant word pairings related to cleanliness, staff behavior, terminal facilities, and other aspects of passenger experiences. Understanding these associations can provide valuable insights for enhancing cleanliness standards, staff friendliness, and overall passenger satisfaction at HAN airport.

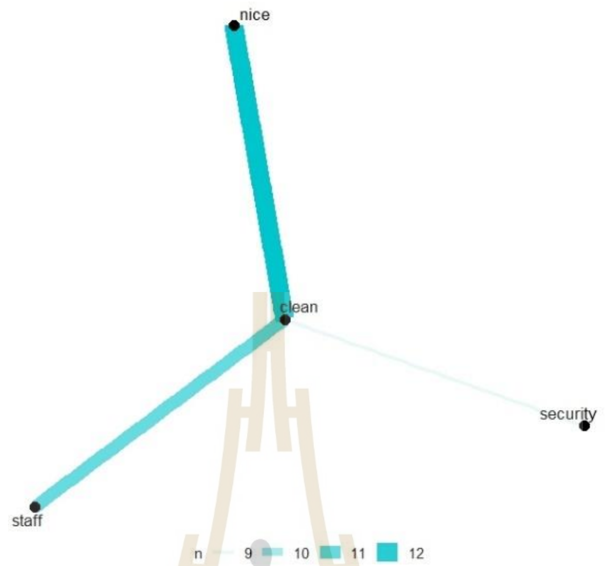


Figure 4.18 Word pairs of HAN airport.

6. Kuala Lumpur International Airport (KUL)

The analysis of passenger reviews specific to Kuala Lumpur International Airport (KUL) highlights key themes, including staff interactions, immigration processes, security measures, gate operations, flight experiences, terminal facilities, time efficiency, passenger experiences, toilet facilities, and check-in procedures.

Word pairings meeting or exceeding the 19-occurrence threshold were analyzed. "Immigration" with "staff" was noted 30 times, followed by "staff" with "flight" at 27 occurrences. Pairings such as "security" with "gate" and "gate" with "staff" were each observed 26 times, while "gate" with "flight" appeared 22 times. Other notable pairings included "staff" with "passengers" and "immigration" with "queue," each occurring 21 times, and "check" with "staff" also noted 21 times. Additionally, "security" with "staff" and "immigration" with "time" were documented 20 and 19 times, respectively.

A word cloud visualization will represent the frequency distribution of various words related to KUL airport, with the size of each word indicating its frequency. Key terms such as "staff," "immigration," "security," "gate," "flight," "terminal," "time," "passengers," "toilets," "check," "people," "water," "departure," "transit," "boarding," "clean," "experience," "international," "food," and "hours" are expected to be prominently displayed, reflecting their significance in traveler discussions. Prominent terms like "staff," "immigration," "security," and "gate" underscore critical operational areas and services, pointing to staff performance, immigration procedures, security measures, and boarding gate operations. Terms like "passengers," "toilets," and "clean" signify passenger-centric facilities and services, highlighting the importance of passenger facilities and cleanliness at the airport.

Less frequently mentioned terms such as "wonderful," "world-class," "worried," and "yawning" will appear smaller due to their lower frequency, yet their inclusion offers a comprehensive view of the diverse topics and sentiments expressed in the dataset.

The word cloud visualization provides a visually compelling snapshot of critical themes and significant terms associated with KUL airport. This visual representation aids in quickly understanding key elements and themes essential to traveler experiences and operational aspects at KUL, offering a succinct and informative summary of the textual data.

The dataset for KUL airport presents significant associations between terms, with frequencies documented for specific word pairings that meet or exceed the 19-occurrence threshold. Notable associations include "immigration" with "staff" (30 times), "staff" with "flight" (27 times), "security" with "gate" (26 times), and "gate" with "staff" (26 times). Associations such as "staff" with "passengers" and "immigration" with "queue" (21 times each) and "security" with "staff" (20 times) provide further insights. Understanding these associations can provide valuable insights into improving staff efficiency, passenger flow management, and overall operational effectiveness at KUL airport.

Figure 4.24 Word cloud of KUL airport.

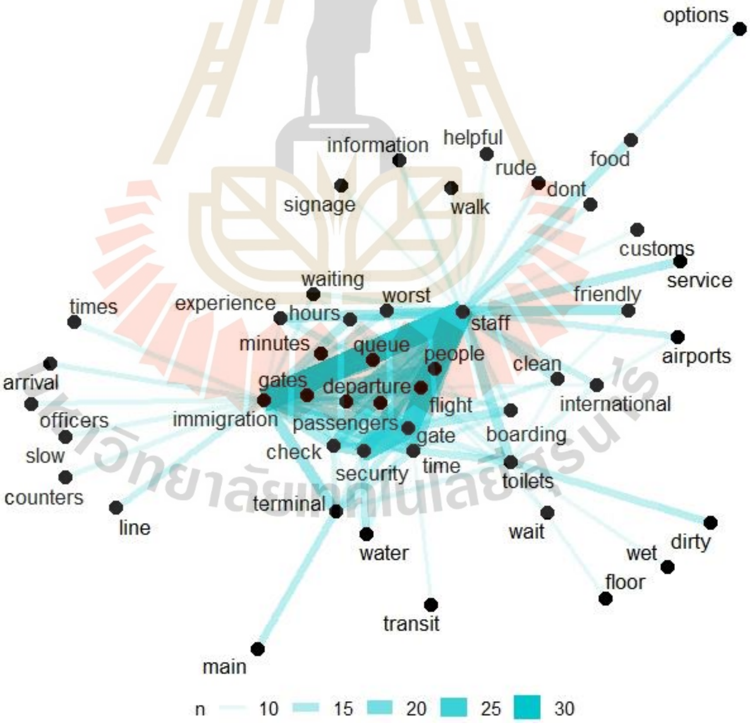


Figure 4.25 Word pairs of KUL airport.

7. Manila Airport (MNL)

The analysis of passenger reviews focused on Manila Airport (MNL) identified prominent terms such as "terminal," "security," "check," and "food." Other significant terms included "immigration," "time," "flight," "staff," "passengers," and "hours." A total of 2,536 distinct words were examined.

Word pairings meeting or exceeding certain thresholds were analyzed. "Terminal" with "food" was noted 45 times, followed by "check" with "security" (44 occurrences) and "terminal" with "flight" (42 occurrences). Pairings such as "terminal" with "security," "passengers," and "immigration" were each observed 41 times. Additional relevant pairings included "terminal" with "international" (39 times) and "check" (36 times). Further pairings such as "terminal" with "time" and "airlines" were recorded 33 times each.

A word cloud visualization is proposed to graphically display the frequency distribution of various words related to MNL airport. Key terms like "terminal," "security," "check," "food," "immigration," "time," "flight," "staff," "passengers," "hours," "international," "worst," "gate," "departure," "people," "seats," "line," "waiting," "boarding," and "wifi" will be prominently highlighted, reflecting their significance. Essential terms such as "terminal," "security," "check," and "food" indicate critical operational areas and passenger services, spotlighting terminal facilities, security protocols, check-in procedures, and dining options. Words like "immigration," "time," "flight," and "staff" symbolize operational processes, time management, flight operations, and personnel management.

Less frequently mentioned terms, such as "worried," "wrapped," "yellow," and "zones," will appear smaller, providing a comprehensive overview of varied topics present in the dataset.

The word cloud visualization effectively encapsulates critical themes and significant terms associated with Manila Airport. This visual approach aids in swiftly grasping key elements and themes relevant to traveler experiences and operational aspects at MNL, offering a concise and insightful summary of the textual data.

The dataset for MNL airport reveals notable associations between terms, with frequencies provided for specific word pairings meeting or exceeding the 33-occurrence threshold. Key associations include "terminal" with "food" (45 times) and "check" with "security" (44 times). Additional pairings such as "terminal" with "flight" (42 times), "security" (41 times), "passengers" (41 times), and "immigration" (40 times) provide further insights. Associations like "terminal" with "international" (39 times), "check" (36 times), "time" (33 times), and "airlines" (33 times) also contribute valuable information.

Figure 4.21 Word cloud of MNL airport.

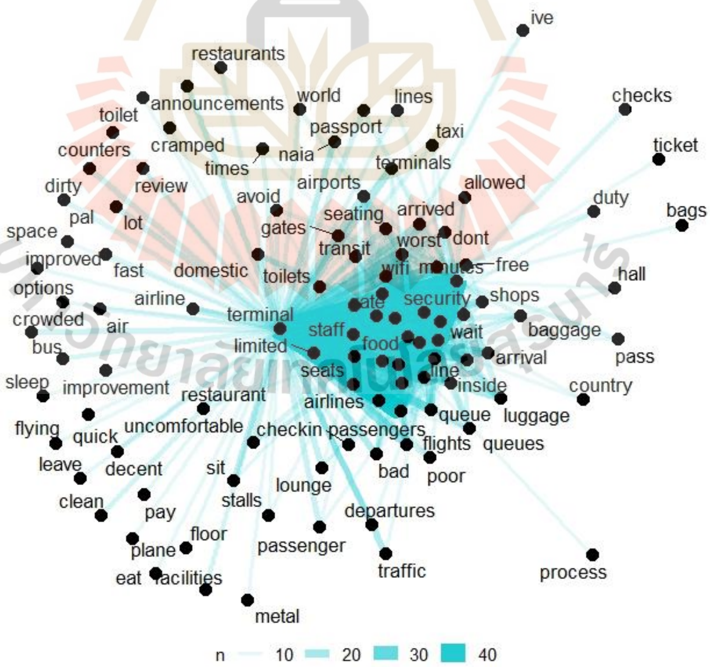


Figure 4.22 Word pairs of MNL airport.

These findings offer insights into significant word associations related to various aspects of operations and services at MNL airport, including terminal facilities, security procedures, flight operations, and passenger experiences. Understanding these associations can aid in identifying key areas for improvement to enhance overall airport performance and passenger satisfaction.

8. Ho Chi Minh City Airport (SGN)

The analysis of data from Ho Chi Minh City Airport (SGN) revealed recurring mentions of essential terms such as "staff," "immigration," "time," and "security," indicating their significance. Additional notable terms included "flight," "queue," "waiting," "check," "terminal," and "people," contributing to a diverse vocabulary observed in the dataset of 816 unique words.

Word pairings meeting or exceeding specific thresholds were analyzed. "Staff" with "time" was noted 11 times, followed by "immigration" with "time" (11 occurrences) and "staff" with "immigration" (9 occurrences). Pairings such as "check" with "security" and "time" with "city" were each observed 9 times. Other relevant pairings included "staff" with "food," "flight" with "time," "waiting" with "time," and "security" with "time," each noted 8 times. The pairing of "staff" with "wifi" was also observed 8 times.

The word frequency data associated with passenger experiences at SGN airport were examined to uncover prevalent themes, challenges, and commendations. Service Excellence: The prominence of terms like "staff" and "immigration" suggests a focus on the service quality of airport personnel and immigration processes. Operational Efficiency: Elevated frequencies of terms such as "time" and "check" indicate a significant emphasis on time management and check-in procedures. Passenger Concerns: The prevalence of terms like "security," "queue," and "worst" highlights common challenges faced by passengers, including security measures, queuing experiences, and potentially negative aspects of the airport journey. Amenities and Comfort: Noteworthy mentions of "wifi," "food," and "terminal" emphasize the significance of amenities, dining options, and terminal facilities in shaping passenger experiences.

The word cloud analysis of SGN airport highlights critical areas warranting attention from airport authorities and service providers. Addressing concerns related to security processes, queue management, and enhancing passenger comfort through facilities and services could improve overall passenger satisfaction.

Given the unique cultural landscape of Vietnam and the bustling city of Ho Chi Minh, factors such as local customs, language barriers, and passenger expectations specific to the region may influence the airport experience. Understanding these nuances can aid in tailoring services to better meet passenger needs and preferences.

The dataset for SGN airport highlights significant associations between terms, with frequencies provided for specific word pairings meeting or surpassing the 8-occurrence threshold. Notable associations include "staff" with "time" and "immigration" with "time," each occurring 11 times. Pairings such as "staff" with "immigration" and "check" with "security" each appear 9 times. Further insights reveal associations like "time" with "city" and "flight" with "time" (9 times each), along with "staff" with "food," "waiting" with "time," and "security" with "time" (8 times each).

These findings provide valuable information on key word associations related to staff interactions, immigration processes, time management, security checks, and passenger experiences at SGN airport. Understanding these associations can aid in identifying areas for potential improvement to enhance operational efficiency and passenger satisfaction at the airport.

Figure 4.23 Word cloud of SGN airport.

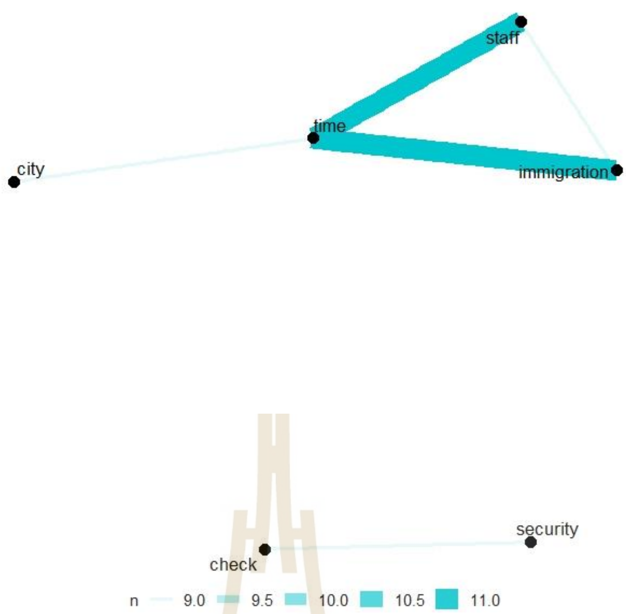


Figure 4.24 Word pairs of SGN airport.

9. Singapore Changi Airport (SIN)

The analysis of data from Singapore Changi Airport (SIN) highlighted the recurring terms "terminal," "staff," "immigration," and "time" as the most frequently mentioned. Additionally, notable terms included "food," "flight," "gate," "clean," "security," and "transit." Overall, the dataset encompassed 2,061 distinct words.

Word pairings meeting or exceeding certain thresholds were investigated. "Clean" with "staff" was noted 32 times, followed by "staff" with "immigration" (27 occurrences) and "staff" with "shopping" (24 occurrences). Other notable pairings included "terminal" with "staff" and "time" with "staff," each observed 23 times. Associations such as "staff" with "friendly" (23 times) and "staff" with "efficient" (22 times) were also significant. Pairings like "terminal" with "immigration" and "security" with "gate" each appeared 21 times, along with "staff" with "gate" (21 times).

By scrutinizing the lexical distribution encapsulating sentiments towards SIN, key themes and prevalent concerns of passengers were elucidated: Frequent mentions of "staff," "clean," and "efficient" suggest a strong emphasis on service quality and operational efficacy. Elevated frequencies of terms such as "time," "check," and "security" highlight a significant focus on procedural and time management aspects, indicating concerns for streamlining operations. Terms like "queue," "waiting," and "departure" indicate common challenges faced by passengers, including queuing experiences and departure processes. Mentions of "food," "shopping," and "wifi" underscore the importance of amenities, dining options, and connectivity, reflecting passengers' preferences and expectations. The term "transit" signals the crucial role of SIN as a major global transit hub, emphasizing the importance of transit infrastructure and passenger-centric amenities.

The word cloud visualization effectively captures the critical themes and significant terms associated with SIN airport. This visual representation aids in grasping key elements and themes relevant to traveler experiences and operational aspects at SIN, offering a concise and insightful summary of the textual data.

The dataset for SIN airport showcases significant associations between terms, with frequencies reported for specific word pairings meeting or surpassing the 21-occurrence threshold. Notable associations include "clean" with "staff" (32 times) and "staff" with "immigration" (27 times). Additionally, pairings such as "staff" with "shopping" (24 times), "terminal" with "staff" (23 times), "staff" with "friendly" (23 times), and "staff" with "efficient" (22 times) provide further insights. Further associations like "terminal" with "immigration" and "security" with "gate" (21 times each) are significant.

These findings offer valuable information on the key word associations related to cleanliness, staff behavior, terminal facilities, security measures, and passenger interactions at SIN airport. Understanding these associations can provide insights for enhancing various aspects of airport operations, ultimately improving service quality and customer satisfaction levels.

Figure 4.25 Word cloud of SIN airport.

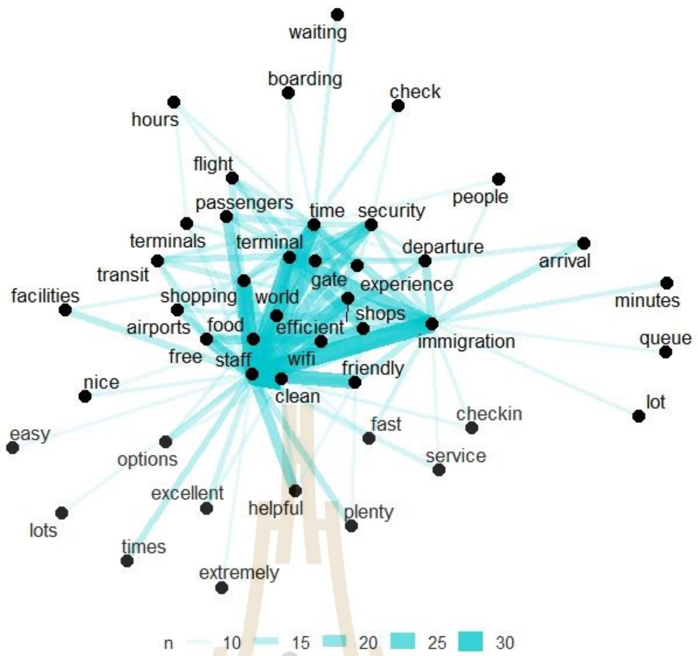


Figure 4.26 Word pairs of SIN airport.

In the text analysis and tokenization activities conducted, the focus was on examining the frequency distribution of words related to a specific airport. However, this analysis did not inherently capture the sentiment behind the words in the dataset, leaving out crucial information regarding the positivity, negativity, or neutrality of passenger feedback. To address this gap, the integration of sentiment analysis into the process becomes necessary as it enables the classification of text data based on the emotional tones expressed.

4.2.3 Sentiment analysis

Sentiment analysis, which is a component of natural language processing, facilitates the categorization of text data into sentiment categories such as positive, negative, or neutral. When applied to the passenger feedback dataset, sentiment analysis allows for a deeper exploration of travelers' experiences and perceptions, providing insights into the underlying sentiments conveyed in their feedback. This analytical approach aims to uncover actionable insights that can inform airport operations, drive service enhancements, and improve overall customer satisfaction strategies.

Through sentiment analysis, positive aspects identification: detection of positive sentiment in passenger feedback sheds light on areas that passengers find satisfying and commendable at airports. This insight helps in highlighting strengths and successful components of the airport experience that contribute to positive passenger perceptions.

Negative feedback revelation: analysis of negative sentiment exposes areas of concern, dissatisfaction, or potential shortcomings that passengers may have encountered at the airport. This critical feedback presents essential input for identifying improvement areas and effectively addressing passenger pain points.

Neutral sentiments comprehension: examination of neutral sentiment provides a nuanced perspective on aspects that do not strongly evoke either positive or negative responses from passengers. Understanding neutral feedback aids in discerning areas that passengers find acceptable but may require further attention or enhancement.

By integrating sentiment analysis with existing tokenization methods, the depth of the analysis can be enhanced, revealing the underlying sentiments expressed by passengers. This comprehensive approach enables airport authorities to customize services, address feedback proactively, and ultimately elevate the overall passenger experience.

The study encompassed a total of 9 airports, evaluating them based on the number of reviews, ranging from 40 for DMK to 197 for KUL, with an average of 105 reviews across all airports. Scores varied across the airports, with CGK achieving the highest score of 39 and DPS receiving the lowest score of -26. On average, the airports exhibited a score of -16, indicating a prevailing negative trend in reviews, with a standard deviation of 6.36 signifying a moderate dispersion in the data.

```
# A tibble: 2,477 × 2
   word        value
   <chr>       <dbl>
 1 abandon        -2
 2 abandoned      -2
 3 abandons       -2
 4 abducted       -2
 5 abduction      -2
 6 abductions     -2
 7 abhor          -3
 8 abhorred       -3
 9 abhorrent      -3
10 abhors         -3
# ℹ 2,467 more rows
```

(a)

```
# A tibble: 6,786 × 2
   word        sentiment
   <chr>       <chr>
 1 2-faces     negative
 2 abnormal    negative
 3 abolish     negative
 4 abominable  negative
 5 abominably  negative
 6 abominate   negative
 7 abomination negative
 8 abort       negative
 9 aborted     negative
10 aborts      negative
# ℹ 6,776 more rows
```

(b)

```
# A tibble: 13,872 × 2
   word        sentiment
   <chr>       <chr>
 1 abacus      trust
 2 abandon     fear
 3 abandon     negative
 4 abandon     sadness
 5 abandoned   anger
 6 abandoned   fear
 7 abandoned   negative
 8 abandoned   sadness
 9 abandonment anger
10 abandonment fear
# ℹ 13,862 more rows
```

(c)

Figure 4.27 Example of sentiment lexicons. (a) AFINN lexicon, (b) Bing lexicon and (c) NRC lexicon

4.2.3.1 Lexicon-based sentiment analysis: AFINN lexicon

Notably, ratings differed among the airports, with HAN obtaining the highest average score of -5 and MNL receiving the lowest average score of -20. This variation in satisfaction levels among passengers underscored the need for further investigation and enhancement of airport services to cater to diverse traveler experiences.

The sentiment analysis results for each airport were meticulously examined in the analysis. BKK Airport housed 135 reviews, showcasing a maximum score of 27 and a minimum score of -18. Similarly, CGK Airport, with 68 reviews, achieved a maximum score of 39 and a minimum score of -16. DMK Airport, reviewed 40 times, reported a maximum score of 12 and a minimum score of -13. DPS Airport garnered 71 reviews, with a maximum score of 17 and a minimum score of -26.

Furthermore, HAN Airport accumulated 51 reviews, demonstrating a maximum score of 16 and a minimum score of -5. KUL Airport, having the highest review count of 197, showed a maximum score of 23 and a minimum score of -19. Conversely, MNL Airport amassed 186 reviews, with a maximum score of 16 and a minimum score of -20. SGN Airport, with 45 reviews, reflected a maximum score of 12 and a minimum score of -19. Lastly, SIN Airport garnered 170 reviews, achieving a maximum score of 33 and a minimum score of -15.

This meticulous examination of sentiment analysis scores across different airports elucidated the diverse sentiments expressed in reviews, paving the way for insightful implications in enhancing airport services and addressing passenger feedback effectively.

A tibble: 9 × 6

	airport	review_number	max_score	min_score	avg_score	sd_score
	<fct>	<int>	<dbl>	<dbl>	<dbl>	<dbl>
1	BKK	135	27	-18	-0.933	6.19
2	CGK	68	39	-16	0.926	8.00
3	DMK	40	12	-13	-1.32	5.57
4	DPS	71	17	-26	-1.77	6.52
5	HAN	51	16	-5	4.49	4.59
6	KUL	197	23	-19	-1.43	6.73
7	MNL	186	16	-20	-3.53	6.19
8	SGN	45	12	-19	-1.87	6.98
9	SIN	170	33	-15	4.99	7.14

Figure 4.28 AFINN score of each passenger review and each airport.

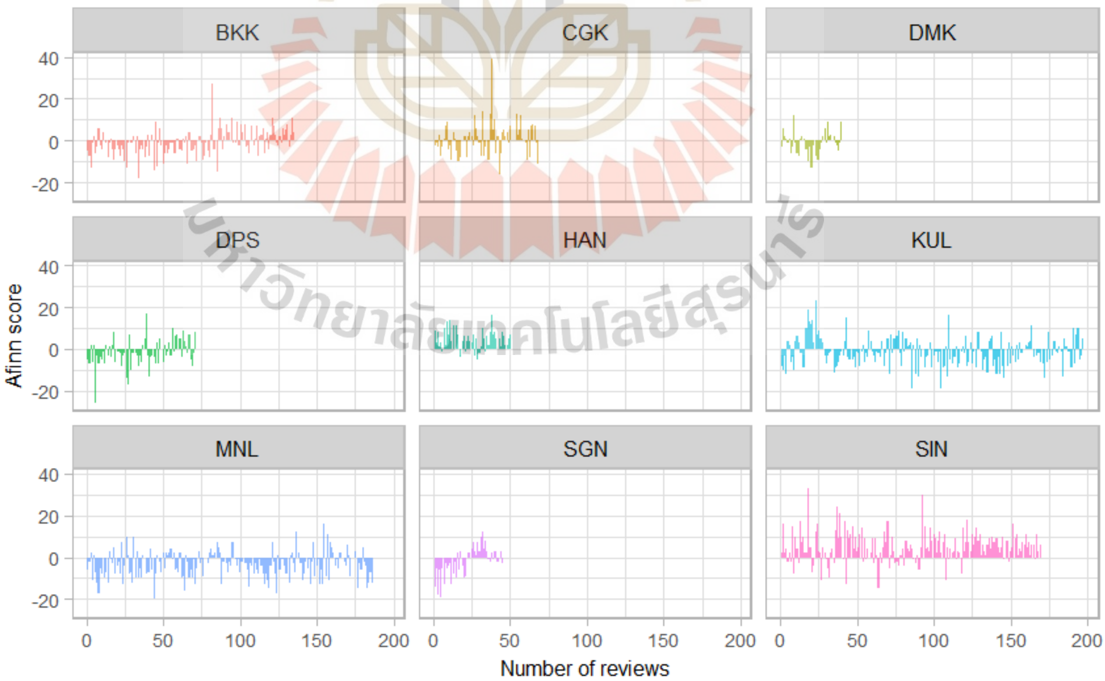


Figure 4.29 Afinn score of each passenger review.

Figure 4.30 presents insights into the total sentiment scores for reviews of various airports. Below is a summary of the total sentiment scores for each airport within the dataset:

BKK Airport: Total Score of -126, CGK Airport: Total Score of 63, DMK Airport: Total Score of -53, DPS Airport: Total Score of -126, HAN Airport: Total Score of 229, KUL Airport: Total Score of -281, MNL Airport: Total Score of -656, SGN Airport: Total Score of -84, SIN Airport: Total Score of 849

These cumulative sentiment scores offer an aggregated measure of the sentiment conveyed in reviews for each airport, providing valuable insights into the overarching sentiment patterns associated with passenger feedback.

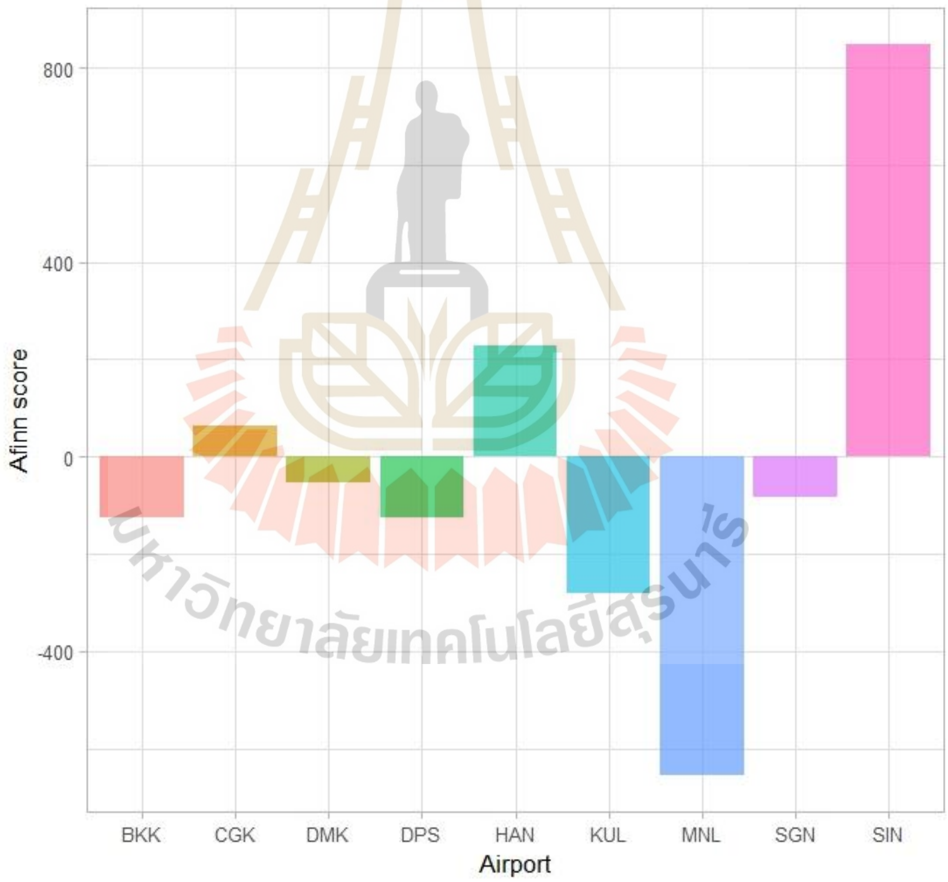


Figure 4.30 Total AFINN score of each airport.

4.2.3.2 Lexicon-based sentiment analysis: Bing lexicon

In the Lexicon-based sentiment analysis employing the Bing lexicon, the frequency of positive and negative words in the text data was examined. The top 10 positive and negative words, along with their respective frequencies, are and illustrated in Figure 4.31.

This analysis offers insights into the sentiment expressed within the text data through the prevalence of these positive and negative words, thereby contributing to a comprehensive comprehension of the emotional nuances and viewpoints conveyed within the text

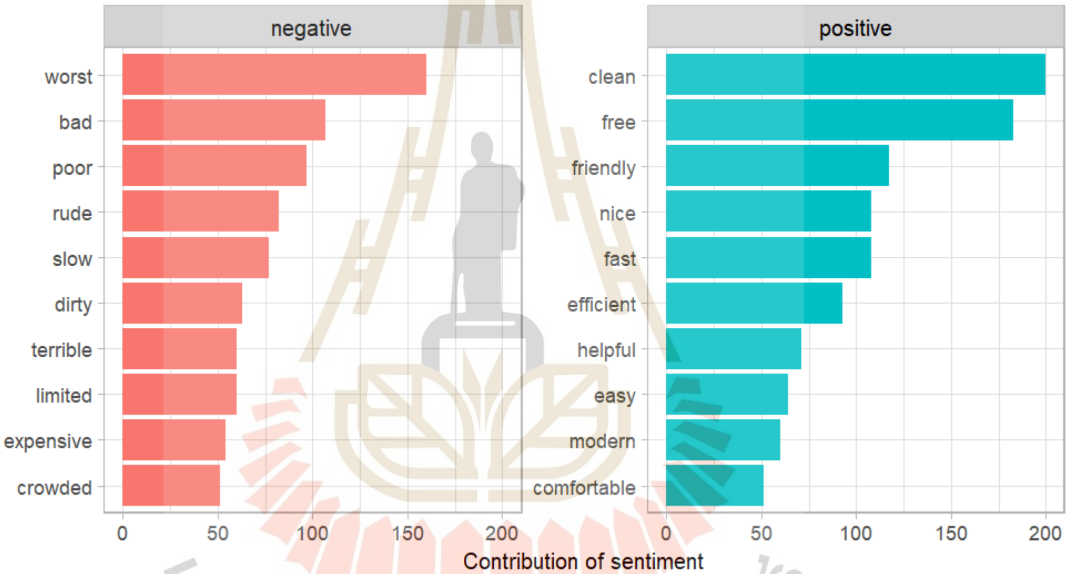


Figure 4.31 Top ten of Bing negative and positive word frequency.

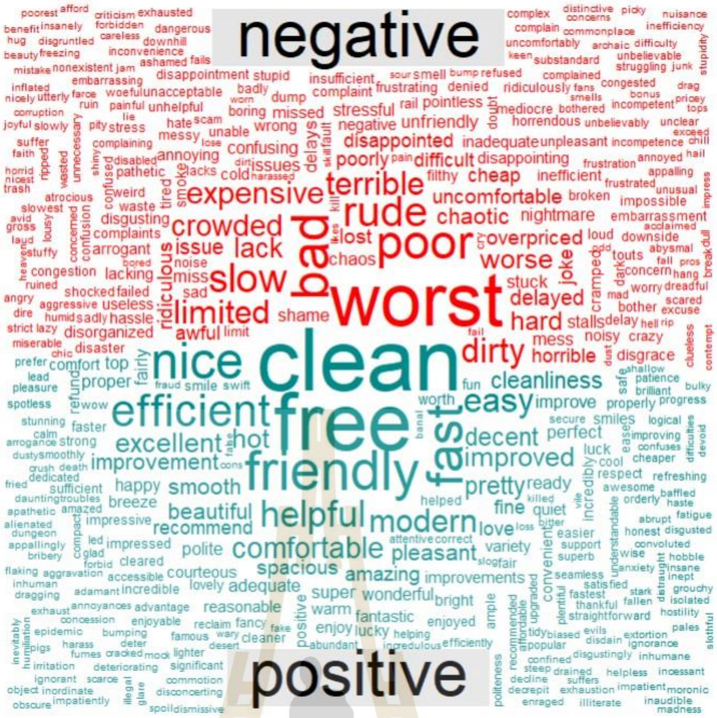


Figure 4.32 Word cloud of Bing negative and positive words.

The sentiment distribution for each airport is provided along with the number of occurrences for negative and positive sentiments in the dataset. Here is the analysis rephrased in an academic research writing style and passive voice:

The sentiment breakdown of each airport was observed, detailing the count of negative and positive sentiments within the dataset. The findings are summarized in Figure 4.33.

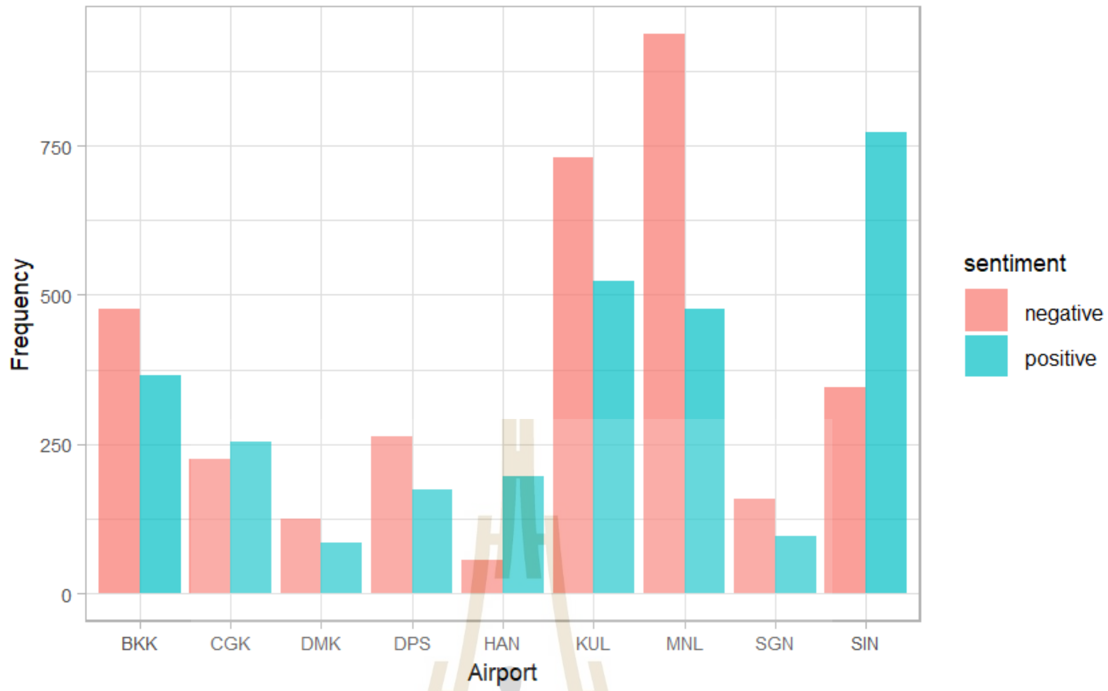


Figure 4.33 Bing negative and positive word frequency of each airport.

4.2.3.3 Lexicon-based sentiment analysis: NRC lexicon

The total scores for various sentiment categories based on the NRC lexicon have been examined to gain insights into the emotional content present in the text data. The results have been arranged below and shown in Figure 4.34.

Across different sentiment categories analyzed using the NRC lexicon, the total scores were determined as follows:

1. Positive sentiment garnered a total score of 4390.
2. Negative sentiment accumulated a total score of 3863.
3. Trust was reflected by a total score of 2962.
4. Anticipation received a total score of 2348.
5. Sadness was indicated by a total score of 2269.
6. Fear accumulated a total score of 1978.
7. Joy was represented by a total score of 1946.
8. Anger showed a total score of 1102.
9. Disgust was illustrated by a total score of 970.
10. Surprise captured a total score of 785.

By analyzing the total scores across these sentiment categories, a deeper understanding of the emotional nuances and prevailing sentiments expressed in the text data can be achieved through the utilization of the NRC lexicon.

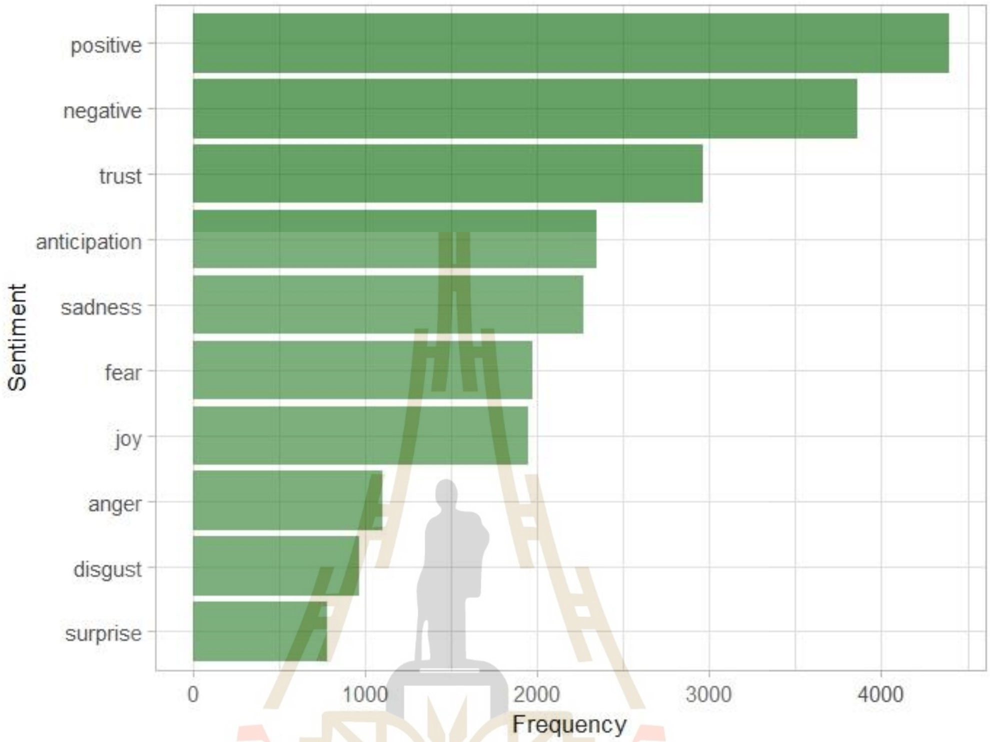


Figure 4.34 NRC sentiment and word frequency.

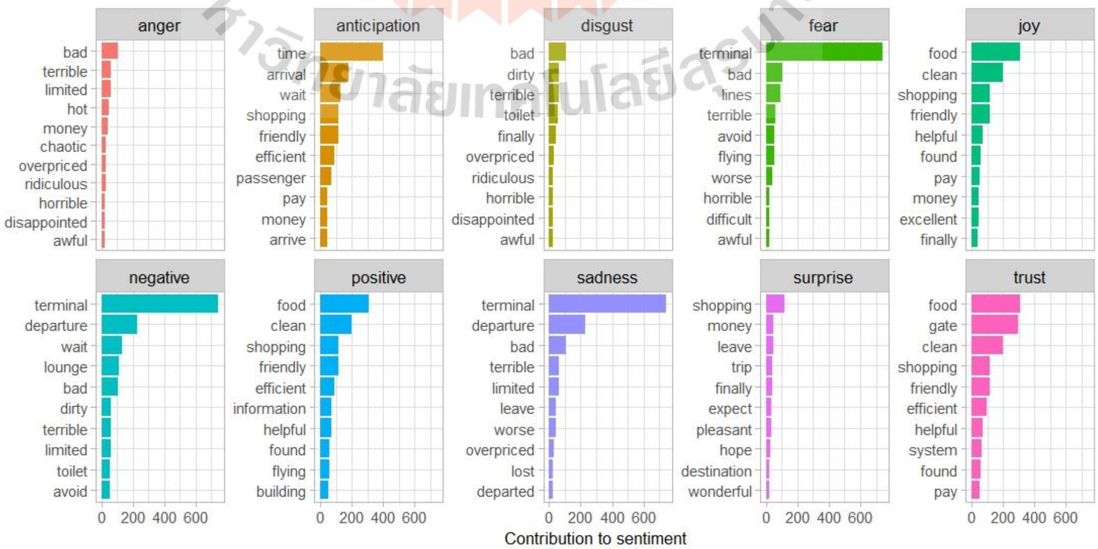


Figure 4.35 NRC sentiment and word frequency of each sentiment.

The sentiment distribution for a specific airport is displayed in Figure 4.36. The sentiment breakdown across different airports reveals unique emotional patterns and expressions within traveler feedback. Let's analyze and compare the sentiment distribution across the airports:

Anger: the highest occurrences of anger are seen at KUL Airport with 215, followed by MNL with 322 and DPS with 97. Among the airports analyzed, CGK Airport displays the lowest occurrences of anger.

Anticipation: MNL Airport observes the maximum instances of anticipation with 525, followed by KUL with 411 and SIN with 482. HAN Airport demonstrates the least anticipatory sentiments among the airports analyzed.

Disgust: MNL Airport showcases the highest occurrences of disgust with 274, while BKK and DMK show lower frequencies with 130 and 26, respectively.

Fear: the highest levels of fear sentiments are noted at MNL Airport, totaling 666, followed by KUL with 310 and SIN with 281. Among the airports, HAN records the lowest occurrences of fear sentiments.

Joy: SIN Airport presents the most instances of joy with 504, while CGK and SGN display fewer occurrences at 137 and 70, respectively.

Negative Sentiments: MNL Airport records the highest number of negative sentiments with 1216, followed by KUL with 719 and SIN with 490. The lowest occurrences of negative sentiments are found at SGN Airport.

Positive Sentiments: KUL Airport demonstrates the highest positive sentiment occurrences at 822, followed by SIN with 950 and MNL with 953. SGN Airport exhibits the fewest positive sentiment occurrences when compared to other airports.

Sadness: MNL Airport reveals the highest instances of sadness with 725, followed by KUL with 366 and DPS with 147. Across the airports, CGK Airport registers the lowest occurrences of sadness.

Surprise: HAN Airport and SIN Airport show the highest instances of surprise with 25 and 194, whereas SGN Airport demonstrates the fewest occurrences.

Trust: SIN Airport exhibits the highest trust sentiments with 648, followed by MNL with 623 and KUL with 572. In contrast, HAN Airport portrays the lowest occurrences of trust sentiments among the airports evaluated.

Through these comparisons, a comprehensive understanding of the diverse emotional expressions and sentiment distributions across different airports is achieved, shedding light on the varying experiences and feedback received at each airport location.

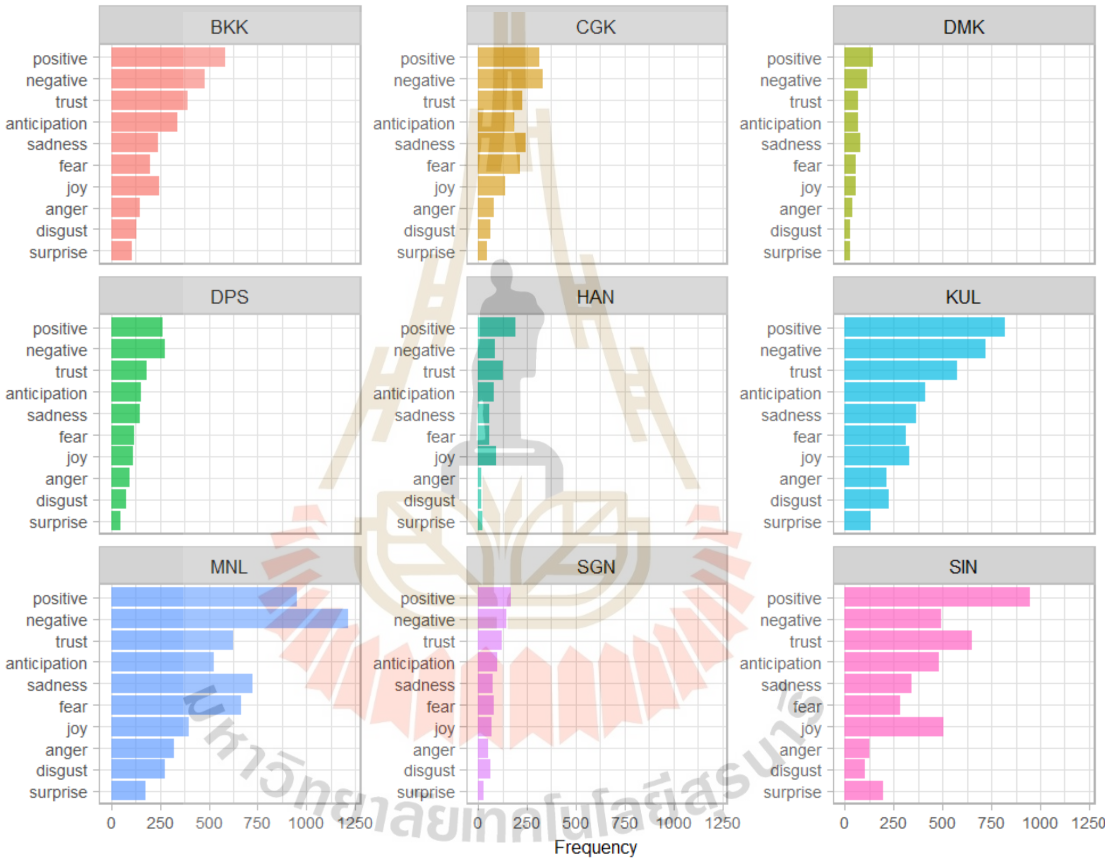


Figure 4.36 NRC sentiment and word frequency of each airport.

4.2.4 Results and comparisons

In the realm of sentiment analysis applied to the evaluation of passenger feedback datasets from various airports, lexicon-based methodologies such as AFINN, Bing, and NRC have played a pivotal role in discerning the underlying sentiments conveyed in traveler reviews. This analytical approach aims to unveil actionable insights that can inform airport operations, enhance service provisions, and elevate overall customer satisfaction strategies.

When considering the results derived from the AFINN lexicon, it becomes evident that there exists a spectrum of sentiment scores across different airports. For instance, CGK airport garnered the highest score of 39, indicative of positive sentiment, while DPS exhibited the lowest score of -26, reflecting a more negative sentiment trend. The average score of -16 collectively across airports suggests a prevailing negativity in reviews, with variations observed among individual airports. Notably, HAN airport recorded the highest average score of -5, whereas MNL airport portrayed the lowest at -20, underscoring the diversity in passenger perceptions and experiences.

Turning to the analysis conducted with the Bing lexicon, a detailed breakdown of positive and negative sentiment occurrences for each airport sheds light on the emotional nuances embedded in the feedback. By pinpointing the frequencies of specific positive and negative words, this lexicon facilitates a granular understanding of the sentiments expressed, thereby aiding in the identification of areas for improvement and service enhancement.

Furthermore, the utilization of the NRC lexicon delves deeper into various sentiment categories, encompassing positive, negative, trust, anticipation, sadness, fear, joy, anger, disgust, and surprise. Through comprehensive scoring mechanisms, each sentiment category provides valuable insights into the emotional content present in the dataset. The comparative analysis of sentiment distributions across different airports unveils distinctive emotional patterns and expressions within traveler feedback, offering a comprehensive view of passenger sentiments.

In the realm of academic research, these lexicon-based sentiment analysis methodologies serve as valuable tools for enhancing airport services, addressing passenger concerns effectively, and tailoring customer experiences to meet diverse traveler expectations. By combining the insights gained from multiple lexicons, airport authorities can gain a nuanced understanding of passenger sentiments, thereby paving the way for targeted improvements and heightened customer satisfaction levels across airport facilities.

CHAPTER V

CONCLUSION AND RECOMMENDATION

5.1 Overview

Both industry experts and academic researchers recognize the significance of assessing airport services (Bezerra & Gomes, 2016). This study employs a multi-method strategy, integrating multiple regression analysis (MRA), Bayesian networks (BNs), and neural networks (NNs) to explore the correlations between diverse service elements and overall airport ratings. The research is rooted in an analysis of data-driven crowdsourcing sourced from user-generated content (UGC) on Skytrax, covering reviews from the nine busiest airports in Southeast Asia. The comprehensive outcomes of this study shed light on critical factors influencing passenger satisfaction, the significance of individual airport service attributes, and the potential implications for airport management. Furthermore, this research not only enhances passenger contentment but also contributes to reducing environmental impacts through efficient resource management. A data-driven crowdsourcing approach was adopted, incorporating sentiment analysis and utilizing cutting-edge natural language processing (NLP) techniques that consider sentence context. This refined sentiment analysis has the potential to offer a more accurate assessment of passengers' viewpoints on airport services, catering to their needs and expectations more effectively.

5.2 Theoretical Implications

Initial findings from the Multiple Regression Analysis (MRA) highlight the positive influence of various factors on airport service quality. Key drivers of airport service ratings include queuing time, cleanliness, seating areas, signage, food services, retail options, and staff courtesy. These results are consistent with previous research studies (Bogicevic et al., 2013; Kichhanagari et al., 2002; Mirghafoori et al., 2018; Yavuz et al., 2020; Zheng, 2014), reinforcing the significance of these elements in enhancing passenger satisfaction. Interestingly, the presence of Wi-Fi was observed to have a minor impact on airport service ratings, contrasting with the influential role of other factors. This finding aligns with research by Halpern and Mwesiumo (2021) and Bakır et al. (2022), suggesting that deficiencies in Wi-Fi services have a limited impact on passenger loyalty. Furthermore, Pandey (2016) noted that internet access is not a high-priority service criterion at Thai airports. This implies that most passengers use their own mobile internet. In contrast, Pamucar et al. (2021) argued that internet access is the most impactful service factor at Spanish airports. Bunchongchit and Wattanacharoensil (2021) found that the internet service significantly affects the satisfaction of business travelers, and Kayapınar and Erginel (2019) emphasized that the internet is a vital requirement at Turkish airports.

The outcomes from the Bayesian Networks (BNs) not only confirmed the conclusions drawn from the Multiple Regression Analysis (MRA) but also provided a detailed visual representation of the associations among different airport service attributes and the overall airport rating. Particularly, the BNs illustrated that the service rating score is distributed evenly across three levels—high, medium, and low—indicating that a considerable percentage of passengers assigned a medium rating. These results signify a notable opportunity for enhancing airport services.

In this study, Neural Networks (NNs) were utilized to explore the nonlinear and non-compensatory relationships between airport service attributes and the overall airport rating. The results obtained from the NNs were in line with the observations from the Multiple Regression Analysis (MRA) and Bayesian Networks (BNs), emphasizing the significance of queuing time and staff courtesy as the most critical factors impacting passenger satisfaction. These findings resonate with the research by Bae and Chi (2022), Fodness and Murray (2007), Halpern and Mwesiumo (2021), Kiliç and Çadirci (2022), and Pantouvakis and Renzi (2016). Antwi, Fan, Nataliia, et al. (2020) revealed that the helpfulness and communication of airport staff significantly influence passenger loyalty and satisfaction. Additionally, Bakır et al. (2022) identified airport employees as the primary determinant of passenger satisfaction.

Consistent with research findings, it has been noted that the courtesy of staff members and queuing duration are the most influential factors impacting passenger perceptions. Conversely, deficiencies in airport retail services and Wi-Fi access have the least effect on passenger satisfaction levels. These findings stress the importance of addressing service deficiencies, particularly concerning staff interactions and wait times, to enhance passenger satisfaction and elevate airport ratings. Moreover, in line with Paramonovs and Ijevleva (2015), staff courtesy and availability were identified as two of the five essential elements that shape passenger satisfaction at airports. This further highlights the crucial role that airport staff play in shaping the overall passenger experience.

5.3 Managerial Implications

The outcomes of this study provide valuable insights for executives within the airport industry, offering a comprehensive understanding of passenger perceptions regarding airport services. By utilizing online reviews as a data-driven representation of passengers' experiences, airports can pinpoint the key elements of their services. The user-generated content (UGC) strategy serves as a sustainable approach that capitalizes on existing platforms, reducing the resources required to gather essential passenger feedback. This method not only presents a cost-effective means for airports to collect feedback but also presents an opportunity to formulate strategies that cultivate positive word-of-mouth. Drawing from authentic reviews, this study furnishes critical information for airport management teams to devise operational strategies that cater to customer requirements.

This study carries significant managerial implications for managers overseeing airports in Southeast Asia to elevate their service standards. The increasing prevalence of UGC platforms has resulted in a surge of travelers willing to share their experiences, making crowdsourced data a valuable asset for airport executives, offering profound insights into consumer expectations and preferences (see Lee & Yu, 2018; Martin-Domingo et al., 2019). The research findings highlight the importance of effective queue management and enhanced staff behavior in augmenting passenger satisfaction.

Reducing long waiting times can be achieved by optimizing processes or augmenting staffing levels during peak periods. Addressing subpar customer service entails providing comprehensive training and establishing accountability for staff conduct. These factors significantly impact on customer dissatisfaction; hence, enhancements in queuing procedures and staff courtesy are imperative.

Implementing self-service check-in kiosks has raised some concerns. Introducing touchless systems with automated gates and sensors could further streamline queuing times across various airport procedures. Leveraging technology has the potential to expedite processes, reduce energy consumption, and lessen the carbon footprint. Enhancements to the environment or the provision of entertainment options could help alleviate waiting times for passengers. Preliminary document checks by airport staff while passengers are queuing could expedite counter processing times and prevent delays that could affect other travelers in line. This entails improving customer service through staff training in handling challenging scenarios, enhancing security procedures for swift passport checks, and ensuring that check-in areas are not congested. As suggested by Fodness and Murray (2007), staff demeanor plays a vital role in elevating airport service levels, and well-trained staff with a focus on exceptional service and communication skills can boost airport efficiency and productivity (Pantouvakis & Renzi, 2016).

When unexpected delays occur at airports, it is essential to consider the facilities and services available to address passengers' needs. This involves assessing how airports manage disruptions, the effectiveness of communication during delays, and the efforts made to ensure passenger comfort and well-being during such circumstances. Reliable airport services should be in place to manage unforeseen events, which includes clear communication between staff and passengers and the provision of amenities like comfortable seating, electric massage chairs, and airport hotels for passenger relaxation. All-day dining options and café services add to passenger convenience. Families traveling with children should have access to family-friendly facilities, play areas, and accommodations customized to their needs. Similarly, passengers with health issues should have access to on-site medical facilities, timely responses to medical emergencies by airport personnel, and additional support services. By incorporating these aspects into Southeast Asian (SEA) airport operations, not only can overall assessments be enhanced, but valuable insights can also be provided to travelers with specific requirements or concerns. Resilience and readiness are key pillars of sustainability. Ensuring airports are equipped to manage disruptions not only improves the passenger experience but also demonstrates a commitment to sustainable practices during challenging scenarios.

The findings of this study have significant implications for the airport management field. By analyzing service components and identifying key factors, airports can improve their operational efficiency and raise service quality. This approach also helps airports and investors allocate resources more effectively, saving costs by focusing on essential areas. This is especially important for developing countries in the SEA region, where resources for airport infrastructure are limited. By using the results of this study, airport management teams, authorities, and stakeholders can strategically address issues and enhance areas that greatly affect passenger experience, operational efficiency, cost-effectiveness, and environmental and economic advantages.

The importance of the findings illustrating sentiment distribution across different airports encompasses several key elements:

Understanding Passenger Sentiment: analyzing the mix of positive and negative sentiments expressed in feedback for each airport provides organizations with valuable insights into how passengers view their experiences. This knowledge is essential for pinpointing areas for enhancement and elevating service quality based on passenger feedback.

Spotting Areas of Improvement: higher instances of negative sentiments for particular airports signal potential areas of concern or dissatisfaction among passengers. Addressing these issues can result in service delivery enhancements and increased overall passenger contentment.

Identifying Strengths and Weaknesses: the disparity between positive and negative sentiment occurrences sheds light on the strengths and weaknesses of each airport. Positive feedback reveals areas of excellence, while negative feedback indicates areas that require attention and improvement.

Informed Decision-Making: the results of sentiment analysis can guide strategic decision-making processes for airport management. Understanding passenger sentiment aids in crafting action plans, improving services, and implementing targeted initiatives to effectively address feedback.

Improving Customer Experience: enhancing service quality based on sentiment analysis outcomes can enhance the overall customer experience. Tackling negative sentiment trends and building on positive feedback can foster greater passenger satisfaction and loyalty.

Competitive Advantage: by utilizing sentiment analysis to effectively address passenger feedback, airports can gain a competitive advantage in the industry. Proactively responding to sentiments and tailoring services based on feedback can distinguish airports and attract more passengers.

In summary, the sentiment distribution findings provide valuable insights into passenger perceptions, enabling airports to prioritize enhancements, boost service quality, and cultivate a more positive and fulfilling travel journey for passengers.

5.4 Limitations and Prospective Research

This study acknowledges several limitations that warrant consideration. Firstly, the research is confined to the nine busiest airports in the Southeast Asia (SEA) region. Future studies could broaden the scope to include a cross-regional comparative analysis, encompassing data from a more diverse array of countries. Such an expansion would facilitate the exploration of cultural influences on passenger satisfaction and offer a more profound understanding of the factors influencing different nations.

Secondly, this study focuses exclusively on one user-generated content (UGC) platform, Skytrax. Future research could enhance the validity of findings by comparing results from additional platforms like Google Maps, TripAdvisor, and Twitter, thereby identifying any consistencies or disparities across these sources.

Thirdly, to bolster the credibility of the research findings, robustness tests or preliminary analyses could be implemented. Employing alternative methodologies, such as panel regression which tracks multiple entities across various time periods, may provide further validation.

Fourthly, the study should consider the potential impact of the COVID-19 pandemic on the data analyzed. A division of data into pre- and post-COVID-19 periods is suggested. However, the current volume of Skytrax reviews for SEA airports might be insufficient for a comprehensive analysis, indicating a need for future research in this area.

Fifthly, subsequent research could integrate qualitative methodologies to provide deeper insights into passenger experiences at airports. Adopting a data-driven crowdsourcing approach combined with advanced sentiment analysis and sophisticated natural language processing (NLP) techniques that account for sentence context could yield a more precise evaluation of passenger sentiments regarding airport services, thereby better addressing their needs and expectations.

Finally, the results derived from Sentiment Analysis are generally presented as numerical data, encompassing metrics such as averages and distributions of the sentiments analyzed. This data can be subsequently employed in various statistical analyses or predictive modeling techniques, including Regression Analysis.

Regression Analysis enables the prediction of specific outcomes based on these numerical datasets, such as changes in consumer sentiment, or the forecasting of stock prices influenced by public opinion.

Following the acquisition of results from Regression Analysis, these outcomes can be compared with alternative models such as Multiple Regression Analysis (MRA), Bayesian Networks (BN), or Artificial Neural Networks (ANN). This comparative analysis aims to identify the model exhibiting the highest accuracy and performance in forecasting or analyzing the given data.

Moreover, if additional techniques or methodological modifications are applied, a comparative evaluation of the results can help determine the most effective approach for achieving optimal outcomes in a particular academic or research context.

REFERENCES

References

Abouseada, A.-A., Hassan, T., Ibraheam Saleh, M., & Radwan, S. (2023). The power of airport branding in shaping tourist destination image: passenger commitment perspective. *GeoJournal of Tourism and Geosites, 47*, 440-449. https://doi.org/10.30892/gtg.47210-1042

ACI. (2020a). *ACI Airport Health Accreditation*. Retrieved October from https://aci.aero/programs-and-services/airport-operations/aci-airport-health-accreditation-program/

ACI. (2020b, July 14, 2020). *ACI introduces new Airport Service Quality questions related to COVID-19* https://aci.aero/2020/07/14/aci-introduces-new-airport-service-quality-questions-related-to-covid-19/

ACI. (2021). *Airport Service Quality Customer Experience*. Retrieved July 6 from https://aci.aero/programs-and-services/asq/

ACI. (2022). *About ACI*. Retrieved October from https://aci.aero/about-aci/

ACI. (2023). *Global passenger traffic expected to recover by 2024 and reach 9.4 billion passengers*. Retrieved January 19 from https://aci.aero/2023/09/27/global-passenger-traffic-expected-to-recover-by-2024-and-reach-9-4-billion-passengers/

Allen, J., Bellizzi, M. G., Eboli, L., Forciniti, C., & Mazzulla, G. (2021). Identifying strategies for improving airport services: introduction of the Gap-IPA to an Italian airport case study. *Transportation Letters, 13*(3), 243-253. https://doi.org/10.1080/19427867.2020.1861506

Aniyeri, R., & Nadar, R. (2018). Passengers queue analysis in international airports terminals in Kerala using multiphase queuing system. *International Journal of Mathematics in Operational Research, 12*, 1. https://doi.org/10.1504/IJMOR.2018.088566

Antwi, C. O., Fan, C.-j., 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. *Journal of Air Transport Management, 89*, 101869. https://doi.org/https://doi.org/10.1016/j.jairtraman.2020.101869

Antwi, C. O., Fan, C.-j., Nataliia, I., Aboagye, M. O., Xu, H., & Azamela, J. C. (2020). Do airport staff helpfulness and communication generate behavioral loyalty in transfer passengers? A conditional mediation analysis. *Journal of Retailing and Consumer Services, 54*, 102002. https://doi.org/https://doi.org/10.1016/j.jretconser.2019.102002

Arasli, H., Saydam, M. B., Jafari, K., & Arasli, F. (2023). Nordic Airports' service quality attributes: themes in online reviews. *Scandinavian Journal of Hospitality and Tourism*, 1-16. https://doi.org/10.1080/15022250.2023.2259345

Bae, W., & Chi, J. (2022). Content Analysis of Passengers' Perceptions of Airport Service Quality: The Case of Honolulu International Airport. *Journal of Risk and Financial Management, 15*(1), 5. https://www.mdpi.com/1911-8074/15/1/5

Bakır, M., Akan, Ş., Özdemir, E., Nguyen, P.-H., Tsai, J.-F., & Pham, H.-A. (2022). How to Achieve Passenger Satisfaction in the Airport? Findings from Regression Analysis and Necessary Condition Analysis Approaches through Online Airport Reviews. *Sustainability, 14*(4), 2151.

Barakat, H., Yeniterzi, R., & Martín-Domingo, L. (2021). Applying deep learning models to twitter data to detect airport service quality. *Journal of Air Transport Management, 91*, 102003.

Bellizzi, M. G., Eboli, L., Forciniti, C., & Mazzulla, G. (2018). Air Transport Passengers' Satisfaction: an Ordered Logit Model. *Transportation Research Procedia, 33*, 147-154. https://doi.org/https://doi.org/10.1016/j.trpro.2018.10.087

Bezerra, G. C. L., & Gomes, C. F. (2015). The effects of service quality dimensions and passenger characteristics on passenger's overall satisfaction with an airport. *Journal of Air Transport Management, 44-45*, 77-81.

Bezerra, G. C. L., & Gomes, C. F. (2016). Measuring airport service quality: A multidimensional approach. *Journal of Air Transport Management, 53*, 85-93.

Bezerra, G. C. L., & Gomes, C. F. (2020). Antecedents and consequences of passenger satisfaction with the airport. *Journal of Air Transport Management, 83*, 101766. https://doi.org/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 Review, 68*(4), 3-18.

Bulatović, I., Dempere, J., & Papatheodorou, A. (2023). The explanatory power of the SKYTRAX's airport rating system: Implications for airport management. *Transport Economics and Management, 1*, 104-111. https://doi.org/https://doi.org/10.1016/j.team.2023.07.002

Bunchongchit, K., & Wattanacharoensil, W. (2021). Data Analytics of Skytrax's Airport Review and Ratings: Views of Airport Quality by Passengers Types. *Research in Transportation Business and Management*.

Cao, M., Li, L., & Zhang, Y. (2023). Developing a passenger-centered airport: A case study of Urumqi airport in Xinjiang, China. *Journal of Air Transport Management, 108*, 102363. https://doi.org/https://doi.org/10.1016/j.jairtraman.2023.102363

Chanpariyavatevong, K., Wipulanusat, W., Champahom, T., Jomnonkwao, S., Chonsalasin, D., & Ratanavaraha, V. (2021). Predicting Airline Customer Loyalty by Integrating Structural Equation Modeling and Bayesian Networks. *Sustainability, 13*(13), 7046.

Chatterjee, S., & Mandal, P. (2020). Traveler preferences from online reviews: Role of travel goals, class and culture. *Tourism Management, 80*, 104108. https://doi.org/https://doi.org/10.1016/j.tourman.2020.104108

Chen, J., Wang, Q., Peng, W., Xu, H., Li, X., & Xu, W. (2022). Disparity-Based Multiscale Fusion Network for Transportation Detection. *IEEE Transactions on Intelligent Transportation Systems, 23*(10), 18855-18863. https://doi.org/10.1109/TITS.2022.3161977

Chickering, D. (2002, 01/01). Optimal Structure Identification With Greedy Search. *Journal of Machine Learning Research, 3*, 507-554. https://doi.org/10.1162/153244303321897717

Chonsalasin, D., Jomnonkwao, S., & Ratanavaraha, V. (2021). Measurement model of passengers' expectations of airport service quality. *International Journal of Transportation Science and Technology, 10*(4), 342-352.

Cooper, G. F., & Herskovits, E. (1992, 1992/10/01). A Bayesian method for the induction of probabilistic networks from data. *Machine Learning, 9*(4), 309-347. https://doi.org/10.1007/BF00994110

Cruz, F. L., Troyano, J. A., Enríquez, F., Ortega, F. J., & Vallejo, C. G. (2013). 'Long autonomy or long delay?'The importance of domain in opinion mining. *Expert Systems with Applications, 40*(8), 3174-3184.

D'Alonzo, L., Leva, M. C., & Bucciarelli, E. (2021). Comparing Passenger Satisfaction, Employees' Perspective and Performance on Quality and Safety Indicators: A Field Study. *Sustainability, 13*(10), 5636. https://www.mdpi.com/2071-1050/13/10/5636

Das, A., & Choudhury, P. (2022). Identifying airline passengers satisfaction and ground airport services perception of kolkata airport during COVID19- ASQ (Airport Service Quality) perspective. *International Journal of Health Sciences, 6*(S7). https://doi.org/https://doi.org/10.53730/ijhs.v6nS7.13285

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

Di Pietro, L., Guglielmetti Mugion, R., Musella, F., Renzi, M. F., & Vicard, P. (2017). Monitoring an airport check-in process by using Bayesian networks. *Transportation Research Part A: Policy and Practice, 106*, 235-247.

Elshafey, M., Rowlands, D., Contestabile, E., & Halim, A. (2007). Airport level of service perceptions before and after September 11: a neural network analysis. *WIT Transactions on The Built Environment, 94*, 337-345. https://doi.org/10.2495/SAFE070331

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. *Research in Transportation Business & Management*, 100648.

Farr, A., Kleinschmidt, T., Johnson, S., Yarlagadda, P., & Mengersen, K. (2014). Investigating effective wayfinding in airports: A Bayesian network approach. *Transport, 29*, 90-99.

Fewings, R. (2001). Wayfinding and Airport Terminal Design. *Journal of Navigation, 54*, 177-184. https://doi.org/10.1017/S0373463301001369

Fodness, D., & Murray, B. (2007). Passengers' expectations of airport service quality. *Journal of Services Marketing, 21*(7), 492-506.

Francis, G., Humphreys, I., & Fry, J. (2003). An international survey of the nature and prevalence of quality management systems in airports. *Total Quality Management & Business Excellence, 14*(7), 819-829.

Freitas, P. T. C., Silva, L. M., Nascimento, M. V., & Borille, G. M. R. (2021). Passenger profile and its effects on satisfaction level in food and beverage establishments: Case study of major Brazilian airports. *Case Studies on Transport Policy, 9*(3), 1219-1224. https://doi.org/https://doi.org/10.1016/j.cstp.2021.06.009

Gitto, S., & Mancuso, P. (2017). Improving airport services using sentiment analysis of the websites. *Tourism Management Perspectives, 22*, 132-136. https://doi.org/https://doi.org/10.1016/j.tmp.2017.03.008

Graham, A. (2009). How important are commercial revenues to today's airports? *Journal of Air Transport Management, 15*, 106-111.

Häger, D., & Andersen, L. B. (2010). A knowledge based approach to loss severity assessment in financial institutions using Bayesian networks and loss determinants. *European Journal of Operational Research, 207*(3), 1635-1644. https://doi.org/https://doi.org/10.1016/j.ejor.2010.06.020

Halpern, N., & Mwesiumo, D. (2021). Airport service quality and passenger satisfaction: The impact of service failure on the likelihood of promoting an airport online. *Research in Transportation Business & Management*, 100667. https://doi.org/https://doi.org/10.1016/j.rtbm.2021.100667

Han, H., Yu, J., & Kim, W. (2018). Airport shopping – an emerging non-aviation business: triggers of traveler loyalty. *Journal of Travel & Tourism Marketing, 35*(7), 835-845. https://doi.org/10.1080/10548408.2017.1422454

Han, S., Ham, S., Yang, I., & Baek, S. (2012). Passengers' perceptions of airline lounges: Importance of attributes that determine usage and service quality measurement. *Tourism Management, 33*(5), 1103-1111.

Hatzivassiloglou, V., & McKeown, K. (1997). Predicting the semantic orientation of adjectives. 35th annual meeting of the association for computational linguistics and 8th conference of the european chapter of the association for computational linguistics,

Homaid, M. S., & Moulitsas, I. (2023). *Measuring Airport Service Quality Using Machine Learning Algorithms* Proceedings of the 6th International Conference on Advances in Artificial Intelligence, Birmingham, United Kingdom. https://doi.org/10.1145/3571560.3571562

Hu, M., & Liu, B. (2004). Mining and summarizing customer reviews. *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*.

Isa, N. A. M., Ghaus, H., Hamid, N. A., & Tan, P.-L. (2020). Key drivers of passengers' overall satisfaction at klia2 terminal. *Journal of Air Transport Management, 87*, 101859.

Jiang, H., & Zhang, Y. (2016). An assessment of passenger experience at Melbourne Airport. *Journal of Air Transport Management, 54*, 88-92.

Jianxin, L., Song, R., Dai, J., & Jiao, P. (2014). Pedestrian Guiding Signs Optimization for Airport Terminal. *Discrete Dynamics in Nature and Society, 2014*, 1-14. https://doi.org/10.1155/2014/125910

Jiao, J., & Zhou, Y. (2011). Sentiment polarity analysis based multi-dictionary. *Physics Procedia, 22*, 590-596.

Kalinic, Z., Marinkovic, V., Molinillo, S., & Liébana-Cabanillas, F. (2019). A multi-analytical approach to peer-to-peer mobile payment acceptance prediction. *Journal of Retailing and Consumer Services, 49*, 143-153.

Kayapınar, S., & Erginel, N. (2019). Designing the airport service with fuzzy QFD based on SERVQUAL integrated with a fuzzy multi-objective decision model. *Total Quality Management & Business Excellence, 30*(13-14), 1429-1448. https://doi.org/10.1080/14783363.2017.1371586

Kichhanagari, R., Motley, R. D., Duffy, S. A., & Fisher, D. L. (2002). Airport Terminal Signs: Use of Advance Guide Signs to Speed Search Times. *Transportation Research Record, 1788*(1), 26-32. https://doi.org/10.3141/1788-04

Kiliç, S., & Çadirci, T. O. (2022). An evaluation of airport service experience: An identification of service improvement opportunities based on topic modeling and sentiment analysis. *Research in Transportation Business & Management, 43*, 100744. https://doi.org/https://doi.org/10.1016/j.rtbm.2021.100744

Lane, P. C. R., Clarke, D., & Hender, P. (2012, 2012/11/01/). On developing robust models for favourability analysis: Model choice, feature sets and imbalanced data. *Decision Support Systems, 53*(4), 712-718. https://doi.org/https://doi.org/10.1016/j.dss.2012.05.028

Lee, K., & Yu, C. (2018). Assessment of airport service quality: A complementary approach to measure perceived service quality based on Google reviews. *Journal of Air Transport Management, 71*, 28-44.

Leong, L.-Y., Hew, T.-S., Lee, V.-H., & Ooi, K.-B. (2015). An SEM–artificial-neural-network analysis of the relationships between SERVPERF, customer satisfaction and loyalty among low-cost and full-service airline. *Expert Systems with Applications, 42*(19), 6620-6634.

Li, L., Mao, Y., Wang, Y., & Ma, Z. (2022). How has airport service quality changed in the context of COVID-19: A data-driven crowdsourcing approach based on sentiment analysis. *Journal of Air Transport Management, 105*, 102298.

Lopez-Valpuesta, L., & Casas-Albala, D. (2023). Has passenger satisfaction at airports changed with the onset of COVID-19? The case of Seville Airport (Spain). *Journal of Air Transport Management, 108*, 102361. https://doi.org/https://doi.org/10.1016/j.jairtraman.2023.102361

Lubbe, B., Douglas, A., & Zambellis, J. (2011). An application of the airport service quality model in South Africa. *Journal of Air Transport Management, 17*(4), 224-227.

Martin-Domingo, L., Martín, J. C., & Mandsberg, G. (2019). Social media as a resource for sentiment analysis of Airport Service Quality (ASQ). *Journal of Air Transport Management, 78*, 106-115.

Medhat, W., Hassan, A., & Korashy, H. (2014, 2014/12/01/). Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal, 5*(4), 1093-1113. https://doi.org/https://doi.org/10.1016/j.asej.2014.04.011

Meidute-Kavaliauskiene, I., Yıldız, B., Çiğdem, Ş., & Činčikaitė, R. (2021). The Effect of COVID-19 on Airline Transportation Services: A Study on Service Robot Usage Intention. *Sustainability, 13*(22), 12571.

Mirghafoori, S. H., Izadi, M. R., & Daei, A. (2018). An integrated approach for prioritizing the barriers to airport service quality in an intuitionistic-fuzzy environment. *Cogent Business & Management, 5*(1), 1532277. https://doi.org/10.1080/23311975.2018.1532277

Molaei, P., & Hunter, W. C. (2019). A qualitative exploration of incheon international airport (ICN) service quality from the passengers' perspective in a web-based environment. *International Journal of Tourism Sciences, 19*(4), 287-306. https://doi.org/10.1080/15980634.2019.1708582

Mooi, E., & Sarstedt, M. (2019). *A Concise Guide to Market Research* (3 ed.). Springer Berlin, Heidelberg. https://doi.org/https://doi.org/10.1007/978-3-642-12541-6

Nghiêm-Phú, B., & Suter, J. R. (2018). Airport image: An exploratory study of McCarran International Airport. *Journal of Air Transport Management, 67*, 72-84.

OAG. (2023). *Top 10 busiest airports in South-east Asia*. Retrieved July from https://www.oag.com

OAG. (2024). *Southeast Asia aviation market*. Retrieved 19 January 2024 from https://www.oag.com/south-east-asia-aviation-flight-data

Pallant, J. (2020). *SPSS Survival Manual: A step by step guide to data analysis using IBM SPSS* (7 ed.). Routledge. https://doi.org/https://doi.org/10.4324/9781003117452

Pamucar, D., Yazdani, M., Montero-Simo, M. J., Araque-Padilla, R. A., & Mohammed, A. (2021). Multi-criteria decision analysis towards robust service quality measurement. *Expert Systems with Applications, 170*, 114508. https://doi.org/https://doi.org/10.1016/j.eswa.2020.114508

Pandey, M. M. (2016). Evaluating the service quality of airports in Thailand using fuzzy multi-criteria decision making method. *Journal of Air Transport Management, 57*, 241-249.

Pantouvakis, A., & Renzi, M. F. (2016). Exploring different nationality perceptions of airport service quality. *Journal of Air Transport Management, 52*, 90-98.

Paramonovs, S., & Ijevleva, K. (2015). Factor Analysis of Passengers' Satisfaction at "RIGA International Airport". *Economics and Business, 27*(1), 46-52. https://doi.org/doi:10.1515/eb-2015-0007

Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: Networks of plausible inference*. Morgan Kaufmann.

Pholsook, T., Wipulanusat, W., Thamsatitdej, P., Ramjan, S., Sunkpho, J., & Ratanavaraha, V. (2023). A Three-Stage Hybrid SEM-BN-ANN Approach for Analyzing Airport Service Quality. *Sustainability, 15*(11), 8885. https://www.mdpi.com/2071-1050/15/11/8885

Punel, A., Al Hajj Hassan, L., & Ermagun, A. (2019). Variations in airline passenger expectation of service quality across the globe. *Tourism Management, 75*, 491-508. https://doi.org/https://doi.org/10.1016/j.tourman.2019.06.004

Qiu, G., He, X., Zhang, F., Shi, Y., Bu, J., & Chen, C. (2010, 2010/09/01/). DASA: Dissatisfaction-oriented Advertising based on Sentiment Analysis. *Expert Systems with Applications, 37*(9), 6182-6191. https://doi.org/https://doi.org/10.1016/j.eswa.2010.02.109

Sadou, A., & Tchouamou Njoya, E. (2023). Applications of Artificial Intelligence in the Air Transport Industry: A Bibliometric and Systematic Literature Review. *Journal of Aerospace Technology and Management, 15*. https://doi.org/10.1590/jatm.v15.1312

Schultz, M., Luo, M., Lubig, D., Mujica Mota, M., & Scala, P. (2021). *Covid-19-Related Challenges for New Normality in Airport Terminal Operations*.

Sezgen, E., Mason, K. J., & Mayer, R. (2019). Voice of airline passenger: A text mining approach to understand customer satisfaction. *Journal of Air Transport Management, 77*, 65-74. https://doi.org/https://doi.org/10.1016/j.jairtraman.2019.04.001

Shadiyar, A., Ban, H.-J., & Kim, H.-S. (2020). Extracting Key Drivers of Air Passenger's Experience and Satisfaction through Online Review Analysis. *Sustainability, 12*(21), 9188. https://www.mdpi.com/2071-1050/12/21/9188

Siegel, A. F., & Wagner, M. R. (2022). Chapter 12 - Multiple Regression: Predicting One Variable From Several Others. In A. F. Siegel & M. R. Wagner (Eds.), *Practical Business Statistics (Eighth Edition)* (pp. 371-431). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-820025-4.00012-9

Skytrax. (2023a). *About Skytrax Rating*. Retrieved June from https://skytraxratings.com/about

Skytrax. (2023b). *Airline and Airport Customer Reviews*. Retrieved July from https://www.airlinequality.com/

Skytrax. (2024). *Explaining Airport Star Rating levels*. Retrieved 13 January 2024 from https://skytraxratings.com/explaining-airport-star-ratings-levels

Stine, R. A. (2019). Sentiment Analysis. *Annual Review of Statistics and Its Application, 6*(Volume 6, 2019), 287-308. https://doi.org/https://doi.org/10.1146/annurev-statistics-030718-105242

Stolletz, R. (2011). Analysis of passenger queues at airport terminals. *Research in Transportation Business & Management, 1*(1), 144-149. https://doi.org/https://doi.org/10.1016/j.rtbm.2011.06.012

Sun, X., Wandelt, S., Zheng, C., & Zhang, A. (2021). COVID-19 pandemic and air transportation: Successfully navigating the paper hurricane. *Journal of Air Transport Management, 94*, 102062.

Tisdall, L., & Zhang, Y. (2020). Preparing for 'COVID-27': Lessons in management focus – An Australian general aviation perspective. *Journal of Air Transport Management, 89*, 101922.

Wakefield, K. L., & Blodgett, J. G. (1996). The effect of the servicescape on customers' behavioral intentions in leisure service settings. *Journal of Services Marketing, 10*(6), 45-61. https://doi.org/10.1108/08876049610148594

Walczak, S., & Cerpa, N. (2003). Artificial Neural Networks. In R. A. Meyers (Ed.), *Encyclopedia of Physical Science and Technology (Third Edition)* (pp. 631-645). Academic Press. https://doi.org/https://doi.org/10.1016/B0-12-227410-5/00837-1

Wankhade, M., Rao, A. C. S., & Kulkarni, C. (2022, 2022/10/01). A survey on sentiment analysis methods, applications, and challenges. *Artificial Intelligence Review, 55*(7), 5731-5780. https://doi.org/10.1007/s10462-022-10144-1

Wattanacharoensil, W., Schuckert, M., & Graham, A. (2015). An Airport Experience Framework from a Tourism Perspective. *Transport Reviews*.

Wattanacharoensil, W., Schuckert, M., Graham, A., & Dean, A. (2017). An analysis of the airport experience from an air traveler perspective. *Journal of Hospitality and Tourism Management, 32*, 124-135.

Wipulanusat, W., Panuwatwanich, K., Stewart, R. A., Arnold, S. L., & Wang, J. (2020). Bayesian network revealing pathways to workplace innovation and career satisfaction in the public service. *Journal of Management Analytics, 7*(2), 253-280.

Xu, K., Liao, S. S., Li, J., & Song, Y. (2011). Mining comparative opinions from customer reviews for competitive intelligence. *Decision Support Systems, 50*(4), 743-754.

Yavuz, N., Olgaç, S., Günay Aktaş, S., & Mert Kantar, Y. (2020). Passenger Satisfaction in European Airports. Travel and Tourism: Sustainability, Economics, and Management Issues, Singapore.

Yeh, C.-H., & Kuo, Y.-L. (2003). Evaluating passenger services of Asia-Pacific international airports. *Transportation Research Part E: Logistics and Transportation Review, 39*(1), 35-48.

Zheng, M.-C. (2014). How Airport Users luggage affects their Perception of Seat Design at Airports. *Journal of Asian Architecture and Building Engineering, 13*(1), 141-148. https://doi.org/10.3130/jaabe.13.141

Zhou, Y., Fenton, N., & Neil, M. (2014). Bayesian network approach to multinomial parameter learning using data and expert judgments. *International Journal of Approximate Reasoning, 55*(5), 1252-1268.

Zou, W., Sun, Y., Zhou, Y., Lu, Q., Nie, Y., Sun, T., & Peng, L. (2022). Limited Sensing and Deep Data Mining: A New Exploration of Developing City-Wide Parking Guidance Systems. *IEEE Intelligent Transportation Systems Magazine, 14*(1), 198-215. https://doi.org/10.1109/MITS.2020.2970185

APPENDIX

APPENDIX A. Publication

Pholsook T., Wipulanusat W., Ratanavaraha V. (2024), "A Hybrid MRA-BN-NN Approach for Analyzing Airport Service Based on User-Generated Contents" Sustainability. 16(3):1164.

APPENDIX B. OROG Scholarship

The study received support from the Doctoral Scholarship of Suranaree University of Technology (OROG) for the academic year 2021 - 2023.

APPENDIX C. Institutional review board statement

The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Suranaree University of Technology (protocol code EC-65-0139; date of approval 18 January 2023).

รายละเอียดโครงการ

รหัสโครงการ	EC-65-0139	**สถานะโครงการ**	รับรอง
ประเภทการพิจารณา	Initial	**การวิจัยด้าน**	สังคมศาสตร์
ลักษณะการพิจารณา	Exemption		
วันที่ยื่นขอ	19 ธันวาคม 2565	**วันที่แก้ไขล่าสุด**	18 มกราคม 2566
เลขใบรับรอง	COE No.126/2565		
วันที่รับรอง	18 มกราคม 2566	**วันที่หมดอายุใบรับรอง**	17 มกราคม 2567
การต่ออายุโครงการ			
การรายงานความก้าวหน้า			

ชื่อโครงการวิจัยภาษาไทย	การวิเคราะห์ความพึงพอใจของผู้ใช้บริการท่าอากาศยานที่มีต่อคุณภาพการให้บริการของท่าอากาศยาน โดยการประยุกต์ใช้ข้อมูลที่สร้างขึ้นโดยผู้ใช้บริการท่าอากาศยาน
Title of protocol	AIRPORT USER SATISFACTION TOWARD AIRPORT SERVICE QUALITY BASED ON USER GENERATED CONTENTS
ลักษณะโครงการ	วิทยานิพนธ์
อาจารย์ที่ปรึกษา	ศาสตราจารย์ ดร. วัฒนวงศ์ รัตนวราห
แหล่งทุนสนับสนุนการวิจัย	แหล่งทุนสนับสนุนทุนวิจัย ไม่มี
วัตถุประสงค์	เพื่อการศึกษาวิจัย
สถานที่ทำวิจัย	มหาวิทยาลัยเทคโนโลยีสุรนารี
ระยะเวลาดำเนินการวิจัย	1 ธันวาคม 2565 - 30 เมษายน 2567 (รวม 16 เดือน 30 วัน)
วิธีการศึกษา	เชิงปริมาณ การศึกษาความสัมพันธ์
วิธีการรวบรวมข้อมูล	อื่นๆ ข้อมูลทุติยภูมิ อื่นๆ รวบรวมข้อมูลที่สร้างขึ้นโดยผู้ใช้บริการท่าอากาศยาน (user-generated contents) ในสื่อออนไลน์สาธารณะ
การคำนวณขนาดตัวอย่าง (Sample size calculation)	

BIOGRAPHY

Thitinan Pholsook, born on 26th January 1986 in Bangkok, Thailand, embarked on her educational odyssey with primary schooling at Sompoch Krung Anusorn 200th year School, followed by secondary education at Sripruetta School. Her academic pursuits led her to earn a Bachelor's degree in Survey Engineering from Chulalongkorn University, and subsequently, a Master's degree in Civil Engineering, specializing in transportation, from the same university.

With a tenure spanning over four years, she emerged as a seasoned and self-driven transport analyst and supply chain solution designer. Through her professional journey, Thitinan demonstrated adeptness in identifying operational efficiencies and troubleshooting challenges for clients. Her acumen extended to crafting optimal logistics solutions encompassing both warehouse management and transportation operations. Her organizational acumen combined with an in-depth comprehension of the logistics service provider sector enabled her to effectively oversee multiple projects. Noteworthy is her track record of fostering robust communication channels and nurturing relationships with colleagues, clients, and vendors.

Having devoted four years to doctoral candidacy at Technical University of Munich, Germany, Thitinan specialized in researching matheuristic algorithms for optimizing logistics networks. Subsequently, she dedicated another three years to doctoral candidacy at Suranaree University of Technology, Thailand, focusing on data-driven analysis, text mining, and sentiment analysis for enhancing airport user satisfaction. Currently, Thitinan shares her expertise as a lecturer in Transportation and Logistics Engineering at Suranaree University of Technology in Thailand.