9 (3): 676-683 (2025)

Journal of Aviation

https://dergipark.org.tr/en/pub/jav

e-ISSN 2587-1676

Multidimensional Seat Comfort and Its Influence on Passenger Recommendation Behavior: Insights from Skytrax Reviews

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Article Info

Received: 30 August 2025
Revised: 22 September 2025
Accepted: 24 September 2025
Published Online: 10 October 2025

Keywords:
Airline industry
Skytrax
Seat comfort
Recommendation
Consumer Behavior

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RESEARCH ARTICLE

https://doi.org/10.30518/jav.1773181

Abstract

This study examines how the multidimensional structure of seat comfort influences passengers' recommendations. To this end, 1,062 passenger reviews from Skytrax of the world's top 20 airlines from August 2008 and April 2025 were analysed using logistic regression. Five seat comfort variables were included: seat legroom, seat recline, seat width, aisle space, and TV screen viewing. The results indicate that all of these variables influence recommendation behavior, though to different degrees. Seat recline and aisle space were the strongest determinants, followed by seat width, viewing the TV screen, and seat legroom. This study contributes to the literature by moving beyond a generic satisfaction perspective and treating seat comfort as a multidimensional driver of passenger behavior. These findings are expected to have theoretical and practical implications, informing scholars' understanding of customer responses and guiding airline managers in improving service and seating strategies.

1. Introduction

"When a journey ends, what passengers often remember is not the destination itself but the physical feeling left in their bodies after sitting for hours. Comfort should not be understood only as the absence of discomfort, since in many cases both comfort and discomfort are experienced at the same time." In travel conducted within restricted and narrow spaces, psychological perception becomes just as important as physical ease (Kremser et al., 2012). In this respect, seat comfort has turned into a decisive factor shaping passengers' overall satisfaction, airline preferences, and their willingness to recommend. Within the aircraft cabin, the perception of comfort is most strongly influenced by the seating experience (Wang et al., 2021). As a core point of the passenger experience, its importance increases depending on the duration and type of the flight. Even minor changes—whether on long-haul flights or short flights with tighter seating—can make a significant difference and reshape passengers' perceptions. Therefore, understanding the multidimensional structure of seat comfort is not only about improving service but also a strategic tool for strengthening customer loyalty and long-term commitment (Akash & Binoosh, 2022).

The literature emphasizes the significance of seat comfort as an important component of service delivery and a key factor in shaping the overall flight experience. Atalık et al. (2019), in their evaluation of in-flight service quality, identified seat comfort as the most critical element affecting value for money. Similarly, Sebjan et al. (2017) reached comparable conclusions, further emphasizing that seat width is the most significant factor influencing perceived seat comfort. Li et al. (2024), using machine learning techniques, demonstrated that seat comfort ranks among the most influential determinants of service quality, noting that improving seat comfort from "very bad" to "very good" could increase passenger satisfaction by 29 percent. Ban and Kim (2019), through their analysis of passenger reviews, found that seat comfort was the most decisive factor influencing recommendation behavior. While these findings underline the importance of seat comfort for service quality and customer satisfaction, they generally approach it as a broad and holistic concept. Only a limited number of studies have examined specific subcomponents of seat comfort in detail. Most existing research has not explored aspects such as seat legroom, aisle space, or viewing screen conditions within a wider perspective. Moreover, studies that simultaneously address both the physical dimensions of seat comfort and passenger behavioral outcomes remain scarce. Therefore, there is a need for research that holistically examines the multidimensional structure of seat comfort. The present study seeks to systematically examine how each element within this multidimensional construct of seat comfort affects passengers' recommendation behavior.

This research makes several contributions to the literature. First, it stands out as one of the earliest studies to examine the impact of seat comfort—evaluated under the "seat" category in Skytrax—on passengers' recommendation behavior.

Second, the concept of seat comfort has not been treated merely as a general satisfaction factor; its direct influence on recommendation behavior has also been assessed. Additionally, the study disentangles its core components and provides a structural evaluation, an approach that is valuable for revealing causal relationships concerning the subdimensions of seat comfort in the existing literature. Third, the research integrates sectoral data into academic modeling. In this respect, it represents one of the notable studies in which real-time customer experiences are systematically organized and analyzed, thereby offering meaningful insights for both theory and practice.

2. Literature Review

2.1. Seat comfort

The physical environment plays a more critical role in the airline industry than in other service industries. Although various types of services are provided to passengers during a flight, these services alone often fail to ensure satisfaction. One of the main reasons behind this is that the physical conditions of the aircraft do not meet expectations, which in turn leads to dissatisfaction (Ban et al., 2019). For this reason, the seats—being the point of greatest contact and the most influential factor in shaping the flight experience—must be maintained at a high level of comfort. Consequently, seat comfort has emerged as a distinct area of research in the literature.

Previous studies have approached seat comfort from two main perspectives: physical design features and perceptual assessments (Wang et al., 2021). Studies focusing on physical design features have highlighted measurable ergonomic parameters such as legroom, seat width, and backrest shape (Phothong & Worasuwannarak, 2021). Other studies, such as Miller et al. (2019), have modeled seat comfort primarily through physical design factors like seat width and pitch, limiting their assessment to seat fit while neglecting perceptual or behavioral outcomes. Similarly, Zhao et al. (2019) investigated seat pitch using physical pressure measurements, focusing exclusively on physical variables. Kokorikou et al. (2016), in their study on ergonomic comfort and sustainable seat design, also concentrated solely on seat-related design elements. By contrast, studies with a perceptual focus emphasize subjective passenger experience and psychological aspects. For instance, Kremser et al. (2012) evaluated seat comfort from a perceptual perspective but considered only seat pitch as a physical variable. Liu et al. (2019) examined how passengers' adopted sitting postures influenced comfort perception, shedding light on behavioral variations rather than seat design itself. Anjani et al. (2020) assessed different seat pitch levels by combining both physical and psychological variables. Vanacore et al. (2019) adopted a multidimensional approach that integrated measurable physical factors with passenger perceptions, though their study did not account for broader cabin comfort factors or behavioral outcomes, thus remaining limited to the seat itself. The present study, however, moves beyond treating seat comfort as a single variable. It conceptualizes it as a multidimensional construct and systematically analyzes how its physical components influence recommendation behavior. In doing so, it provides a holistic assessment that integrates both physical design and customer behavior perspectives into a single model. Furthermore, the study classifies the subcomponents of seat comfort structurally and contributes to the literature by presenting a multidimensional framework based on secondary data.

2.1. Hypotheses

Seat legroom is one of the most important factors influencing passenger comfort, particularly in the economy class. It is defined as the actual knee space derived from the concept of seat pitch but varying depending on the seat structure (Phothong & Worasuwannarak, 2021). As a key component of passenger comfort, seat legroom has been recognized in the literature for its impact on consumer behavior. Lee and Luengo-Prado (2004) demonstrated that increasing legroom in two U.S. airlines significantly influenced passenger preferences. Business class passengers, in particular, were observed to assign a high value when provided with additional legroom. Panda et al. (2025) analyzed factors affecting passenger satisfaction by comparing different models, including logistic regression, and found that legroom had a significant effect on satisfaction across all models. Phothong and Worasuwannarak (2021) further noted that even minor differences in legroom can substantially affect passenger comfort on long-haul flights. Therefore, legroom is expected to influence both the flight experience and passengers' likelihood of recommending the airline.

H1. Seat legroom has a positive and significant effect on passengers' recommendation behavior.

Seat recline emerges as one of the key components of passenger comfort, particularly influencing perceptions of relaxation and sleep quality during long flights (Eversdijk et al., 2024). Findings in the literature support this view. McGill and Fenwick (2009) argued that lumbar support and seat recline allow the spine to return to a natural position, which directly enhances comfort perception. The physiological dimension of comfort, therefore, is likely to improve satisfaction and indirectly influence recommendation behavior. Caballero-Bruno (2022), in an experiment on sleeping quality across different seat positions in autonomous vehicles, found that a flat position provided higher sleep quality compared to a reclined one. Similarly, Roach et al. (2018) showed that different backrest angles had a significant effect on sleep duration and quality during a daytime, highlighting not only the physiological but also the psychological contribution of recline to perceived restfulness. This suggests that seat recline may enhance comfort and, in turn, trigger recommendation behavior.

H2. Seat recline has a positive and significant effect on passengers' recommendation behavior.

Seat width refers to the distance between armrests, a dimension that directly shapes comfort perception. Variations in seat width affect not only perceived comfort but also physical well-being, as narrower seats create additional body pressure that may result in passenger discomfort and tension (Miller et al., 2019). For this reason, it is a factor that must be carefully addressed in seat design. Anjani et al. (2021), in their study measuring the influence of different seat widths on comfort, reported that even a one-inch increase in width significantly enhanced perceived comfort and lowered discomfort scores. Similarly, Mendoza (2018) emphasized that minor increases in seat width positively affect comfort and the overall flight experience. Vredenburgh et al. (2015) further noted that one of the most common conflicts among passengers arises when seatmates encroach upon personal space, which heightens discomfort and irritation. Therefore, seat width is a critical factor for both comfort and satisfaction.

H3. Seat width has a positive and significant effect on passengers' recommendation behavior.

Aisle space is another important component of passenger comfort, often regarded as an indicator of personal space (Lacic et al., 2016). Several studies have noted its direct and indirect influence on seat comfort. Fuchte (2014) argued that congestion in aisles, particularly during luggage storage, limits perceptions of personal space and negatively affects comfort. Ban et al. (2019), analyzing passenger reviews from Skytrax, identified aisle space as a significant determinant of comfort, which also influences satisfaction and recommendation behavior. Findings from Lacic et al. (2016) support this conclusion, underlining its relevance for the passenger experience.

H4. Aisle space has a positive and significant effect on passengers' recommendation behavior.

The concept of the seat should be considered not only in terms of its physical characteristics but also with respect to surrounding elements. One such factor is the presence of the in-flight TV screen, a feature that significantly contributes to both comfort and overall service quality (Park et al., 2020). In the literature, TV screens and similar in-flight entertainment elements are often examined not merely as ergonomic aspects but as multidimensional components of comfort that affect the time passengers spend seated. Most prior studies have assessed TV experience under the broader category of entertainment, focusing on its role in comfort. Atalık et al. (2019) noted that entertainment is an essential determinant of passenger satisfaction. Similarly, Liu et al. (2019) emphasized the importance of ergonomics, suggesting that TV screens should be placed closer and allow for adjustable personal lighting, thereby improving the comfort associated with the viewing experience. Enhancing this experience can thus strengthen seat comfort and positively affect passenger perceptions.

H5. Viewing TV screen has a positive and significant effect on passengers' recommendation behavior.

Based on these hypotheses, the research model has been developed (Figure 1).

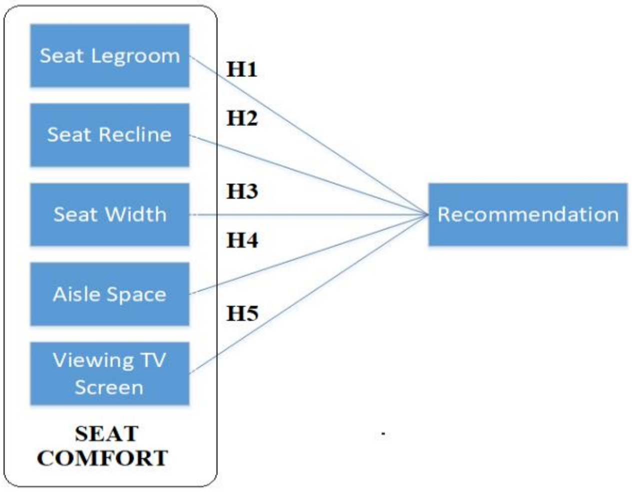

Figure 1. Research Model

3. Methodology

3.1. Data and Data Process

Since airlines do not publish passenger reviews directly on their websites, several independent, web-based platforms offer this service. These platforms allow passengers to evaluate every stage of the air transport service they receive. One of the most widely used is Skytrax (Skytrax, 2024; Song et al., 2020). Skytrax is an international rating organization that aims to improve service quality for airlines and airports worldwide through surveys and customer reviews. In addition to enabling passengers to share their evaluations, Skytrax grants various awards to the aviation companies that provide these services (Alanazi et al., 2024). For researchers, Skytrax passenger reviews also represent a valuable source of data. As secondary data, they provide meaningful insights for studies conducted from different perspectives (Bakır et al., 2022). This study included secondary data obtained from Skytrax in the analysis.

A total of 1,352 passenger reviews were collected for the study. However, 290 reviews were excluded due to being incomplete, leaving 1,062 valid evaluations for analysis. Due to the insufficient number of observations in other classes, only economy and premium economy classes were included in the analysis. Reviews posted between August 2008 and April 2025 were included, and the dataset was retrieved on April 12, 2025. Data collection was carried out using the "Web Scraper" program. The airlines included in the study correspond to the top 20 carriers listed in "The World's Top 100 Airlines" in 2024. These are: Qatar Airways, Singapore Airlines, Emirates, ANA All Nippon Airways, Cathay Pacific Airways, Japan Airlines, Turkish Airlines, EVA Air, Air France, Swiss International Air Lines, Korean Air, Hainan Airlines, British Airways, Fiji Airways, Iberia, Vistara, Virgin Atlantic, Lufthansa, Etihad Airways, and Saudi Arabian Airlines.

3.2. Data analysis

In this study, data on seat comfort obtained from the Skytrax platform was analyzed to examine passengers' recommendation behavior. Since the dependent variable is binary, a logistic regression analysis was performed. Logistic regression is a statistical model that explains the relationship between a categorical dependent variable (e.g., the presence or absence of a condition) and one or more independent variables that may be continuous or categorical. Logistic regression is also referred to in the literature as a logistic model or logit model (Nick & Campbell, 2007). This method estimates the probability of an outcome based on the independent variables (Domínguez-Almendros et al., 2011). Logistic regression is modeled according to the following equation (Kleinbaum, 1994):

$$P(X) = \frac{1}{1+e^{-(\alpha+\sum \beta_i X_i)}} \tag{1}$$

In this equation:

P(X): represents the probability that a passenger will recommend the airline (1 = recommendation, 0 = no recommendation).

α: denotes the constant term of the model.

βi: indicates the coefficient of each independent variable.

Xi: represents the independent variables related to seat comfort (seat legroom, seat recline, seat width, aisle space, viewing TV screen).

Through this equation, the probability of a passenger recommending the airline was modeled based on their evaluations of seat comfort. Before proceeding with the analysis, several prerequisites were addressed to ensure the robustness of the model. First, descriptive statistics were generated for the variables, and a correlation matrix was constructed to determine the direction and strength of the relationships among them. To assess potential multicollinearity among the independent variables, variance inflation factor (VIF) and tolerance values were calculated and examined. In addition, the omnibus likelihood ratio test was conducted to evaluate the overall validity and significance of the model. Model explanatory power was further assessed through R^2 statistics, which revealed the extent to which the dependent variable was explained (McFadden, Cox & Snell, Nagelkerke, and Tjur). The coefficients and significance levels of the predictors were then reported. Furthermore, a classification table and a receiver operating characteristic (ROC) curve were generated to evaluate the classification performance of the model. All analyses were carried out using Jamovi software (version 2.4.28), an open-source statistical package known for its user-friendly interface that facilitates the execution of statistical procedures.

4. Results

The results of the logistic regression analysis conducted to examine the effects of the independent variables on passengers' recommendation behavior are presented below. During the analysis process, descriptive statistics were first reported, VIF values were calculated, and a correlation matrix was generated. The purpose of this matrix was to check for multicollinearity, observe the direction and strength of the relationships among the variables, and better understand the structure of the data (Hair et al., 2019). As shown in Table 1, the correlation between aisle space and seat legroom was found to be 0.735, while the remaining correlation coefficients ranged from 0.534 to this value. Since all correlation coefficients were below the 0.8 threshold, there was no indication of multicollinearity (Schreiber-Gregory, 2018). In addition, VIF values ranged between 1.04 and 1.23, which is well below the cut-off point of 3.3, further confirming the absence of multicollinearity (Kock, 2017). Similarly, tolerance values varied between 0.815 and 0.964, all above the threshold of 0.2, again suggesting no multicollinearity risk (Senaviratna & A. Cooray, 2019).Table 1 also reports descriptive statistics for passenger satisfaction levels with respect to seat comfort factors, measured on a five-point scale. Among these, the highest mean was observed for viewing TV screen at 3.151 (std. dev = 1.418), followed by aisle space at 2.832 (std. dev = 1.348), seat legroom at 2.788 (std. dev = 1.471), seat recline at 2.763 (std. dev = 1.318), and seat width at 2.712 (std. dev = 1.383).

Table 1. Descriptive statistics and correlation matrix

	Mean	Std. Dev.	VIF	Tolerance	1	2	3	4	5
Seat Legroom	2.788	1.471	1.230	0.815	-				
Seat Recline	2.763	1.318	1.120	0.889	0.700*	-			
Seat Width	2.712	1.383	1.200	0.834	0.719*	0.693*	-		
Aisle Space	2.832	1.348	1.220	0.818	0.735*	0.642*	0.732*	-	
Viewing TV Screen	3.151	1.418	1.040	0.964	0.534*	0.562*	0.540*	0.568*	-

Note: p<0.001*

In addition, the omnibus likelihood ratio test was conducted to examine whether the independent variables made a significant contribution to the model. This test evaluates the combined effect of all variables on recommendation behavior (Cheng et al., 2010). As shown in Table 2, the results indicate that all predictors played a significant role in improving the model's predictive accuracy ($p < 0.001$). Among them, seat recline made the strongest contribution, with the highest chi-square value ($\chi^2 = 50.6$). This was followed by aisle space ($\chi^2 = 42.8$), seat width ($\chi^2 = 22.7$), viewing TV screen ($\chi^2 = 19.1$), and seat legroom ($\chi^2 = 12.5$), respectively.

Table 2. Likelihood ratio tests for individual predictors

Predictor	χ^2	df	p
Seat Legroom	12.469	1	<.001
Seat Recline	50.593	1	<.001
Seat Width	22.709	1	<.001
Aisle Space	42.735	1	<.001
Viewing TV Screen	19.056	1	<.001

In logistic regression analysis, the overall validity and explanatory power of the model are reported in the model summary. Table 3 presents the results related to the model summary. A low deviance value (591) indicates that the model fits the data well (Lei & Bae, 2013). The explanatory strength of the model was assessed through several pseudo R^2 measures. The values were found as follows: McFadden's $R^2 = 0.589$, Cox & Snell $R^2 = 0.549$, Nagelkerke $R^2 = 0.741$, and Tjur $R^2 = 0.651$. The McFadden's R^2 value of 0.589 exceeds the recommended range for a good fit (0.2–0.4), suggesting a very strong explanatory power (McFadden, 1974). In addition, the Cox & Snell R^2 value of 0.549 indicates that the independent variables explain 54.9% of the variance in the dependent variable (Engel et al., 2016). The Nagelkerke R^2 value of 0.741 also reflects the explanatory strength and accuracy of the model (Ardiansyah & Nurjanah, 2022; Lincoln et al., 2022). Likewise, the Tjur R^2 value of 0.651 shows that the model achieves a 65.1% discrimination performance in predicting the two categories of the dependent variable (Tjur, 2009). Finally, the model significantly outperformed the null model ($\chi^2 (5) = 846$, $p < .001$), with a deviance reduction from approximately 1,437 to 591. These findings confirm that the model explains a substantial portion of the variance in the dependent variable.

Table 3. Model summary

						Overall Model Test		
Model	Deviance	R^2_{McF}	R^2_{CS}	R^2_N	R^2_T	χ^2	df	p
Full Model	591	0.589	0.549	0.741	0.651	846	5	< .001

Note: R^2McF = McFadden's R^2, R^2CS = Cox & Snell R^2, R^2N = Nagelkerke R^2, R^2T = Tjur R^2

Table 4 shows the coefficients and related statistical findings for the variables that affect recommendation behavior. For each independent variable, the estimates, confidence intervals, standard errors, z-values, and p-values are reported. The estimated coefficients explain the log-odds difference between a recommendation of 1 and a recommendation of 0 (Hosmer, 2000). As shown in Table 4, the p-values of all predictors were below .001, indicating that each variable significantly influences recommendation behavior. The estimated coefficients were 0.347 for seat legroom, 0.773 for seat recline, 0.522 for seat width, 0.753 for aisle space, and 0.380 for viewing the TV screen. Accordingly, the highest log-odds coefficients were observed for seat recline and aisle space.

Table 4. Model coefficient- recommendation

Predictor	Estimate	95% Confidence Interval Lower	Upper	SE	Z	p
Intercept	-8.633	-9.659	-7.606	0.524	-16.48	< .001
Seat Legroom	0.347	0.155	0.540	0.098	3.53	< .001
Seat Recline	0.773	0.550	0.996	0.114	6.79	< .001
Seat Width	0.522	0.305	0.739	0.111	4.71	< .001
Aisle Space	0.753	0.519	0.987	0.119	6.31	< .001
Viewing TV Screen	0.380	0.207	0.553	0.088	4.30	< .001

Note. Estimates represent the log odds of "Recommendation = 1" vs. "Not Recommendation = 0"

Table 5 shows how well the logistic regression model distinguished between recommendation and non-recommendation behavior. For the "No Recommendation" group, the model correctly classified 573 out of 627 cases, for an accuracy rate of 91.4%. In the Recommendation group, the model correctly predicted 371 out of 435 cases, for an accuracy rate of 85.3%. Overall, the accuracy rate was 88.9%. These results suggest that the model performs well in classifying passenger recommendation behavior.

Table 5. Classification table

	Predicted No Recommendation	Predicted Recommendation	Percentage Correct
No Recommendation	573	54	91.4
Recommendation	64	371	85.3
Accuracy			88.9
AUC			0.95

In Figure 2, the discriminative power of the model was evaluated using the ROC curve (Roumeliotis et al., 2024). The AUC was found to be 0.95. This value reflects the model's ability to distinguish between recommendation and non-recommendation behavior. The closer the value is to 1, the stronger the model's discriminatory power. According to Hosmer et al. (2000), an AUC greater than 0.90 indicates that the model demonstrates an excellent level of classification performance.

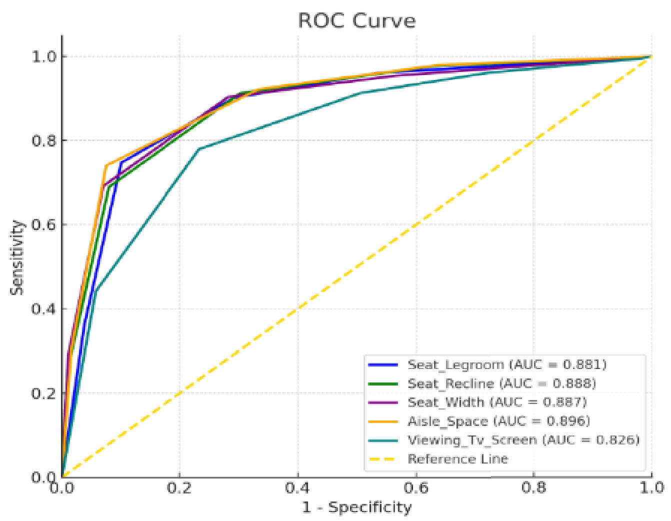

Figure 2. ROC curve

5. Conclusion

Seat comfort, as an essential part of the passenger experience, goes beyond its physical attributes and represents a multidimensional construct that shapes customer behavior. This study provides a new perspective in the literature by systematically examining the effects of the main components of passenger comfort on recommendation behavior. Several important theoretical contributions emerge. First, seat recline was identified as the strongest predictor of recommendation behavior (β = 0.773, p <0.001; χ^2 = 50.6). This finding highlights that seat recline is not merely a posture adjustment but a factor central to the passenger experience, enhancing restfulness and comfort during the flight. While the existing literature emphasizes the physiological benefits of seat recline (Eversdijk et al., 2024; McGill & Fenwick, 2009), this study statistically confirms its influence on recommendation behavior, demonstrating how physical comfort dimensions can directly shape customer actions. Second, aisle space was also found to have a significant effect on recommendation behavior (β = 0.753, p <0.001; χ^2 = 42.8). Prior studies have linked aisle space to satisfaction (Ban et al., 2019), with passenger comments noting that crowded aisles diminish perceptions of personal space and lower satisfaction (Fuchte, 2014). This research extends those insights by showing that aisle space also shapes recommendation behavior, establishing it as an independent predictor. Third, seat width was shown to have a positive and significant effect on recommendation behavior (β = 0.522, p <0.001; χ^2 = 22.7). While earlier research highlighted its role in passenger satisfaction, the present study reveals that seat width, by combining physical comfort with psychological factors such as perceived personal space, also influences post-flight behavioral outcomes such as recommendation (Anjani et al., 2021; Mendoza, 2018). Thus, seat width impacts not only an immediate sense of comfort, but also brand perception and recommendation after the flight. Fourth, the viewing TV screen variable significantly affected recommendation behavior (β = 0.380, p <0.001; χ^2 = 19.1). As a central feature of the modern airline experience, in-flight entertainment systems allow passengers to use their time more effectively while reducing stress and anxiety during flights. Theoretically, this finding underscores the importance of technological and experiential innovations not only for short-term satisfaction but also for building sustainable satisfaction and a positive brand image. This highlights the strategic role of technology-based components in shaping customer experience. Finally, seat legroom was also found to have a significant effect on recommendation behavior (β = 0.347, p <0.001; χ^2 = 12.5). Although prior studies have emphasized the critical role of legroom in seat comfort (Lee & Luengo-Prado, 2004; Panda et al., 2025; Phothong & Worasuwannarak, 2021), this study shows its limited effect on recommendation behavior. This result theoretically indicates that the influence of comfort elements on customers is multidimensional, with each factor carrying different weight. It also suggests that different combinations of these factors may influence passengers' recommendation behavior.

The study also provides valuable managerial implications for airline managers and practitioners. First, the findings reveal that ergonomic elements of seat comfort, such as seat recline and aisle space, play an important role in shaping recommendation behavior. Accordingly, one key managerial implication is that seat layout optimization should not be limited to increasing seating capacity alone, but should also involve the development of supportive policies. This issue becomes particularly relevant for long-haul flights, where passengers' expectations regarding seat comfort are even higher (Kuprikov et al., 2021). Airlines should therefore design dynamic seating policies that vary depending on flight duration and route. For instance, on routes with lower load factors or high service expectations, corridor width and seat recline could be optimized to provide passengers with a more spacious and comfortable seating environment. Implementing such flexible practices has the potential to positively influence recommendation and choice behavior, thereby providing airlines with a competitive advantage in the long run.

Psychological and perceptual factors also play a significant role in shaping passengers' comfort experiences. Therefore, rather than depending solely on traditional technical standards, airline managers should revise comfort criteria in seat design and layout by considering passenger feedback (Ahmadpour et al., 2022; Lacic et al., 2016). Feedback gathered from various channels, including social media, could serve as a practical guide in this regard. This approach would enable airlines to establish a minimum comfort threshold that considers the needs of various passenger groups, such as business travelers, and update it periodically through a dynamic standardization process. When feedback indicates that comfort levels fall below this threshold, managers should proactively respond and promptly make adjustments.

This study has several limitations. First, it relies on secondary data and only covers the top 20 airlines in 2024, focusing on economy and premium economy classes. Future studies could expand the scope by including additional airlines, other cabin classes, and various business models. This could reveal differences between airline types and service strategies. Second, the analysis focused on only five variables related to seat comfort. Including factors such as seat privacy, storage space, and sleep comfort would likely improve the model. Third, the study used logistic regression. While this method is suitable, it cannot fully capture nonlinear relationships or interaction effects. Alternative approaches, including machine learning, could provide richer insights. Finally, the sample reflects passengers traveling with the top 20 airlines. Therefore, the results cannot be generalized to all regions or customer groups. Future studies should examine a wider set of airlines and consider cultural and demographic variations among passengers.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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Cite this article: Akan, S. (2025). Multidimensional Seat Comfort and Its Influence on Passenger Recommendation Behavior: Insights from Skytrax Reviews. Journal of Aviation, 9(3), 676-683.