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A Hybrid Shadowed Fuzzy Based MCDM Methodology for Analyzing Airlines Service Quality

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Abstract
The airline industry is undergoing a challenging time as the post-COVID market has changed the definition of customer satisfaction and integrated high uncertainties into service quality. Thus, this study aims to integrate post-COVID customer sentiments into redefining airline service quality and uses operations-research applications to mitigate the uncertainty in identifying the concerning factors. This paper identifies critical factors to be included in the post-COVID definition of airline service quality from the customers' perceived experience. To reformulate a definition aligned to the present scenario, this study builds on the traditional SERVQUAL dimensions with COVID-19 safety, flight cleanliness, onboard environment, and flight delay factors. The paper uses the Shadowed Fuzzy application for the integrated Best-Worst-Method (BWM)-WASPAS method and evaluates the service quality of Indian domestic airlines via customer surveys. The results reveal a definite transition of customers' concerns towards assurance of flight safety and security, smooth onboarding, and maintaining COVID protocols from traditional factors like price, luggage handling, and complimentary services. The result also implies that fulfilling responsiveness and empathy needs is less significant to the current consumer than reliability, tangible services, and assurance of flight and COVID safety and security. The responsiveness and empathy needs have now been aligned to crisis management. The study also performed a sensitivity analysis to analyze the robustness of the proposed model. Based on this current transition, this study suggests the airlines-companies to focus more on platform database management and process transparency management to assure the best quality to the customer.

Keywords- Shadowed fuzzy set, Best-Worst Method (BWM), WASPAS, Airlines-service-quality, SERVQUAL.

1. Introduction

The outbreak of the COVID-19 pandemic in early 2019 brought an exceptional disruption across numerous sectors, especially for the global aviation industry which experienced harsh challenges. Significant operational changes, strict travel restrictions by the government, and a sharp decline in passenger traffic were among the many profound effects of the pandemic that completely changed the face of air travel (Dehnavi et al., 2023; Kavus et al., 2022; Murugesan et al., 2024; Tanriverdi et al., 2023). As per International Air Transport Association (IATA) reports, global air passenger traffic fell through 60% in 2020 in comparison to the preceding year, marking the steepest decline in aviation history (IATA annual review, 2020). Amidst these changes and in order to adjust to the post-COVID-19 world, airlines had to make significant adjustments to service quality parameters, which are crucial elements of the customer experience (Katiyar et al., 2025). Service quality, which traditionally has been assessed through five standard 'RATER' dimensions of reliability, assurance, tangibles, empathy, and responsiveness, is now more focused on COVID-safety and security-related issues (Rubio-Andrada et al., 2023). However, adding more safety-protocols hampers on-boarding and in-flight experience of the passenger. Therefore, understanding the essential COVID-safety protocols, leveraging them through airline's capability, and provide a smooth experience to customer became strategically important for airlines to optimize the risk of losing customers (Schutte & Barkhuizen, 2015). A reassessment of the current service model became necessary in order to reassure customers and strengthen trust in air travel. This study attempts to examine the revised notion of service quality dimensions for aviation so that airlines know the newly evolved criteria to focus upon and modify their service offerings through strategically leveraging organization's capabilities. In addition, this study aims to determine how these modifications will affect customer satisfaction and loyalty, the future path of service quality criteria in aviation sector.

The novelty of this study is in its exploration of the shift of customer perception of service quality from traditional service quality dimensions to post-COVID evolved factors. The study explored the dynamics of service quality through lenses of improved hygiene procedures (Omrani et al., 2021), contactless services (Law et al., 2022), and altered in-flight experience (Zahrsee et al., 2023). From an airline's operational perspective, these changes are fostered by the airline's innovation through digital boarding cards (Booranakittipinyo et al., 2024), mobile check-in (Brakewood et al., 2020; Murgesan et al., 2024), and UV cleaning and disinfection procedures (Bakhshayesh et al., 2024; Pereira et al., 2023). Innovation in the service process has altered the way that "*Tangible*" components of service quality were perceived, and it also had an impact on how customers perceived the airlines' "*Assurance*" and "*Reliability*." The traditional service quality dimension' responsiveness', which has been valued to date, is now given value on different criteria like the minimum-distance standard and contactless operations opted by airlines.

The second novelty of the study is to connect these newly evolved criteria of the RATER framework to airlines' strategic management domain so that the organizations can better understand their capabilities. The proposed framework links the post-COVID factors with the four major strategic management domains: platform management, process management, people management, and culture management.

Airlines organizations can use platform database management to track regular cleaning operations and arrange resources to maintain COVID protocols during on-boarding and in-flight (Costa et al., 2020). As a measure of service providers' individual level of resource management for Airbus cleanliness, *'Flight cleanliness,'* and a measure of maintaining the government's COVID regulations, '*Covid protocol maintaining'* factors are incorporated. Process management in the airline's context is integrated with process transparency management (Zhao et al., 2024). *'On-board environment'* as a measure of airlines' contactless-on-boarding process transparency and '*Delay-in-service'* as a measure of pre-board, on-board, and in-flight service-related information transparency is incorporated. People management, also known as customer management, is significantly influenced by an organization's strategic management (Reid & Moffett, 2017). This study incorporates the air hostesses' behavior and '*response to the complaints'* aspects as a measure of degree to the customer-prioritized service of the airlines. Culture management, though very similar to people management, differs in that it not only talks about the customer-centric culture of the employee but also emphasizes the organization's culture. Culture management in service is highly connected with the theory of reciprocity (Gouldner, 1960), which summarizes that people usually respond similarly to others (Sharif & Lemine, 2024). So, despite the social exchange between airline employees and employers, a measure of empathy and a helpful attitude toward the customer reciprocates a good work culture of the organization (Sorourkhah & Edalatpanah, 2022). **Figure 1** presents the post-COVID factors added to the RATER dimensions of service quality and the strategy needed by the organization to deploy them.

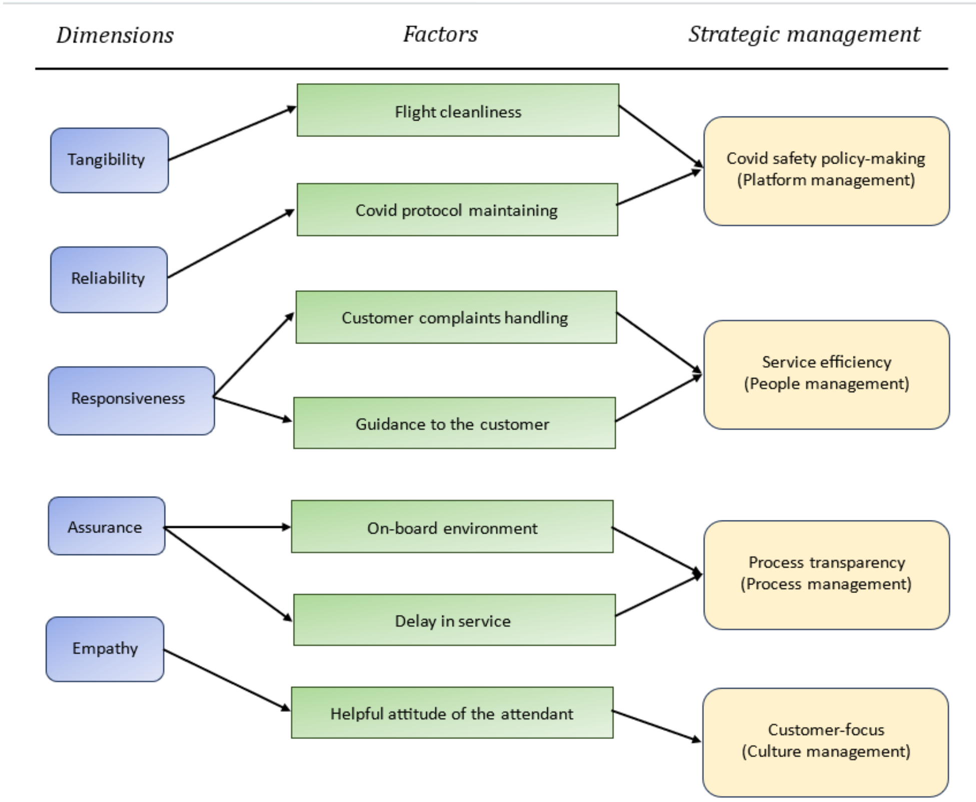

Figure 1. Post-covid factors and their connection with strategic management.

The process of assessing service quality involves decision-making that requires simultaneous consideration of several standards under unclear circumstances. In this fiercely competitive aviation industry, airlines must better understand their customers' needs, expectations, and priorities. However, the relationship between service quality and customer satisfaction may be nonlinear, and the effect of service quality is different based on their categories (Law et al., 2022).

The third novelty of this study is addressing the uncertainty of customer behavior and constructing a normalized scale for the RATER factors to understand the customer response better. Fuzzy modeling is very popular in airline applications for handling the uncertainty in customer behavior. However, a normalized scale formation to mitigate the non-linear uncertainty in customer responses is new to the airline's service application. This paper proposes a shadowed-fuzzy (SF) scale to handle the uncertainty inherent within each response and includes uniformity in the overall response data. The SF set's basic foundation helps efficiently reduce uncertainty related to the mid-range values (shadowed regions). In practice, it allows the study to eliminate uncertainty from those criteria that are neither extremely important nor least important and add uniformity to all the criteria responses. Also, from the customer review side, the SF set eliminates the uncertainties related to the average-valued ratings. However, formulating the most precise SF scale, incorporating the scale for an airline application, and getting an efficient result is subject to analysis. Thus, the following objectives were constructed.

RO1: To propose a SERVQUAL framework using RATER model which structures the post-COVID customer's behavioral changes, and identify their preferences.

RO2: To evaluate the performance of the different airlines with respect to the changed customer's preferences.
RO3: To propose an efficient SF scale to handle the uncertainties in the customer behavior and smoothen the randomness present in the customer's responses.

This study identifies suitable airline service improvement criteria, categorize them as per RATER model, and determine their weightage for measuring and improving airline service quality. For this purpose, a combined multi-criteria decision-making (MCDM) model based on a Best Worst Method (BWM) and WASPAS methodology is proposed. There are numerous precision-based multicriteria cost-benefit management techniques available for assessing service quality and choosing alternatives but the majority of these techniques compare all options using synthesized ranks. Analytic Hierarchy Process (AHP) and TOPSIS are two other popular non-entropy-based MCDM techniques. However, BWM advances AHP in terms of lower computation complexity (Bansal et al., 2021), TOPSIS and VIKOR in terms of higher accuracy of the weight (Sorourkhah & Edalatpanah, 2021), and ARAS in terms of higher stability of the weight (Anjum et al., 2020).

Airlines-service-quality-assessment is a complex problem where fuzzy based models are very popular. The type-1 and type-2 fuzzy models help in reducing the uncertainty created using the preferable criteria selection from the expert's side and review rating to those criteria from the customer side (Sanghoon & Daekook, 2019). Traditional type 1 or type 2 fuzzy sets consider the uncertainty to be uniformly distributed within the response. However, in practice, responses regarding the unexplored and average quality of service include much more randomness than the regular and extreme quality of service. For a passenger, providing a rating of 5 and 1 on a [1-5] Likert scale is easier than providing a rating of [2/3/4]. Thus, this study has adopted the concept of the SF set, which partitions the area into the core, shadowed, and buffer regions, reduces uncertainty from the core and buffer regions, and increases uncertainty in the shadowed region. While integrating the SF set with BWM-WASPAS techniques, the proposed methodology offers uncertainty handling regarding post-COVID new criteria listing and computing their weightage (SF-BWM part) and assessing airlines' performance under the new-normal service delivery process (SF-WASPAS part). Later, in the result-discussion section, we analyzed the proposed SF-BWM-WASPAS performance in smoothing uncertainty. Considering the post-COVID dynamics of airline service quality from the customer side, identifying the customer's priorities, and assessing the airline performance, this study proposes to contribute to the research by integrating the application with post-COVID factors, integrating two MCDM approach to find the customer's preferences, and handling the uncertainties involved into the responses.

The structure of this paper is as follows: Section 2 deals with a brief literature review on service quality in the aviation sector and MCDM applications for Shadowed fuzzy operation. Section 3 described the proposed methodology, Shadowed fuzzy operations, and data collection. Section 4 describes the results. Section 5 shows the sensitivity analysis and stability of the proposed method. A comparative analysis of the ranking result is given in Section 6. The conclusion and future direction are given in Section 7.

2. Literature Review

2.1 Review of Papers in Service Quality in Aviation Industry

Parasuraman et al. (1985) were the first to introduce the service-quality assessment model, known as the SERVQUAL model, which comprises five primary and 22 secondary criteria. Despite alternative models, this framework has gained widespread adoption among researchers (Dehnavi et al., 2023; Dožić, 2019; Grzegorzewski, 2013). In addition, researchers have frequently employed the AIRQUAL model to appraise the quality of airline services (Chung & Tan, 2022; Kavus et al., 2022; Shiwakoti et al., 2022; Rady, 2018).

Researchers have utilized diverse Multiple-Criteria Decision Making (MCDM) methods to rank customer satisfaction criteria and service quality. Chang & Yeh (2002) were the first to introduce the fuzzy multicriteria analysis model to reflect the inherent subjectiveness and imprecision of the customers' perception under market uncertainty. Further significant research is done in fuzzy MCDM to address the service quality (Tsaur et al., 2002) by identifying the dimensions of customer satisfaction (Gilbert & Wong, 2003), improving the quality through non-additive methods (Liou & Tzeng, 2007), and sampling-based MCDM method to verify the degree of relation between various evaluating criteria (Wang, 2007). Several researchers used purely qualitative approaches like VIKOR (Liou et al., 2011), GRA (Liou & Tzeng, 2007), DEMATLE (Wang, 2007), ELECTRE (Lupo, 2015), and hybrid approaches like VIKOR-GRA (Joshi et al., 2023), AHP-TOPSIS (Prakash & Barua, 2016; Tsaur et al., 2002), DEMATEL-ANP (Chen, 2016), and BWM-VIKOR (Guo & Zhao, 2017; Gupta, 2018) to evaluate the airline service quality.

Several researchers have contributed to identifying the customer's behavioral changes in post-COVID situation. Kim et al. (2024) observed a spike in customer's priorities in assurance and reliability dimensions. The primary changes in the tangibility dimension modifies cleanliness to COVID-protocol maintaining including hand-hygiene, physical distancing, and respiratory etiquette changes the definition of cleanliness in airlines (Amankwah-Amoah, 2021). Budd et al. (2020) predicted an increase in the number of passengers in airlines during post-COVID times. This enhances the importance of swift on-boarding, flight frequency, and flight-on-time (*Assurance*) (Rita et al., 2022; Sulu et al., 2021). Kavus et al. (2022) upgraded the tangibility and assurance dimensions with the post-COVID hygiene and operations precautions through digital innovation in-flight and on-boarding. They suggested improvements in health and hygiene including ultraviolet (UV) technology for cabin cleaning an efficient measurement through UV device. Baumeister et al. (2022) suggested that the brand-image (*Reliability*) of airlines in terms of using sustainable technology and compatible pricing and are important to attract post-COVID customer. Zahraee et al. (2022) mostly upgraded the COVID-safety protocols during boarding and in-flight (*Reliability*). Pereira et al. (2023) included flight cleanliness, hygiene (*Tangibility*) and on-boarding process (*Assurance*) as post-COVID factors. Also, Hayward & Bower (2020) discussed about process innovation through biometric check-in-service and process transparency through displaying and following the government COVID-protocols, like mandatory social distancing, middle seat blockage, deep cleaning of aircraft after each service, and COVID-19 insurance (*Assurance*). However, researchers mostly focused on single dimension for upgrading with post-COVID factors and tried to identify the customer preference.

2.2 Review of Papers in Shadowed Fuzzy Applications

Ever since, Pedrycz (1998) initiated the use of the SF set as a possible solution to deal with highly uncertain scenarios using granular computing, other researchers began to adopt it in multiple mathematical and engineering fields (Maity & Roy, 2019; Pedrycz & Vukovich, 2002). Shadowed fuzzy numbers and their operations were brought to limelight by Grzegorzewski (2013) and since then, it attracted a lot of attention in Decision-making problem. Kahraman et al. (2014) applied an interval type-2 fuzzy sets (IT2FS) to the analytic hierarchy process that has been used in the previous papers and presented the interval type-2 fuzzy AHP method combined with the new ranking technique for interval type-2 fuzzy sets. Based on this, Mohamed et al. (2015) put forward a new approach by utilizing the measures of uncertainty to generate the preferable values of the shadowed set. They implemented a new method for producing shadowed sets from ISFNs, and different uncertainty measures of ISFNs are preserved. The idea of capturing dynamicity of fuzzy number through shadowed set was constructed by Cai et al. (2017). They provided an analytical method that enabled them to calculate the pair of thresholds and seek for an optimum level of h-factor inside the shadowed set context. The entropy-based shadowed fuzzy model decision-making was used by Zhang et al. (2020). Ibrahim et al. (2020) applied the shadowed fuzzy decision-making technique based on the minimum least cost/minimum distance technique. The approach of decision-making used by William-West

Ibrahim & Ibrahim (2023) was a shadowed-fuzzy-based optimum partition. Except the methodological contribution, few application-based researches include T2SF inference-engine simulator (Chatterjee et al., 2019, Ontiveros-Robles & Melin, 2019), and word-processing model (Li et al., 2020). However, SF has not been used to capture the post-COVID uncertain and changed behavior of the customer in airlines application. **Table 1** shows the details about the methodologies used by the researchers for post-COVID uncertainty modeling in airlines applications.

Table 1. Literature of SERVQUAL model for airlines service quality inspection.

Paper	Finding importance of criteria	Ranking of alternatives	Considers post-Pandemic behavior	Post-COVID contribution to SERVQUAL dimensions for airlines					Fuzzy logic	Shadowed-Fuzzy logic
				Tangibility	Reliability	Responsiveness	Assurance	Empathy		
Parasuraman et al. (1985)	✓									
Tsaur et al. (2002)	✓								✓	
Liou & Tzeng (2007)	✓	✓							✓	
Tseng (2009)	✓								✓	
Nejati et al. (2009)	✓								✓	
Liou et al. (2011)	✓								✓	
Kuo & Liang (2011)	✓	✓							✓	
Wang et al. (2011)	✓								✓	
DU et al. (2012)	✓								✓	
Grzegorzewski (2013)	✓									
Lupo (2015)	✓								✓	
Ardakani et al. (2015)	✓								✓	
Ali et al. (2015)	✓								✓	
Chiappa et al. (2016)	✓								✓	
Prakash & Barua (2016)	✓								✓	
Rady (2018)	✓									
Gupta (2018)	✓	✓								
Hayward & Bower (2020)							✓			
Leon & Martin (2020)	✓								✓	
Rita et al. (2022)	✓		✓				✓			
Amankwah-Amoah (2021)	✓		✓	✓						
Sulu et al. (2021)			✓				✓			
Tumsekcali et al. (2021)	✓		✓						✓	
Shiwakoti et al. (2022)	✓									
Chung & Tan (2022)	✓									
Law et al. (2022)	✓									

Table 1 continued…

Boubker & Naoui (2022)	✓									
Kavus et al. (2022)	✓		✓	✓			✓			
Baumeister et al. (2022)	✓		✓		✓					
Zahraee et al. (2022)	✓		✓		✓		✓			
Dehnavi et al. (2023)	✓	✓								
Pereira et al. (2023)	✓		✓	✓			✓			
Kim et al. (2024)			✓			✓	✓			
Gao et al. (2023)	✓								✓	
This model	✓	✓	✓	✓	✓	✓	✓		✓	✓

2.3 Contribution of this Paper

The customer's preference spike in '*Assurance*' and '*Reliability*' factors through identifying the brand reliability and in-flight and airport experience are well-supported by the post-COVID literature. However, the researchers either considered dimension-specific COVID factors or did topic-modelling or text-mining models to identify the importance from secondary data. There is a lack of studies who considered the SERVQUAL model, upgraded all dimensions with possible post-COVID factors, and identified the preferences. Second gap in the literature is handling the opinion-uncertainty of the customers regarding their service experience. The uncertainty context is very important because the post-COVID service upgradation like Digital-onboarding and seat-booking, following COVID-guidelines during boarding and within flight, and following health and hygiene rules during travel are almost new to the customer. Thus, for the same level of services, the opinion variety of the customer is very high.

This study has contributed to these gaps in primarily two ways. First, the proposed research-structure allows the post-COVID and traditional factors to be aligned together to identify the absolute priority of the factors for the customer. The proposed research has upgraded traditional factors with post-COVID factors like 'COVID protocol maintenance,' to the '*Reliability*' dimension, 'Cleanliness of the flight,' to the '*Tangibility*' dimension, 'Safety and security measures' and 'Onboarding environment' to the '*Assurance*' dimension, and 'Guidance' to the '*Responsiveness*' dimension. At the same time, this study has considered the conventional factors like 'Food quality', 'Seat-comfortability', 'Baggage handling', and 'ticket price' to identify their current standing. Second, to addressing the dynamic definition of the service-quality and capturing the uncertainty in the customer's behavior this study has formulated SF modeling and applied it through an integrated MCDM method of BWM-WASPAS. Finally, the results help to identify different knowledge management principles to deploy to continue the service excellence.

3. Proposed Methodology

This section briefly discusses the SERVQUAL dimensions and its application in airlines' service quality. Other than that, a brief on shadowed fuzzy scale formation (Section 3.3) along with two new hybrids algorithmic MCDM methodologies, namely, shadowed fuzzy-best worst method (BWM) (Section 3.4) and shadowed fuzzy-WASPAS methodology (Section 3.5) is also presented.

3.1 Evaluating Airlines Service Quality Dimensions

This study aims to analyze the service attributes of Indian airlines corresponding to the expressive performance of airline services. The study got influenced by empirical studies in aviation industries

(Basfirinci & Mitra., 2015; Kavus et al., 2022; Sorourkhah & Edalatpanah, 2022; Wang et al., 2011) and thus, taking the reference of the most popular SERVQUAL models, we integrate the traditional model with changing notion of post-COVID attractiveness parameters. A comprehensive literature synthesis and experts' knowledge contribution identifies that the five dimensions of the SERVQUAL model cover 12 attributes essential to enhance customer attraction and support the airlines to provide higher service quality.

3.1.1 Tangibles
Experts all over the world highlighted that in post-covid situation, cleanliness of the flight (Dehnavi et al., 2023; Kavus et al., 2022) is going to be the most essential criteria for this attribute. Apart from that, good food quality (Patel & Patel, 2020) and comfortable seat arrangement (Boubker & Naoui, 2022) can be desirable for passengers with middle and higher economic backgrounds.

3.1.2 Reliability
Earlier reliability meant safe passenger transportation (Tsaur et al., 2002) and errorless baggage handling (Gupta, 2018). In post-covid situation, customers are more concerned with reliability of airlines in COVID protocol maintaining (Booranakittipinyo et al., 2024; Brakewood et al., 2020).

3.1.3 Responsiveness
Though these parameters are mostly intangible, efficient complaint handling (Chung & Tan, 2022; Zahraee et al., 2022) and guidance to the customer (Ardakani et al., 2015; Nejati et al., 2009) are the primary measurements of this attribute.

3.1.4 Assurance
Assurance primarily deals with trustworthiness of the crew. Some aircraft may be very trustworthy in swift on-board process (Law et al., 2022) or flight delays (Gupta, 2018). Flight safety and security assurance (Baumeister et al., 2022) during onboarding and journeys also play an important role.

3.1.5 Empathy
The heartiest touch of personalized attention and standing by the customer's needs most warmly gives ethical support to the industry. In this highly competitive era, a small addition of attendants' helping and heartful attitude can increase customer attraction (Ali et al., 2015; Prakash & Barua, 2016).

3.2 Interviews and Criteria Selection
Data collection was done through a 32-item questionnaire which mostly focused on airline service quality dimensions. A brainstorming session was conducted with customer service managers of domestic airline companies, who were peer-review-team of the target research study and are considered to be the subject matter specialists. The panelists fine-tuned and grouped the listed 32 potential items into the final list of 15 service characteristics of domestic airlines. The refined questionnaires were also pre-tested through social media, whereby one-hundred and fifty passengers were asked. From the literature review, the research identified 44 possible service attributes that in turn, form the element of SERVQUAL. The experts reduced the pre-test list to 12 elements in order to cover all the identified SERVQUAL dimensions. On this basis, it became possible to conclude that the content validity of the developed questionnaire is satisfactory. The questions are constructed in a way to be related to the Indian domestic airlines' and contain specific service contexts by perceived.

The second part of the survey and data collection was performed through social media. Consistency of the response was checked and the false responses were filtered out. For the primary survey, we targeted passengers through networks who traveled through any domestic airline at least once in the last six months. Three different kinds of information were obtained from them: flight details, expectations and satisfaction ratings for every service feature, and profiles. The first section of the questionnaire asks about the flight, including the name of the airline, the number of flights the customer takes each month, the seat class, the reason for the trip, and the booking and ticketing channels utilized. Airline service characteristics were covered in Part 2. Using a 3-point Shadowed fuzzy (SF) scale, respondents were asked to rank the perceived relevance of each trait. The final section of the survey gathered demographic data, including age, sex, occupation, and level of education. Depending upon the questions and the passenger's response we set twelve most important criteria. The criteria are shown in a **Table 2**. The detailed questions are listed in appendix A section.

Table 2. Criteria table.

Service quality dimensions	Name of criteria	References
Tangibility	Cleanliness level of aircraft (C2)	Ardakani et al. (2015), Gupta (2018), Pereira et al. (2023), Rady (2018), Tsaur et al. (2002)
	Seat comfortability (C3)	Ali et al. (2015), Hussain et al. (2015), Tsaur et al. (2002)
	Food quality (C4)	Ardakani et al. (2015), Chen & Chang (2005)
Reliability	COVID safety protocol (C1)	Dehnavi et al. (2023), Tumsekcali et al. (2021)
	Handling of luggage loss (C6)	Bisfirnci & Mitra (2015), Gupta (2018), Liou et al. (2011), Tsaur et al. (2002)
	Price of Ticket (C7)	Jiang & Zhang (2016), Tsaur et al. (2002), Wu & Cheng (2013)
Responsiveness	Handling of customer complains (C8)	Ardakarni et al. (2015), Chung & Tan (2022), Nejati et al. (2009), Tsaur et al. (2002)
	Guidance (C9)	Chang & Yeh (2002), Patel & Patel (2020), Zahraee et al. (2022)
Assurance	Flight safety and security (C5)	Baumeister et al. (2022), Boubker & Naomi (2002)
	On Board environment (C10)	Kavus et al. (2022), Law et al. (2022), Zahraee et al. (2022)
	Delay in service (C11)	Gupta (2018), Jiang & Zheng (2016), Liou et al. (2011), Nejati et al. (2009), Suki (2014)
Empathy	Helpful attitude and courtesy for personnel (C12)	Ali et al. (2015), Ardakani et al. (2015), Chou et al. (2014), Pakdil & Aydin (2007), Prakash & Barua (2016)

There is a usual practice to note the responses on a 5-point Likert scale. However, the responses from the experts and the passengers can be biased due to personal liking and disliking, some unfortunate experiences, and other unpredictable mistakes. While responding to any question, human nature is usually very certain about the worst and best experiences but uncertain about the average one. For, instance, the average responses of the 5-point Likert scale (2,3,4) contains higher uncertainty because of these perception bias. Also, the Likert scale doesn't provide an option to overlap induvial responses between two rating. Thus, the responses for comparatively insignificant criteria contain higher uncertainty than the most significant criteria. To eliminate these uncertainties associated with the Likert scale, this paper formed a shadowed fuzzy (SF) scale influenced by the capability of SF to handle uncertainty (Bargiela & Pedrycz, 2003; Chatterjee et al., 2019; Zhou et al., 2017). The proposed SF model allows the respondents to provide the degree of belongingness of their responses along with the choices (high, med, or low). This study used this SF-scale to construct an integrated BWM-WASPAS method to identify the significant factors for airline service quality in the post-COVID context. The next three sections elaborate on the SF-scale formation and BWM-WASPAS methodologies. **Figure 2** represents the detailed flowchart of the SF-BWM-WASPAS methodology.

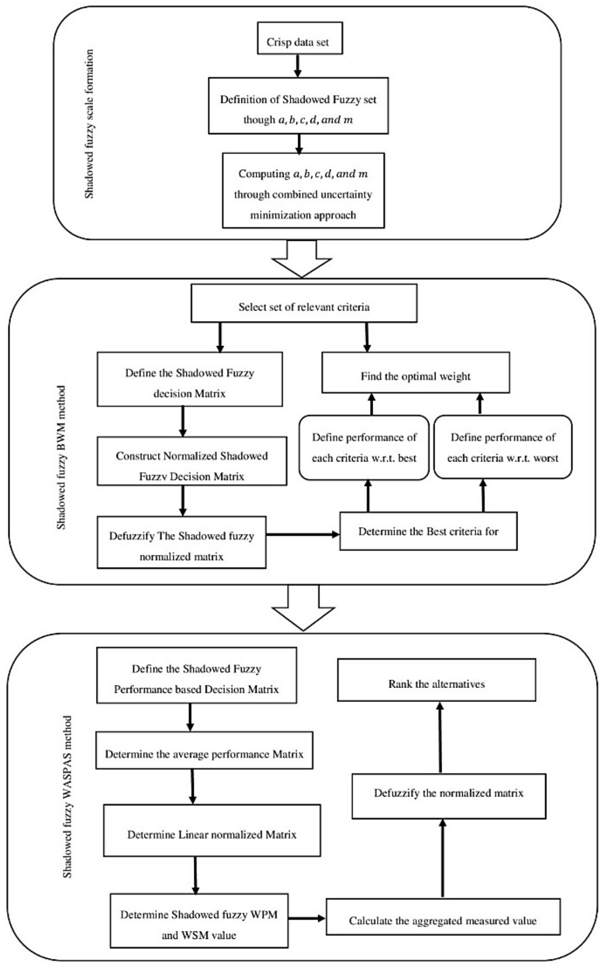

Figure 2. Flowchart of shadowed fuzzy BWM-WASPAS algorithmic methodology.

3.3 Shadowed Fuzzy Scale Formation

The Shadowed fuzzy scale formation operation, which is developed by this study only, is supported by the elements of granular computing (Bargiela & Pedrycz, 2003; Chatterjee et al., 2019; Zhou et al., 2017). Since the customer behavior usually follows a normal distribution, the corresponding fuzzy set appears gaussian. Depending upon the range of responses involved in past researches, this paper has created three SF membership grades: Low, Medium, and High. The scale formation involves computing the values of a, b, c, d though uncertainty minimization approach. **Figure 3** presents the scale.

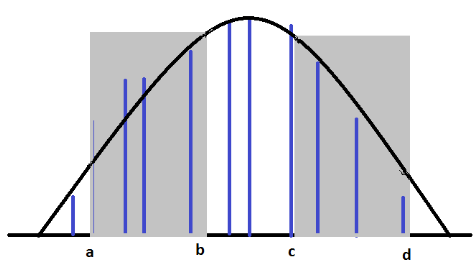

Figure 3. Scaling of shadowed fuzzy number.

To derive value of a, b, c, d, we formulate this as a minimization problem
$min \sum_{a \le r_i \le m} \mu^a(r_i)\, exp(-\alpha|m-a|) - \sum_{b \le r_i \le m} \mu^b(r_i)\, exp(-\alpha|m-b| - \sum_{m \le r_i \le c} \mu^c(r_i)\, exp(-\alpha|c-m|) + \sum_{m \le r_i \le d} \mu^d(r_i)\, exp(-\alpha|d-m|)\}$.

Subject to constraints,

$$m = \sum_{i=1}^{n} r_i / n \tag{1}$$

$$\mu^a(r_i) = \frac{r_i - a}{m - a} \tag{2}$$

$$\mu^b(r_i) = \frac{r_i - b}{m - b} \tag{3}$$

$$\mu^c(r_i) = \frac{c - r_i}{c - m} \tag{4}$$

$$\mu^d(r_i) = \frac{d - r_i}{d - m} \tag{5}$$

α is a value between 0 and 1. In this problem $\alpha = 0.5$. r_i is the crisp responses extracted from the past research.

Example 1: Let's understand the process of SF scale formation from a 5-point Likert scale past data. The study checked the customer's comments on food-quality, who had a poor experience with the food quality. The researcher can filter the numeric responses on poor food quality experience from Skytrax customer review database (https://www.airlinequality.com/review-pages/a-z-airline-reviews)) through comments and rating noted at the database. Now, for example, 5 such ratings are $r = \{1,2,1,1,3\}$. Now, based on these data, we can find the values of $m, \mu^a(r_1), .., \mu^a(r_5), \mu^b(r_1), ... \mu^b(r_5), \mu^c(r_1), .., \mu^c(r_5), \mu^d(r_1), .., \mu^d(r_5)$. **Table 3** provides the membership values of each r_i.

Table 3. Illustration of SF scale formation.

Crisp data	Constraints set for a	Constraints set for b	Constraints set for c	Constraints set for d
r_i	$\mu^a(r_i)$	$\mu^b(r_i)$	$\mu^c(r_i)$	$\mu^d(r_i)$
1	$\frac{1-a}{1.6-a}$	$\frac{1-b}{1.6-b}$	$\frac{c-1}{c-1.6}$	$\frac{d-1}{d-1.6}$
2	$\frac{2-a}{1.6-a}$	$\frac{2-b}{1.6-b}$	$\frac{c-2}{c-1.6}$	$\frac{d-2}{d-1.6}$
1	$\frac{1-a}{1.6-a}$	$\frac{1-b}{1.6-b}$	$\frac{c-1}{c-1.6}$	$\frac{d-1}{d-1.6}$
1	$\frac{1-a}{1.6-a}$	$\frac{1-b}{1.6-b}$	$\frac{c-1}{c-1.6}$	$\frac{d-1}{d-1.6}$
3	$\frac{3-a}{1.6-a}$	$\frac{3-b}{1.6-b}$	$\frac{c-3}{c-1.6}$	$\frac{d-3}{d-1.6}$
$m = 1.6$	Objective function			
$Min = \left(\frac{1-a}{1.6-a}\right)\exp(-0.5\lvert 1.6-a\rvert) + \frac{2-a}{1.6-a}\exp(-0.5\lvert 1.6-a\rvert) + \left(\frac{1-a}{1.6-a}\right)\exp(-0.5\lvert 1.6-a\rvert) + \left(\frac{1-a}{1.6-a}\right)\exp(-0.5\lvert 1.6-a\rvert) + \left(\frac{3-a}{1.6-a}\right)\exp(-0.5\lvert 1.6-a\rvert) - \left(\frac{1-b}{1.6-b}\right)\exp(-0.5\lvert 1.6-b\rvert) - \frac{2-b}{1.6-b}\exp(-0.5\lvert 1.6-b\rvert) - \left(\frac{1-b}{1.6-b}\right)\exp(-0.5\lvert 1.6-b\rvert) - \left(\frac{1-b}{1.6-b}\right)\exp(-0.5\lvert 1.6-b\rvert) - \left(\frac{3-b}{1.6-b}\right)\exp(-0.5\lvert 1.6-b\rvert) - \frac{c-1}{c-1.6}\exp(-0.5\lvert c-1.6\rvert) - \frac{c-2}{c-1.6}\exp(-0.5\lvert c-1.6\rvert) - \frac{c-1}{c-1.6}\exp(-0.5\lvert c-1.6\rvert) - \frac{c-1}{c-1.6}\exp(-0.5\lvert c-1.6\rvert) - \frac{c-3}{c-1.6}\exp(-0.5\lvert c-1.6\rvert) + \frac{d-1}{d-1.6}\exp(-0.5\lvert d-1.6\rvert) + \frac{d-2}{d-1.6}\exp(-0.5\lvert d-1.6\rvert) + \frac{d-1}{d-1.6}\exp(-0.5\lvert d-1.6\rvert) + \frac{d-1}{d-1.6}\exp(-0.5\lvert d-1.6\rvert) + \frac{d-3}{d-1.6}\exp(-0.5\lvert d-1.6\rvert)$.				

3.4 Shadowed Fuzzy BWM Method

The shadowed fuzzy BWM method involves similar operations to the BWM method (Anjum et al., 2020), except the responses are in fuzzy domain. The steps for shadowed-fuzzy BWM are elaborated as follows.

Step 1: *Defining the shadowed fuzzy decision matrix.*
Unlike crisp BWM, shadowed fuzzy BWM involves experts' input in SF scale (Anjum et al, 2020). The input decision matrix $D = [d_{ij}]_{m\times n}$ contains the data in the form of low, medium, and high scale along with membership grades. A generic decision matrix containing m decision makers to respond on n criteria are represented by Equation (6).

$$D = \begin{bmatrix} d_{11} & d_{12} & \dots & \dots. & d_{1n} \\ d_{21} & d_{22} & \dots & \dots & d_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ d_{m1} & d_{m2} & \dots & \dots & d_{mn} \end{bmatrix}_{m\times n} \tag{6}$$

where, $d_{ij} = \{S_{ij1}, S_{ij2}, S_{ij3}, S_{ij4}, (\mu_{ij})\}$ represents the reaction of i^{th} decision maker for j^{th}criteria $C_j(j = 1,2,\dots,n)$.

Step 2: *Defining the performance of each criterion with respect to the best and worst criteria.*
Next task is to identify the best and worst criteria from the criteria list and define the performance of each criterion with respect to the best and the worst criteria. Each decision-maker select a best and a worst criterion, and depending on that the performance each of the criteria $C_j(j = 1,2,\dots,n)$ with respect to the best criteria (*determined using above step*) for k^{th} decision-maker $DM_k(1 \le k \le m)$is evaluated using Equation (7) as follows:

$$\tilde{x}_{B_{ij}} = 1 - \frac{x_{ij}}{\max\limits_{1\le j\le n}\{x_{ij}\}}, i = 1,2, \dots, m \tag{7}$$

The performance of each of the criteria $C_j(j = 1,2,\dots,n)$ with respect to the worst criteria (*determined using above step*) for k^{th} decision-maker $DM_k(1 \le k \le m)$is evaluated using Equation (8) as follows:

$$\tilde{x}_{W_{ij}} = 1 - \frac{\min\limits_{1\le j\le n}\{x_{ij}\}}{x_{ij}}, i = 1,2, \dots m \tag{8}$$

Here, x_{ij} is the normalized value of the input matrix, determined using Equation (9).

$$\begin{Bmatrix} x_{ij} = \dfrac{d_{ij}}{\max\{d_{ij}\}} & for\ benfical\ criteria \\ x_{ij} = \dfrac{\min\{d_{ij}\}}{d_{ij}} & for\ non-benefical\ criteria \end{Bmatrix}, i = 1,2, \dots m; j = 1,2, \dots n. \tag{9}$$

Step 3: *Finding the optimal weights*
To find the optimal weight, for each decision maker, we need to minimize the absolute difference between $\left\{\left|W_B - \tilde{x}_{B_{ij}}W_j\right|, \left|W_j - \tilde{x}_{W_{ij}}W_w\right|\right\}\ \forall j.$

where, W_B =Weight of Best criteria, W_j =Weight of j^{th}criteria, W_w =Weight of worst criteria.

This can be formulated, as per Equation (10), as follows:

$$\begin{cases} minmax_j \left\{\left|W_B - \tilde{x}_{B_{ij}}W_j\right|, \left|W_j - \tilde{x}_{W_{ij}}W_w\right|\right\} \\ \qquad suchthat \sum_j W_j = 1 \\ \qquad\qquad W_j \ge 0, (\forall j) \end{cases} \tag{10}$$

Now, this can be solved by transferring it into a linear programming problem as per Equation (11):

$$\left\{\begin{array}{c} \min \xi^L \\ subject\ to \\ \left|W_b - \tilde{x}_{B_{ij}} W_j\right| \le \xi^L \quad for\ all\ j \\ \left|W_j - x_{w_{ij}}\right| \le \xi^L \quad for\ all\ j \\ \sum_j W_j = 1 \\ W_j \ge 0; \qquad (\forall\ j) \end{array}\right\} \tag{11}$$

Using proposed shadowed fuzzy-BWM methodology, we get the optimal weight $W_{lj}(j = 1,2, \dots n), (l = 1,2, .. m)$ of each criterion $C_j(j = 1,2, \dots n)$. For each decision maker $DM_l(l = 1,2, \dots, m)$, we get the n numbers of weight of each criterion. After getting the weights of criteria $C_j(j = 1,2, \dots n)$ for different alternatives, we compute the average weightage of each criterion $C_j(j = 1,2, \dots n)$ by computing Equation (12):

$$W_j = \sum_{l=1}^{m} \frac{W_{lj}}{m} \quad (\forall\ j;\ j = 1,2 \dots n) \tag{12}$$

Now, the weights of the criterion are used to evaluate the performance of different alternatives through SF-WASPAS method. Section 3.5 elaborates the SF-WASPAS method.

3.5 Shadowed Fuzzy WASPAS Method

Every MCDM problem starts with a set of alternatives to be ranked depending upon a set of criterions $C_j(j = 1,2, \dots n)$. Let there are p number of alternatives $A_i(i = 1,2, \dots p)$ to be evaluated and ranked accordingly. An SF-MCDM problem can be represented as decision-matrix form $D^q = \left[d_{ij}^q\right]_{p\times n}$, shown in Equation (13).

$$D^q = \begin{bmatrix} d_{11}^q & d_{12}^q & \cdots & \cdots\cdot & d_{1n}^q \\ d_{21}^q & d_{22}^q & \cdots & \cdots & d_{2n}^q \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ d_{p1}^q & d_{p2}^q & \cdots & \cdots & d_{pn}^q \end{bmatrix}_{p\times n} \tag{13}$$

where, $d_{ij}^q = \left\{a_{ij1}^q, a_{ij2}^q, a_{ij3}^q, a_{ij4}^q, \left(\mu_{ij}^q\right)\right\}$.

Here, d_{ij}^q is the SF-rating the passengers have given to different airlines. Then we identify the beneficial and non-beneficial criteria and evaluate the normalized rating matrix as B_{ij}. Note that in this case 'Price' (C7) is non-beneficial criteria only.

$$B = \begin{bmatrix} y_{11} & y_{12} & \cdots & \cdots\cdot & y_{1n} \\ y_{21} & y_{22} & \cdots & \cdots & y_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ y_{p1} & y_{p2} & \cdots & \cdots & y_{pn} \end{bmatrix}_{p\times n} \tag{14}$$

$$\begin{cases} y_{ij} = \frac{r_{ij}}{max\{r_{ij}\}}; & for\ benefical\ \ criteria \\ y_{ij} = \frac{min\{r_{ij}\}}{r_{ij}};\ for\ non-benefical\ criteria \end{cases} \tag{15}$$

$$r_{ij} = \sum_{q=1}^{m} d_{ij}^{q} \tag{16}$$

Finally, we reach to significant part of WASPAS method, determining weighted product, weighted sum, and finally the aggregate values as per Equations (17)-(19).

$$Q_i^{sum} = \sum_{j=1}^{n} W_j * y_{ij} \tag{17}$$

$$Q_i^{product} = \prod_{j=1}^{n} (y_{ij})^{W_j} \tag{18}$$

$$Q_i^{avg} = \beta Q_i^{sum} + (1-\beta) Q_i^{product} \tag{19}$$

where, β is the basic parameter of SF-WASPAS method, in the range of 0 to 1. Usually, when $\beta = 1$, aggregated value $Q_i^{avg}(i = 1,2, \dots p)$ changes to WSM (Q_i^{sum}) and for β =0, aggregate changes to WPM($Q_i^{product}$).

$$Q_i^{avg} = \begin{bmatrix} q_1 \\ q_2 \\ \cdots \\ q_p \end{bmatrix}_{p\times 1}, \text{ where, } q_i = \{\acute{V_{i1}},\ \acute{V_{i2}}, \acute{V_{i3}}, \acute{V}_{i4}, (\acute{\mu_i})\} \tag{20}$$

Once the SF-average rating is produced for all alternatives, we defuzzify the values and produce the final ranking as per Equations (21)-(23).

$$\tilde{Q}_{i1} = V'_{i1} + \mu` * (V'_{i2} - V'_{i1}) \tag{21}$$

$$\tilde{Q}_{i2} = V'_{i4} - \mu` * (V'_{i4} - V'_{i3}) \tag{22}$$

$$\tilde{Q}_i = \sqrt{\tilde{Q}_{i1} * \tilde{Q}_{i2}} \tag{23}$$

The alternatives $A_i(i = 1,2,..p)$ are finally assessed and ranked based on the de-fuzzified value $\tilde{Q}_i(i = 1,2,..p)$. To analyze the stability of the algorithm, changes in ranking are determined based on the change of β and the correlation of ranking with β.

4. Result Discussion

4.1 Data Collection

This paper has replicated the sentiment analysis done by Murugesan et al. (2024) and collected some of the customer sentiment analysis data from Ogao report, 2024 (https://www.oag.com) and Skytrax Airlines review database (https://www.airlinequality.com/review-pages/a-z-airline-reviews). Based upon the proposed criteria list (**Table 1**) the authors have linked the reviewed factors from Skytrax database. The authors have collected the customer ratings and the customer reviews to connect the low, medium, and high scale. For each level of experience, corresponding rating SF scale is created. The detail description of SF scale formation along with an illustration is presented in section 3.3. The detailed SF-scale for all twelve criteria is presented in **Table 4**.

Table 4. SF scale formation.

Criteria	Low				Medium				High			
	a	*b*	*c*	*d*	*a*	*b*	*c*	*d*	*a*	*b*	*c*	*d*
C1	0.987	1.23	1.651	2.002	1.987	2.86	3.452	3.722	3.698	4.096	4.555	5
C2	1.45	1.665	2.037	2.348	2.325	3.107	3.631	3.869	3.848	4.2	4.606	5
C3	0.523	0.922	1.417	1.716	1.698	2.478	3.231	3.597	3.575	4.377	4.801	5
C4	0.523	0.923	1.417	1.716	1.695	2.478	3.231	3.597	3.576	4.377	4.8	5
C5	0.523	0.923	1.417	1.716	1.694	2.478	3.231	3.597	3.573	4.377	4.801	5
C6	1.044	1.163	1.399	1.613	1.592	2.295	2.914	3.398	3.377	4.296	4.746	5
C7	0.158	0.381	0.822	1.222	1.208	2.217	3.005	3.45	3.429	3.678	4.466	5
C8	0.985	1.275	1.777	2.197	2.176	2.832	3.54	3.863	3.842	3.92	4.468	5
C9	0.212	0.512	0.984	1.351	1.336	1.949	2.538	2.939	2.922	4.029	4.667	5
C10	0.212	0.513	0.984	1.351	1.335	1.949	2.538	2.939	2.924	4.029	4.667	5
C11	0.523	0.923	1.417	1.716	1.698	2.478	3.231	3.597	3.575	4.377	4.801	5
C12	1.043	1.163	1.399	1.613	1.591	2.295	2.914	3.398	3.376	4.296	4.746	5

In the next step, this study approached three customer service managers from different domestic airlines to collect input regarding criteria evaluation. The researchers conducted two-round telephonic interviews with these three experts and noted their opinions. The expert's opinion contained the finalized criteria and their importance in a SF scale (low, medium, and high with membership grades). These SF inputs were further validated through customer data. We circulated a Google form containing finalized questionnaires to collect the customer data. Out of 150 responses received, 139 were consistent enough to be considered. However, among these 139 responses, seven passengers have not traveled on a single flight post-COVID times. Thus, we discarded their responses too. In total, the survey finalized 132 responses. The respondents are diverse, although 95 are Indian. The rest are 16 Asian, 8 European, and 13 from African nations. 65% of respondents availed flights for professional, business, and study purposes, and the rest for traveling. Since the respondents are from three continents with slightly different cultural and socio-economic upbringings, the responses are noted under three categories. Each category is represented by its corresponding mean. From the distribution of the respondents' origin, we can observe most of the respondent are Indian. This distribution is helpful for this analysis because this study is concerning the Indian domestic airlines only. Also, during averaging out the non-Indian responses we observed that the responses other than Europeans are almost similar to the Indian respondents. However, the non-Indian percentage is not very significant and those responses are not adding any potential extremeness. Thus, we did not discard those responses. In addition, this research also received multicultural variation. These customer data were further used in airlines' performance evaluations. The detailed descriptive is presented in **Table 5** and the response data is presented in **Table 6**. The average of SF data is calculated using shadowed fuzzy numerical operations (Grzegorzewski, 2013; Mohamed et al., 2015; Zavadskas et al., 2014).

Table 5. Descriptive statistics of the respondent.

Variable	Frequency	Proportion
Age		
Below 20	13	9.70%
20-34	40	29.85%
35-54	59	44.02%
above 55	22	16.41%
Ethnicity		
Indian	97	72.38%
Asian(non-Indian)	16	11.94%
African	8	5.97%
European	13	9.70%

Table 6. Average response of different respondent.

Criteria	C1	C2	C3	C4	C5	C6
Asian	med(0.225)	med(0.256)	med(0.965)	med(0.694)	med(1)	med(1)
African	med(1)	low(0.623)	med(0.552)	med(1)	high(0.964)	med(0.659)
European	med(0.695)	low(0.995)	med(0.065)	med(0.902)	high(0.892)	low(0.444)
	C7	C8	C9	C10	C11	C12
Asian	high(0.062)	low(0.985)	high(1)	med(1)	low(0.659)	low(0.687)
African	high(0.526)	low(0.895)	high(0.562)	high(0.274)	low(0.995)	low(0.526)
European	med(0.897)	med(0.156)	med(0.902)	high(0.052)	med(0.229)	med(0.256)

4.2 Evaluation of Criteria Weights by Shadowed Fuzzy BWM Method

The shadowed fuzzy BWM method computes the weightage of the criteria and the dimensions of SERVQUAL. Different researchers observed a post-COVID shift of the customer priorities from tangibility to reliability and assurance dimension (Budd et al., 2020; Kim et al., 2024). This result identifies that the basic priority of the customers still remains in getting the tangible services at their best quality. However, the concerning factors have been upgraded from traditional to advanced forms. For instance, some of the basic tangible factors like flight cleanliness has been upgraded with deep cleaning (Amankwah-Amoah, 2021) and electrostatic spraying (Kavus et al., 2022). Food quality has been upgraded with health and hygiene (Rita et al., 2022). Airlines can use platform database management to monitor and control the flight deep and surface cleaning, food quality, and packaging (Law et al., 2022). Chou et al. (2023) and Rezaei (2016) derived reliability as the most crucial dimension. This study also supports their observation as the result says that reliability is another most important dimension after tangibility. The reason is very clear because recent customers mostly trust the brand instead of their performance level. Customers believe that big brand are more reliable in maintain the service quality standard and COVID-safety protocols throughout their service delivery process. One very critical observation in post-COVID situation is that the assurance dimension has achieved a quite similar significance to the tangibility and reliability dimensions. If we compare this result with Gupta (2018) and Rezaei (2016), we notice that the weightage of tangibility has reduced in post-covid times and the weightage of reliability and assurance is significantly improved. This observation implies that apart from the brand values, new generation customers focus on performance capability and technology-adaptability of the airlines. This is the area where the airlines can focus on process transparency management to assure the customer about their adaptability. Another major observation is that more than 85% weightage is distributed within tangibility, reliability, assurance, and responsiveness dimension. Empathy has very low weightage. This observation implies that in post-COVID times, with a significant percentage of frequent flier, customers are already expert and bother less about the human interventions.

While analyzing the factors individually, we noticed that in the post-COVID scenario, COVID-safety protocols and cleanliness became the most important criteria for passengers. As respondents mostly filled the responses immediately after the third-wave, these two criteria gained higher weightage than others. The result also describes that some traditional factors like food quality, luggage handling, flight delay always remain a concern for passengers. Also, guidance during onboarding, and safety and security instructions have been increasingly important for non-regular customers. Platform online database management regarding tracking and scheduling of regular cleaning and maintenance to airbuses and lounge, luggage tracking system, food procurement system plays an essential role to assure these factors. At the same time, process transparency regarding on-boarding, live tracking of airbuses, luggage tracking system can help customer get more assurance regarding service quality.

Another major observation is that the competitive pricing and economic growth in developing countries has reduced the significance of ticket prices. On the other hand, safety, security, and comfort started drawing more attention. **Table 7** mentions the weightage and ranking of different factors and dimensions of the proposed SERVQUAL model.

Table 7. Criteria weightage and ranking.

Dimensions	Name of criteria	Weightage	Dimension weightage	Rank
Tangibility	Cleanliness level of aircraft (C2)	0.1180	0.3031	2
	Seat comfortability (C3)	0.0673		9
	Food quality (C4)	0.1178		3
Reliability	COVID safety protocol (C1)	0.1180	0.2706	1
	Handling of luggage loss (C6)	0.0935		4
	Price of Ticket (C7)	0.0591		10
Responsiveness	Handling of customer complains (C8)	0.0412	0.1347	12
	Guidance (C9)	0.0935		5
Assurance	Flight safety and security (C5)	0.0861	0.2505	7
	On Board environment (C10)	0.0777		8
	Delay in service (C11)	0.0867		6
Empathy	Helpful attitude and courtesy for personnel (C12)	0.0412	0.0412	11

4.3 Ranking of Alternatives by Shadowed Fuzzy WASPAS Method

The weights of different criteria from the Fuzzy BWM method are fed to the SF-WASPAS method. Depending on the passengers' responses who have traveled to different Indian Domestic airlines in post-COVID times, this paper ranked the airlines. Very less percentage of the responses were from the business class. Thus, this result mostly reflects economy class. Aircraft traffic in economy class has increased drastically in the last few years. Thus, in the Indian context, economic class is essential, and this result also focuses on the economic class.

Since, WASPAS method itself balances between weightage sum and product, the paper represents the ranking through varying the β value. $\beta = 0$ implies the method consider only weighted sum, and $\beta = 1$ implies that the method considers only weighted product technique. The ranking of all alternatives is present in **Table 8**.

Table 8. Ranking of alternatives for different β value.

β	R1	R2	R3	R4	R5	R6
0	6	2	4	1	3	5
0.1	6	2	4	1	3	5
0.2	6	2	4	1	3	5
0.3	6	2	4	1	3	5
0.4	5	2	4	1	3	6
0.5	5	2	4	1	3	6
0.6	5	2	4	1	3	6
0.7	5	2	3	1	4	6
0.8	5	2	3	1	4	6
0.9	5	3	2	1	4	6
1	5	3	2	1	4	6

5. Sensitivity and Robustness Analyses

Sensitivity analysis and robustness test of MCDM techniques primarily contains two stages, examining the impact of changing β into the final ranking and examining the effect of criteria weight change on the ranking result. The first test can identify the stability and robustness of the proposed model (Li et al., 2024) and the last tests the efficiency of the model in handling uncertainty (Leon & Martin, 2020).

5.1 Sensitivity Analysis Depending upon Weighted Sum or Product

Sensitivity analysis of the ranking by changing the β value in very traditional and common in literature. β close to 1 interprets a weighted sum model (WSM), where the model is linear and the model parameters are mostly independent. β close to 0 interprets weighted product model (WPM) where the model is non-linear and the parameters are interlinked (Li et al., 2024). Less variation in ranking ensures the robustness of the model as it presents a low impact of the parameter-interdependence into the result. The ranking for different β value is already present in **Table 6**. Further, we present **Figure 4** to graphically identify the variation.

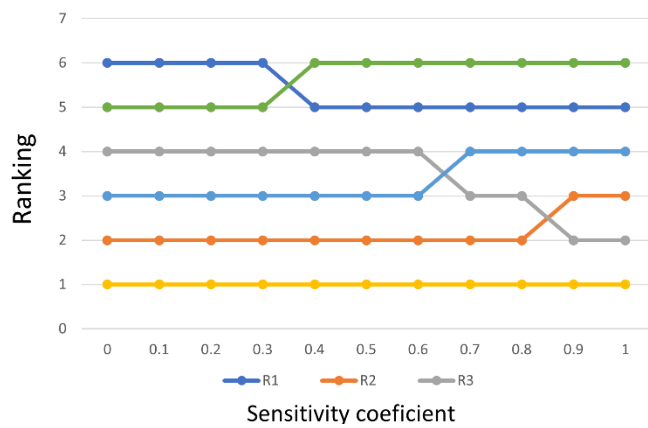

Figure 4. Shadowed fuzzy stability (X-axis= interval of λ; Y-axis= rank of alternatives).

The graph indicates ranking interchangeability is there for mostly the mid-range alternatives. High-rank and low-rank players did not interchange their ranking with respect to the change in the β value. This result indicates that this integrated SF-BWM-WASPAS model is robust and not impacted by the non-linearity and the interdependence present within the criteria.

5.2 Sensitivity Analysis for Changed Criteria-Weight

Sensitivity analysis determines the system's sensitivity in a similar way done by Anjum et al. (2020). This analysis tries to identify whether a change in the criteria weightage can affect the ranking of the alternatives. A highly sensitive model indicates that the identified criteria are well-defined and strengthening the model's efficiency.

To analyze sensitivity, we increased the weightage of three criteria with maximum weightage by a total of 20%, decreased the weightage of three criteria with minimum weightage by a total of 20%, and reranked the alternatives. The ranking with the modified criteria weight is presented in **Table 9**. We also determined Spearman's rank correlation to check the correlation. Most of the pairwise correlation is significant and the correlation matrix presents that the coefficients lie in the range of [0.886-1].

Then, we considered the ranking for $\beta = 0.6$ and checked the Spearman's rank correlation coefficient. The reason behind choosing this β value is this value is showing the most variation. Also, this value perfectly balances between WPM and WSM in terms of variations. The Spearman's rank correlation coefficient for $\beta = 0.6$ came as 0.886. **Table 10** presents the changed and original ranking for $\beta = 0.6$ and **Figure 5** presents a graphical representation.

Table 9. Ranking for changed weight for analyzing sensitivity.

β	R1	R2	R3	R4	R5	R6
0	6	2	4	1	3	5
0.1	6	2	4	1	3	5
0.2	6	2	4	1	3	5
0.3	6	2	4	1	3	5
0.4	6	2	4	1	3	5
0.5	6	2	4	1	3	5
0.6	6	2	3	1	4	5
0.7	5	2	3	1	4	6
0.8	5	2	3	1	4	6
0.9	5	2	3	1	4	6
1	5	2	3	1	4	6

Table 10. Comparison of both ranking at $\beta = 0.6$.

$\beta = 0.6$	R1	R2	R3	R4	R5	R6
Original	5	2	4	1	3	6
Changed	6	2	3	1	4	5

Figure 5 shows that the ranking of R2 and R4 are intact and R1, R3, R5, and R6 has been changed. However, the position changes are not very abrupt and the rank correlation for this maximum changed value is 0.886. This result shows a high stability of the proposed model.

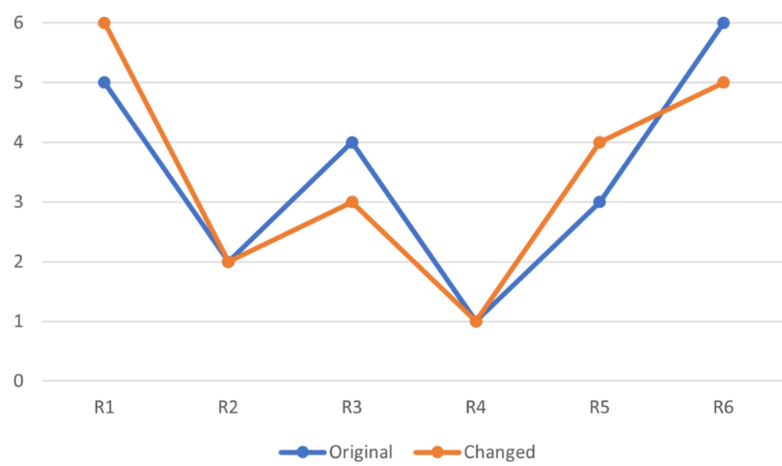

Figure 5. Shadowed fuzzy sensitivity (X axis = alternatives; Y axis = rank of alternatives).

6. Result Comparison

Since the proposed SF-BWM-WASPAS is concerned about the uncertainty present in the data, this study intends to determine the total uncertainty smoothen by this model. Shannon-entropy, a very popular method to determine the model's randomness can be computed. The Shannon-entropy, also popular as information entropy, presents the uncertainty involves with each possible event. This study has used the step-by-step process of Shannon-entropy calculation suggested by Li et al. (2024). Then the entropy-based criteria weight is compared with the original weight. **Table 11** presents the comparison of Shannon-entropy based weight and SF-BWM weight of the criteria along with the entropy values.

Table 11. Comparison of criteria weight with Shannon-entropy.

Criteria	SF-BWM weight	SF-BWM ranking	Weight through Shannon entropy	Shannon-entropy ranking	Entropy
Cleanliness level of aircraft (C2)	0.118	2	0.112159	2	0.8645
Seat comfortability (C3)	0.0673	9	0.066171	5	0.5642
Food quality (C4)	0.1178	3	0.110526	3	0.6258
COVID safety protocol (C1)	0.118	1	0.107845	1	0.9865
Handling of luggage loss (C6)	0.0935	4	0.086276	9	0.3349
Price of Ticket (C7)	0.0591	10	0.064397	10	0.3574
Handling of customer complains (C8)	0.0412	12	0.060466	11	0.4467
Guidance (C9)	0.0935	5	0.084814	4	0.4962
Flight safety and security (C5)	0.0861	7	0.086584	7	0.6456
On Board environment (C10)	0.0777	8	0.087304	8	0.7198
Delay in service (C11)	0.0867	6	0.087661	6	0.753
Helpful attitude and courtesy for personnel (C12)	0.0412	11	0.0458	12	0.2337

The result shows that the ranking of the criteria determined from experts' opinion through SF-BWM model is quite similar to the objective weight determined through Shannon's entropy. This indicates a high validity of the expert's ratings and good performance of the proposed model in handling uncertainty. The criteria-wise comparison of weights is presented in **Figure 6.**

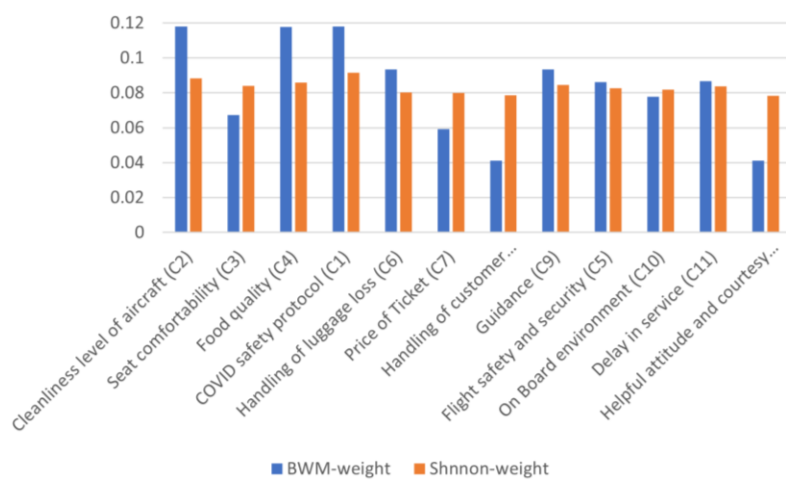

Figure 6. Comparison between SF-BWM weight and Shannon's entropy weight.

Another observation from the entropy analysis is that the entropy for the criteria 'luggage loss', 'Ticket price', and 'Courtesy for personnel' have low value because of the high subjectivity and variety of opinions. Now, to further check the validity of our WASPAS model we compared the model with other established MCDM methods like ARAS and TOPSIS. The detailed result is shown in **Table 12**.

Table 12. Comparison with ARAS and TOPSIS.

Alternatives	WASPAS	ARAS	TOPSIS
R1	5	3	4
R2	2	2	3
R3	4	6	2
R4	1	1	1
R5	3	4	5
R6	6	5	6

We did a two tailed hypothetical T-test to check whether the ranking or our technique matches with ARAS and TOPSIS. For comparison with ARAS, we got *t*-value = 2.501, which ensures 95% acceptance of null hypothesis. In case of TOPSIS also we got *t*-value = 2.501, which ensures 95% acceptance of null hypothesis. We can conclude that the newly proposed method gives alike result with two well established MCDM methods. From the comparison and robustness test, we identified that the proposed model is highly robust and comparable with the other established MCDM models.

7. Conclusion

In order to enhance the overall service quality of the airlines, this paper has made additions to the traditional SERVQUAL model with post-COVID factors and suggested an efficient knowledge-management to the organizations. At the same time, the study has applied the Shadowed-Fuzzy BWM-WASPAS technique to adapt the uncertainty related to the customers' perception on quality. The study has further checked the model's stability and sensitivity to justify the relevance of the identified factors and the efficiency of this model. Finally, the model compared its result with ARAS and TOPSIS to establish its relevance. This comparison assures the validation and robustness of the proposed methodology for airlines' service quality evaluation.

8. Implications

8.1 Theoretical Implications

This study contributes to several implications for academia. First, the developed model contributes to theory building of MCDM by integrating BWM and WASPAS under shadowed fuzzy logic to eliminate the uncertainty in the responses. The SF-model, popular for handling higher uncertainty than traditional fuzzy models, has also been compared with other MCDM models and validated through Shannon-entropy model. Also, on the other hand, the SF-MCDM models are very limited, and this study can be considered as one of the foundations for further research in SF-MCDM domain. Second, this study is one of the primary studies which considers the post-COVID behavioral shift of customer, thus creating a theoretical foundation for discerning service quality in disrupted environments. Third, the study also links post-covid factors with strategic management domains thus creating a coupling between theories of service quality and strategic management literature. Lastly the study develops a theoretical understanding of how adoption of technology changes consumer evaluation of service quality and contributes to service encounter theories.

8.2 Managerial Implications

The overall analysis reveals that post-covid there is a fundamental shift in consumer priorities from cost to safety, reliability and assurance in service to choose airlines. Airlines should consider creating safety and reliability scorecards which are visible to the customer in real time so as to position safety compliance as differentiator. They should develop platforms where cleaning schedules as per covid protocols and manpower deployment is done automatically. Information and visibility to customers on flight operations, baggage handling and boarding process should be the focus. Redefining the competencies of the staff should include crises management skills. Airlines should invest in adopting technologies like chatbots for health-related queries and a biometric boarding system. Airlines should measure their service quality by protocol compliance rates, transparency index, contact service adoption rates, safety confidence levels of consumer.

Also, this high passenger growth has impacted criteria like 'On board environment' and 'Delay in service,' gaining attention from customers and strengthening the Assurance dimension.

Some traditional factors like flight cleanliness, food quality, seat arrangement, and baggage handling remain critical even in recent times. The airlines can leverage database management at their best level to ensure regular airbus deep and surface cleaning and maintenance and assures the passenger regarding

COVID-safety measures.

9. Limitations and Future Scopes

Although the work identifies and addresses the possible gaps, this study is not free from limitations. Proposed model concludes that the result mostly follows Indian domestic airlines travelers. Though the collected data serve the research purpose best because of the rapid growth of Indian domestic air-business, the result could differ for developed countries. Also, the model uses type-1 SF to reduce the uncertainty in the customer's responses.

The proposed SF model can be further extended to capture higher-order uncertainties through type-2 fuzzy modeling and handling passengers' risks through stochastic analysis. Future research on SERVQUAL can consider heterogenous customer data, segment the customer based on socio-economic level, and compare the results for different country and socio-economic contexts.

Conflict of Interests

The authors confirm that there is no conflict of interest to declare for this publication.

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AI Disclosure

The authors confirm no usage of generative AI during preparing this paper.

Appendix A

The questions are as follows.

1) How much satisfied you are with the cleanliness of the aircraft?
2) Do you think the ticket price is costly?
3) How is the food quality?
4) Is the airhostess' behavior good?
5) How do you rate your seat comfortability?
6) How frequently have you been in unsafe situations?
7) Does the oxygen mask work properly in unsafe situation?
8) Did you ever lose or damage your luggage due to fault of the aircraft?
9) Did you complain any time about any issues?
10) Did they take immediate steps to solve your problem?
11) Does the aircraft take a long time to reach its destination or delays a lot before take-off?
12) How frequent is another flight of this aircraft for your destination?
13) How swift was the onboarding environment?
14) How clear was the onboarding instructions?
15) Did the aircraft maintain COVID safety protocols during onboarding and in the flight?

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