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Distribution of Air Tickets through Online Platform Recommendation Algorithms*

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Abstract

Purpose: The purpose of this study is to collect and analyze a large amount of data from online ticket distribution platforms that offer multiple airlines and different routes so that they can improve their ticket distribution marketing strategies and provide services that are more suitable for consumer's needs. The results of this study will help airlines improve the quality of their online platform services to provide more benefits and convenience by providing access to multiple airlines and routes around the world on one platform. **Research design, data and methodology**: For the study, 200 people completed the survey between May 1 and June 15, 2024, of which 191 copies were used in the study. **Results**: The hypothesis testing results of this study showed that among the components of the recommendation algorithm, decision comport, novelty, and evoked interest recurrence had a positive effect on perceived recommendation quality, but curiosity did not have a positive effect on recommendation quality. The perceived recommendation quality of the online platform positively influenced recommendation satisfaction, and the higher the perceived recommendation quality, the higher the intention to continue the relationship. Finally, higher recommendation satisfaction was associated with higher relationship continuation intention. **Conclusion:** it's important to continue researching online ticketing platforms. Online platforms will also need to be systems that use technology and data analytics to provide a better user experience and more benefits.

Keywords: Airline Tickets Distribution, Online Platform, Recommendation Algorithms, Decision Comport, Curiosity, Novelty, Evoked Interest, Perceived Recommendation Quality, Recommendation Satisfaction, Relationship Continuation Intention

JEL Classification Code: D30, L81, M37, P42

1. Introduction

As the COVID-19 period stabilizes, domestic and international travel is back on the rise, bringing many changes to the aviation industry. Demand for air travel is picking up, and so is the range of non-face-to-face services that COVID-19 has brought to a wide range of industries.

In addition, consumers used to have to visit a travel agent or book through a ticketing agency to purchase airline tickets, but now they can use the online platform directly to book tickets quickly and easily from anywhere, anytime. Consumers can also compare ticket prices and benefits from different airlines at a glance to find the best deal.

Airlines are striving to offer better prices and services in a competitive market environment, and the market for travel-related online platforms is expected to become increasingly diverse and competitive. Therefore, it is important for airlines to create a system that makes information easily accessible to consumers in the ticket distribution market.

In addition to online platforms that previously sold travel-related products, even online platforms that mainly sold accommodation are trying to sell not only

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accommodation but also airline services by launching 'Global Air Service'.

As the range of products and services that consumers can choose from online has expanded, recommendation systems that can help consumers make decisions have been widely applied. Airline ticket recommendation systems are being utilized in a variety of online services, from suggesting other products that may be preferred based on previous purchases, to providing news based on interests, to suggesting friends on social networks.

From products to services, online recommendation systems are now more commonplace than unusual (Pu et al., 2011). Recommendation systems are designed to help users make better choices among many alternatives and make personalized suggestions that can be tailored to the user's preferences (Knijnenburg et al., 2012).

The Yanolza app is a one-stop shop for domestic and international flights, from searching, booking, and paying for tickets through flight categories. The Yanolza app also offers a 'Best Price Reward Program' and rewards users with points if the price is higher than other online platforms. Existing travel-related online platform giants are also strengthening their airline services.

Naver Air Ticket provides information on airline tickets and hotel ticket packages through 'Naver Ticket-Package Travel-Service'. In the case of Kakao, it sells various airline-related products through 'KakaoTalk Booking' and is expected to participate in direct travel product opportunities by registering as a comprehensive travel agency.

The airline industry is also competing for discounted tickets early on. Airlines are offering fare discounts when booking through online platforms, and are selling discounted tickets to differentiate services targeting specific customers. In addition, they are expanding the market share of online platforms by linking with simple payment systems such as Apple Pay, Naver Pay, and TOSS.

This competition for discounted tickets is becoming a strategy to increase market share and gain loyal customers as airline passenger demand normalizes. The airline industry's race to capture the growing demand for international travel is likely to continue for some time.

This is a positive development as the market for online platforms to sell airline tickets is growing. The distribution of tickets on online platforms provides consumers with convenience in booking and accessing information. The proper use of recommendation systems can be a source of differentiated competitive advantage for services, as they can provide consumers with personalized alternatives that encourage them to visit more and stay longer.

Recommendation systems are a way to recommend content that users may be interested in and have been actively studied in various fields such as e-commerce products, movies, music, and news. With the recent increase in non-face-to-face services, recommendation systems that are tailored to consumers' tastes and lifestyles are becoming more important.

Online ticket distribution platforms offer multiple airlines and a variety of routes, so travelers can choose a ticket that suits their preferences and budget. Consumers can also manage their bookings on mobile through apps, which allow them to manage a variety of options, including additional services and seat options.

Currently, there are several studies on airline ticket distribution that focus on online platforms, but there are no studies on the recommendation of various airline online platforms, which is a recent trend.

Online recommendation systems are software-based algorithms that analyze data from a consumer's past purchases or browsing history to suggest personalized recommendations, and they are already widely used in everyday life. Online shopping malls actively recommend products that shoppers might like and use them as a marketing tool, and OTT companies such as Netflix score predicted preferences to help make program selection decisions.

Therefore, this study focuses on the algorithmic characteristics of the recommendation system in the distribution process of airline tickets through online platforms. This study aims to understand the quality value of online platforms through the algorithm of the recommendation system and explore ways to improve online platforms by checking satisfaction and relationship continuation.

The purpose of this study is to accumulate a large amount of data on how online platforms offer different airlines and different routes, and to analyze it so that they can improve their ticket distribution marketing strategies and provide services that better suit the needs of consumers. Online platforms provide access to multiple airlines and routes, both domestic and international, on one platform. This makes traveling both domestically and internationally easier and allows customers to discover different destinations. The analysis of this study will contribute to the development of online platforms that offer a better user experience and more benefits.

2. Theoretical Background

2.1. Recommendation Algorithms

A well-built recommendation system plays an important role in marketing as a tool to trigger personalized experiences for users. A recommendation system is an automated algorithm that utilizes and analyzes a variety of data, including a user's browsing history, purchase history, star rating history, and feedback on the purchase experience, to suggest products, services, and prices that the potential customer may be interested in first (Adomavicius & Tuzhilin, 2005).

Amazon, Netflix, and YouTube are among the companies that are actively incorporating AI into their recommendations, using hybrid systems to make personalized movie and content recommendations. These recommendation systems have also recently been adopted and used in aviation-related industries, including many airlines and travel agencies, and have been shown to strengthen users' purchasing behavior (Choi et al., 2021).

Price comparison-oriented recommendation systems are helping airlines increase ticket sales and substantially increase profitability. Recommendation systems help airlines to effectively manage seat demand and fleet management, and the basic information about supply and demand gathered by the recommendation system allows airlines to develop pricing strategies that maximize profitability (Gupta et al., 2006).

In their study, Pu et al. (2011) identified three essential characteristics of recommendation systems: first, interaction-based applications, second, the presentation of recommended alternatives through information filtering techniques, and third, the role of supporting users' decision-making. Therefore, an integral part of the discussion on recommendation systems is how online services can support users' decision-making by analyzing data based on their interactions with customers and providing personalized alternatives. Gong et al. (2022) combined an airline ticket price prediction model with a personalized recommendation system to recommend the best airline tickets to customers. Burke (2002) categorized five types of algorithms: collaborative algorithms recommend alternatives that are of interest to users who have similar preferences to a particular user; content-based algorithms suggest alternatives based on similarity to previously selected alternatives; demographic algorithms recommend alternatives based on the choices made by people with similar demographic information; and utility algorithms recommend alternatives based on the delivery method, packaging, type of promotional activity, etc. Utility algorithm means recommending products that provide similar services to the existing selection based on delivery method, payment method, packaging, type of promotion, etc.

Recommendation algorithms on online platforms take into account a number of factors to provide users with the most suitable ticket options.

2.2. Relationship between Recommendation Algorithms and Perceived Recommendation Quality

Meuter et al. (2005) confirmed that convenience has recently been considered as a key factor in the purchase of goods, as consumers are very concerned about the ‘decision comport’ of online platforms and how quickly they can get the goods they want at the lowest possible cost. This means that consumers recognize convenience as a key area of service.

Tam et al. (2021) found that 'benefit convenience' is the most important core convenience for consumers, and the demand for benefit convenience is increasing due to the variety and speed of information available online.

The ‘curiosity’ of online platforms can experience satisfaction when users perceive that the results provided by the recommendation system are surprising, unexpected, and valuable (Lu & Cheng, 2020).

Chen et al. (2013) describes the ‘novelty’ of online platforms as the unexpectedness of receiving a good gift in a random box as a prize, and argue that this has a positive effect on perceived recommendation quality. Matt et al. (2015) argue that perceived recommendation quality is likely to be higher when the offer is particularly surprising. Kaminskas and Bridge (2016) argue that it is necessary to identify the role of novelty and satisfaction in recommender systems based on the results of a user survey.

In online platforms, 'evoked interest' is a positive experience that is one of the key requirements for a satisfactory experience (Lee et al., 2022), and De Gemmis et al. (2015) argued that in movie recommendation systems, positive interest is a prerequisite for perceived recommendation quality. Therefore, users can positively influence recommendation quality by showing high interest in the suggestions of the recommendation system.

In this study, the components of the algorithm that positively influence the perceived recommendation quality for online platforms are presented as four variables of decision comport, curiosity, novelty, and evoked interest based on previous studies, and the following hypotheses are set up.

H1: Decision comport on an online platform will positively influence perceived recommendation quality.
H2: Curiosity of the online platform will have a positive effect on perceived recommendation quality.
H3: Novelty of the online platform will have a positive effect on perceived recommendation quality.
H4: Evoked interest of online platforms will have a positive effect on perceived recommendation quality.

2.3. Relationship between Perceived Recommendation Quality and Recommendation Satisfaction

Benlian (2015) showed that the perceived appropriateness and enjoyment of recommendations in web services are differentially affected by the presentation method, which in turn affects the intention to continue using and the intention to pay. Nilashi et al. (2016) demonstrated that the accuracy, novelty, and diversity of perceived recommendation quality influence perceived information quality. Xiao and Benbasat (2007) showed that the perceived recommendation quality of a recommendation system leads to user satisfaction. Furthermore, if users perceive high recommendation quality as a cognitive response, it positively affects their perception of enjoyment, which is an effective response.

Chen et al. (2013) studied the effects of perceived service quality of O2O platforms on perceived usefulness and user satisfaction, and found that perceived ease of use, informativeness, responsiveness, and mobility positively affect perceived usefulness, and perceived usefulness positively affects customer satisfaction. Therefore, based on the previous research that if users of online platforms perceive high recommendation quality, they will be more satisfied with the service and their perception of enjoyment will increase, this study proposes the following hypothesis.

H5: The higher the perceived recommendation quality of an online platform, the higher the recommendation satisfaction.

2.4. Relationship between Perceived Recommendation Quality and Relationship Continuation Intention

Morgan and Hunt (1994) defined relationship continuance intention as the intention of a customer to continue to use a particular service or product for future benefit, with the possibility of repurchase, or to maintain a continuous transactional relationship. Relationship continuance intention is a dependency that is formed between a particular firm and an individual and is the result of customer satisfaction with the products or services provided by a particular firm with which the consumer intends to do business in the long term, and the behavior of the consumer to continue to do business or receive services from the firm (Zeithaml et al., 1996). Consumers gain satisfaction from a product or service by evaluating the difference between the expectations formed before consumption and the outcome after consumption (Caruana, 2002).

In line with previous research that perceived quality affects relationship continuance intention, this study hypothesizes the following.

H6: The higher the perceived recommendation quality of an online platform, the higher the relationship continuation intention.

2.5. Relationship between Recommendation Satisfaction and Relationship Continuation Intention

Relationship continuance intention is when customers who are satisfied with a transaction strengthen their relationship with the firm, which is manifested in word-of-mouth and repeat purchase intention. It has also been shown that higher perceived service quality increases satisfaction with the transaction, and higher satisfaction increases positive behavioral intention (Hsieh & Hiang, 2004). Oliver (1989) found that satisfaction influences attitude and affects the intention to continue the relationship.

Hsieh and Hiang (2004) found that higher perceived service quality increases satisfaction with the transaction, and higher satisfaction increases positive behavioral intentions. Most studies based on the late acceptance model, such as Lin et al.'s (2005) study on the continued use of web portal sites, show the same result that expectancy matching affects perceived usefulness and perceived usefulness affects relationship continuance intention. In addition, several studies on relationship continuance intention of information systems have verified that expectancy matching affects satisfaction and usefulness, and satisfaction is the main variable explaining relationship continuance intention.

Therefore, this study proposes the following hypotheses.

H7: Higher recommendation satisfaction from online platforms will increase relationship continuance intention.

3. Research Methodology

3.1. Research Model and Samples

This study expected that the characteristics of the recommendation algorithm of an online platform for airline ticket distribution would influence the relationship between perceived recommendation quality, recommendation satisfaction, and relationship continuance intention by reviewing the theoretical background of previous studies. It was expected that the characteristics of online platform recommendation algorithms, such as ease of decision comport, curiosity, novelty, and evoked interest, would lead to perceived recommendation quality, and then to recommendation satisfaction and relationship continuance intention. The research model of this study is shown in Figure 1.

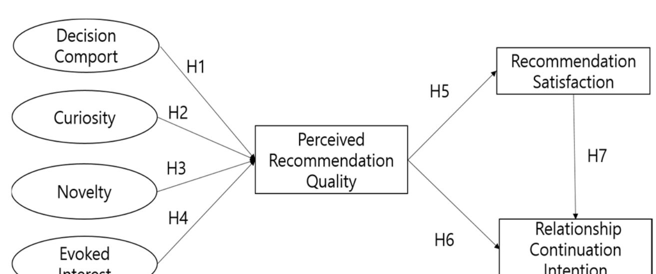

Figure1: Research Model

3.2. Measurement of Variable

Prior to conducting this study, the survey items were reformulated for the study by operationalizing the key variables. The definitions of manipulated variables are shown in <Table 1>.

4. Results

4.1. Empirical Analysis Result

The study utilized a non-face-to-face survey methodology.

The survey was conducted from May 1, 2024 to June 15, 2024 using a self-completion method by selecting consumers between the ages of 20-50 who have used online platforms to purchase airline tickets.

A total of 200 questionnaires were answered, but a total of 191 questionnaires were used for analysis, excluding those with problems.

The demographic characteristics of the 191 participants in the study's sample are shown in <Table 2>.

In this study, the construct validity of the measurement instrument is about the congruence between the construct and the variable measuring it, which indicates how well the construct is measured by the observed variable. Convergent validity, discriminant validity, and norm validity were verified, and the reliability of the measurement instrument was verified by evaluating internal consistency based on Cronbach's α coefficient. For construct validity and reliability, this study conducted confirmatory factor analysis using AMOS 18.0 and reliability analysis using PASW 18.0.

The final results of confirmatory factor analysis and reliability analysis are shown in <Table 3>.

This study utilized 7 latent variables and 26 observed variables to design the model, and the overall fit according to the confirmatory factor analysis results was very high.

In addition, the standardized factor loadings for the 26 measures were statistically significant and above 0.5.

The average variance extracted (AVE) and conceptual reliability (CCR), which are measures of convergent validity, met the criteria of AVE>0.5 and CCR>0.7, respectively.

Therefore, the measurement items of this study were determined to have sufficient convergent validity, and the Cronbach's α coefficients of all constructs were higher than the threshold of 0.6, indicating that the reliability of the measurement items selected in this study was also secured.

Table 1: Variable Definition

Factors		Definitions of Manipulative Variables	References
Recommendation Algorithms	Decision Comport	Comfort level with deciding to accept a recommended suggestion	Parker et al. (2016)
	Curiosity	The degree to which the suggestion sparks curiosity about something new	Peterson & Seligman (2007)
	Novelty	The degree to which the suggestion is novel enough to change your mind	Matt et al. (2015)
	Evoked Interest	The degree to which a suggested offer is engaging	Lee et al. (2022)
Perceived Recommendation Quality		Quality of information and practical usefulness of the suggestion	Benlian (2015)
Recommendation Satisfaction		Overall satisfaction with the recommendations	Zhao et al. (2014)
Relationship Continuation Intention		The customer's intent to use a particular service on an ongoing basis	Hsieh & Hiang (2004)

Table 2: Demographic Characteristics of the Respondents

Classification		Frequency (person)	Percentage (%)	Classification		Frequency (person)	Percentage (%)
Gender	male	99	51.8	Occupation	sales/service	52	27.2
	female	92	48.2		office job	46	24.0
Age	20 years of age	68	35.6		professional	39	20.4
	30 years of age	79	41.4		self-employment	7	3.7
	40 years of age	22	11.5		housewife	12	6.3
	50 years of age	22	11.5		students	32	16.8
Academic Background	College graduate	122	63.9		Etc.	3	1.6
	Graduate school	69	36.1	Use Platform In a year	over 1time	76	39.8
	Naver Ticket	95	49.8		over 3times	63	33.0
zOnline Platform	Interpark	29	15.2		over 5times	31	16.2
	Skyscanner	50	26.1		over 7times	17	8.9
	My real trip	15	7.9				
	Etc.	2	1.0				

Table 3: Verification Factor Analysis

Measurement		Standardization factor loading value	Std. error	C. R.	AVE (CCR)	Cronbach's α
Decision Comport	Decision Comport1	.831	-	-	.711 (.880)	.766
	Decision Comport2	.764	.046	7.684***		
	Decision Comport3	.927	.013	7.702***		
Curiosity	Curiosity1	.775	-	-	.719 (.887)	.754
	Curiosity2	.808	.084	12.202***		
	Curiosity3	.950	.070	14.900***		
Novelty	Novelty1	.776	-	-	.508 (.754)	.815
	Novelty2	.743	.144	8.468***		
	Novelty3	.608	.111	8.038***		
Evoked Interest	Evoked Interest 1	.811	-	-	.699 (.874)	.844
	Evoked Interest 2	.869	.074	14.714***		
	Evoked Interest 3	.827	.090	13.640***		
Perceived recommendation quality	Perceived Recommendation Quality1	.886	-	-	.650 (.917)	.815
	Perceived Recommendation Quality 2	.829	.081	8.045***		
	Perceived Recommendation Quality 3	.765	.077	8.691***		
	Perceived Recommendation Quality 4	.738	.071	8.383***		
	Perceived Recommendation Quality 5	.753	.060	9.660***		
	Perceived Recommendation Quality 6	.856	.094	9.017***		
Recommendation Satisfaction	Recommendation Satisfaction 1	.900	-	-	.818 (.947)	.785
	Recommendation Satisfaction 2	.797	.056	14.944***		
	Recommendation Satisfaction 3	.955	.042	22.892***		
	Recommendation Satisfaction 4	.956	042	19.806***		
Relationship Continuation Intention	Relationship Continuation Intention 1	.945	-	-	.825 (.950)	.799
	Relationship Continuation Intention 2	.830	.032	28.994***		
	Relationship Continuation Intention 3	.905	.042	18.343***		
	Relationship Continuation Intention 4	.949	.030	29.597***		
x^2(df)=942.09(278), nomal- x^2=3.389, RMR=.046, GFI=943, AGFI=.806, NFI=.937, TLI=.901, CFI=.956, RMSEA=.050						

***: p<.001

On the other hand, the correlation analysis results of this study are shown in <Table 4>. All correlations between each latent variable are less than or equal to 0.4 in absolute value, indicating that multicollinearity cannot be suspected, and the AVE values of all latent variables are greater than the squared values of the correlations between each latent variable, indicating that discriminant validity between each construct is satisfied.

In addition, the direction of the correlation between each construct is consistent with the hypotheses set in this study, and the law validity is also satisfied. Therefore, the construct validity of the measurement instrument of this study is satisfied.

Table 4: Verification of Discriminant Feasibility and Legal Feasibility

	Decision Comport	Curiosity	Novelty	Evoked Interest	Perceived Recommendation Quality	Recommendation Satisfaction	Relationship Continuation Intention
Decision Comport	.711^a	.018^b	.027^b	.066^b	.013^b	.027^b	.018^b
Curiosity	.135	.719^a	.030^b	.035^b	.012^b	.070^b	.040^b
Novelty	.164	.174	.508^a	.028^b	.040^b	.060^b	.060^b
Evoked Interest	.256	.188	.166	.699^a	.151^b	.075^b	.024^b
Perceived Recommendation Quality	.115	.111	.199	.388	.650^a	.106^b	.028^b
Recommendation Satisfaction	.165	.264	.244	.274	.325	.818^a	.024^b
Relationship Continuation Intention	.133	.199	.245	.155	.168	.155	.825^a

a: AVE, b: R^2

Table 5: Structural Equation Model Analysis Results

Path				Std.factor	Std.error	C.R.[c]	p-value	SMC[a]
H1	decision comport	→	perceived recommendation quality	.185	.031	3.103	.003	.826
H2	curiosity			.127	.748	1.214	.225	
H3	novelty			.595	.093	4.503	***	
H4	evoked interest			.766	.079	5.473	***	
H5	perceived recommendation quality	→	recommendation satisfaction.	.672	.238	5.127	***	.451
H6			relationship continuation Intention	.491	.076	6.430	***	.675
H7	recommendation satisfaction	→	relationship continuation intention	.406	.183	4.034	***	
x^2= 897.507(df=292, p=0), Normed-x^2 =3.074, RMR=.046, GFI=.918, AGFI=.805, NFI=.938, IFI=.958, TLI=.906, CFI=.925, RMSEA=.051								

***: p<.001, a. C.R. (Critical Ratio), b. SMC (Squared Multiple Correlation)

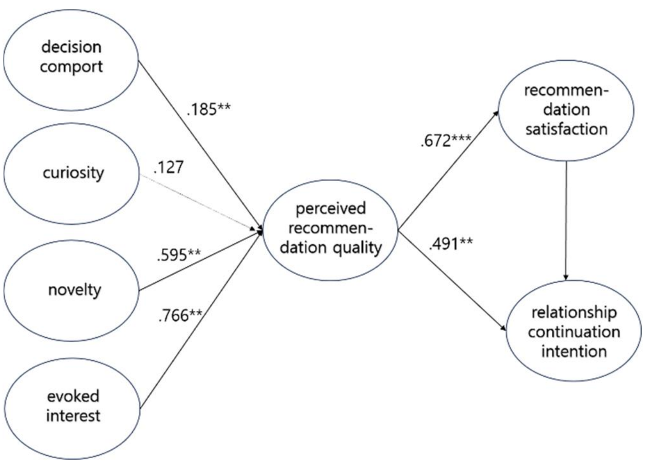

Figure 2: Analyzing Structural Equations

4.2. Hypothesis Verification

The results of the validation based on this research model are shown in <Table 5> and <Figure 2>.

Similar to the confirmatory factor analysis, the results of the fit analysis of this study showed that AGFI did not meet the criteria, but it is not an absolute criterion, and the rest of the indices except for this index highly met the criteria, so the setting of this research model was judged to be appropriate (=897. 507 (df=292, *p*=.000), Normed-=3.074, RMR=.046, GFI=.918, AGFI=.805, NFI=.938, IFI=.958, TLI=.906, CFI=.925, RMSEA=.051).

4.2.1. Relationship between Recommendation Algorithms and Perceived Recommendation Quality

To test Hypothesis 1, the effect of online platforms' decision comports on perceived recommendation quality, the standardized path coefficient of the effect of decision comport on perceived recommendation quality was .185 and the C.R value was 3.475 (p<.001), indicating a statistically significant effect. Therefore, H1 is accepted.

To test Hypothesis 2, the effect of curiosity of online platforms on perceived recommendation quality, the standardized path coefficient of the effect of curiosity on perceived recommendation quality was .227 and the C.R value was 1.214 (p>.05), which is not statistically significant. Therefore, H2 was rejected.

As a result of testing Hypothesis 3, the effect of online platform novelty on perceived recommendation quality, the standardized path coefficient of the effect of novelty on perceived recommendation quality was .595 and the C.R value was 4.503 (p<.001), indicating a statistically significant effect. Therefore, H3 is accepted.

To test Hypothesis 4, the effect of online platforms' evoked interest on perceived recommendation quality, the standardized path coefficient of the effect of novelty on perceived recommendation quality was .766 and the C.R value was 5.473 (p<.001), indicating a statistically significant effect. Therefore, H4 is accepted.

4.2.2. Relationship between Perceived Recommendation Quality and Satisfaction

To test Hypothesis 5, the effect of higher perceived recommendation quality of online platforms on recommendation satisfaction, the standardized path coefficient of the effect of perceived recommendation quality on recommendation satisfaction was .672 and the C.R value was 5.127 (p<.001), indicating a statistically significant effect. Therefore, H5 is accepted.

4.2.3. Relationship between Perceived Recommendation Quality and Relationship Continuation Intention

To test Hypothesis 6, the effect of higher perceived recommendation quality of online platforms on relationship continuation intention, the standardized path coefficient of the effect of perceived recommendation quality on relationship continuation intention was .491 and the C.R value was 6.43 (p<.001), indicating a statistically significant effect. Therefore, H6 is accepted.

4.2.4. Relationship between Recommendation Satisfaction and Relationship Continuation Intention

To test Hypothesis 7, the effect of higher recommendation satisfaction of online platforms on relationship continuation intention, the standardized path coefficient of the effect of recommendation satisfaction on relationship continuation intention was .406 and the C.R value was 4.034 (p<.001), which showed a statistically significant effect. Therefore, H7 was accepted.

5. Conclusion

5.1. Research Implications

The purpose of this study is to accumulate a large amount of data on how online platforms offer different airlines and different routes, and to analyze it so that they can improve their ticket distribution marketing strategies and provide services that better suit the needs of consumers.

The significance of this study is that first, this study extends the study of online platforms to online platforms related to airline ticket distribution. Second, this study focuses on the algorithmic characteristics of the recommendation system in the distribution process of airline tickets through online platforms. Third. Understanding the value of recommendation quality of online platforms by the algorithmic characteristics of the recommendation system, we analyzed in-depth the influence relationship between recommendation quality satisfaction and relationship continuation.

The hypothesis test results and theoretical implications of this study are as follows.

Hypothesis 1, 'Decision comport of online platforms will have a positive effect on perceived recommendation quality.' is accepted. It is found that the perceived decision comport of online platforms has a positive effect on consumers' perceived recommendation quality. These findings support previous research (Davis, 1989; Teo et al., 2003) that perceived decision comport has a significant impact on perceived quality.

Hypothesis 2, 'Curiosity of online platforms will have an effect on perceived recommendation quality,' was rejected. The curiosity provided by the online platform, which is defined as 'the degree to which the recommended offer arouses curiosity about the novelty of the offer,' was found to have no effect on generating positive recommendation quality. This result suggests that consumers using online platforms have the advantage of trusting the services provided by airlines and travel agencies first because they perceive the third-party online platform as already operating impartially (Xuemei et al., 2023). Although curiosity does not directly affect the quality of recommendations, it is an attribute of online platform algorithms that needs to be continuously improved.

Hypothesis 3, 'Novelty of online platforms will influence perceived recommendation quality,' was accepted. This result supports previous research (McCay & Toms, 2011; Matt et al., 2015) that suggests that the positive perception of unique and unexpected situations may have a positive impact on recommendation quality.

Hypothesis 4, 'Evoked interest of online platforms will influence perceived recommendation quality,' was accepted. This result supports the findings of previous studies that suggest that positive interest is a prerequisite for perceived recommendation quality (De Gemmis et al., 2015).

Hypothesis 5, 'The higher the perceived recommendation quality of the online platform, the higher the recommendation satisfaction', was accepted. Perceived recommendation quality refers to the information quality and practical fluidity of suggestions (Pu et al., 2011), and Wang and Benbasat (2009) suggested that high recommendation quality can lower users' information processing costs, leading to positive user responses.

Hypothesis 6, 'The higher the perceived recommendation quality of an online platform, the higher the relationship continuance intention,' is accepted. Therefore, it can be understood that the higher the perceived recommendation quality, the more useful it is to consumers, which is in line with previous studies that perceived quality affects relationship continuance intention (Kedah et al., 2015; Yan & Huping, 2019).

Hypothesis 7, 'The higher the recommendation satisfaction of online platforms, the higher the relationship continuance intention,' is accepted. Therefore, there is a relationship between recommendation satisfaction and relationship continuation intention of airline ticket online platforms and supports the findings of previous studies on the relationship between recommendation satisfaction and relationship continuance intention (Suhartanto et al., 2019; Yan & Huping, 2019).

The practical implications of the above results are as follows.

First, we can expect the components of the recommendation algorithm to affect the quality of recommendations, as shown in the results of H1, H2, H3, and H4. In order for the configuration of the recommendation algorithm to improve the quality of recommendations, the algorithm components should be easy to learn and provide convenience. It is also necessary to display current status information to help users understand what is going on in the process, and to provide a way to deal with errors if they occur during use. The design should be concise and consistent so that modifications and cancellations are easy to make and you can always go back to a previous step. The algorithmic configuration should also be interesting to the user and include alternatives that can pique their curiosity.

This means that the algorithm should have a wide range of alternatives for customers to choose from, and the perceived quality of recommendations will improve when online platforms can offer a variety of content and themes in their recommendations.

Second, in accordance with the results of H5, in order to increase satisfaction with the recommendation system, it is necessary to improve the quality of the recommended alternatives provided by the recommendation system. The services provided by online platforms are still limited. Although airlines are investing in promoting and marketing their online platforms, they are limited in recommending airline tickets based on customers' information and search history. Online ticketing platforms are accumulating a lot of data, which can be analyzed to identify travel trends and consumer preferences. This will allow airlines and the travel industry to improve their marketing strategies and provide services that better suit the needs of consumers. Subjective perceptions based on user experience are manifested as perceived recommendation quality, which directly affects system satisfaction and requires strategic management.

Third, as shown in H6, in order to improve the quality of online platform recommendations to increase the intention to continue the relationship, online platform operators need to continuously track and manage the perceived quality of recommendations as an indicator of consumer behavior. In addition, it is necessary to utilize online technologies and services of various portals (e.g., Naver, Instagram, Facebook) as well as online platforms to manage the quality of online platforms in order to ensure that the high quality of online platform recommendation systems can satisfy users.

Finally, the results of H7 confirm that relationship continuation intention increases when recommendation satisfaction increases. In various online services, recommendation systems are used as a strategic asset to increase competitiveness, suggesting that online platforms need to actively utilize recommendation systems to gain a differentiated competitive advantage. By building a recommendation system that satisfies users, online platforms can encourage users to visit more often and stay for a longer period of time, which can directly affect the platform operator's revenue and profit, including advertising revenue.

It is important to make such a system easily accessible to consumers, as it allows them to compare ticket prices of different airlines at a glance and find the cheapest tickets, as well as to get better prices and services in a competitive market environment. Online platforms not only provide access to multiple airlines and routes around the world on one platform, but they also make international travel easier and allow us to discover different destinations. For these reasons, it's important to continue researching online ticketing platforms. Online platforms will also need to be systems that use technology and data analytics to provide a better user experience and more benefits.

5.2. Limitations

This study has the following limitations and suggestions for further research.

First, this study focused on the recommendation system of online platforms for airline tickets and examined the satisfaction and relationship continuation intention of consumers, but the variables that determine the recommendation quality of the recommendation system should be expanded and applied to future studies.

Second, the study did not investigate and compare the differences in the recommendation quality perceived by users for different characteristics of online ticket distribution platforms. Therefore, future research should compare the actual mobile environment and service differences perceived by customers for airline ticket distribution online platforms to identify environmental improvements and problems of airline ticket distribution online platforms, and then conduct research related to airline ticket distribution online platforms.

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