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Shaping the itinerary: Perceived quality of recommendation systems on travel intentions a case study in Vietnam

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Abstract: This study aims to explore how recommendation systems (RS) influence the decision-making process of tourists. By examining the quality of RS, their impact on travel intentions, and the mediating role of satisfaction, the study seeks to model the decision-making process more effectively. Data were collected through a survey of 523 consumers in Vietnam who had previously used RS, employing a convenience sampling method. The survey questionnaire was distributed via email in the form of Google Forms. The study established a conceptual framework and tested the hypotheses using structural equation modeling (SEM). SPSS 26 was employed to assess the reliability of measurement scales, while AMOS 28 was used to evaluate the measurement and structural models. The findings indicate that consumers' positive perceptions of information quality, system quality, trust, and the usefulness of RS significantly enhance satisfaction and travel intentions. Notably, personalization does not directly influence perceived RS quality but exerts an indirect effect through the usefulness of RS. Satisfaction serves as a critical mediator in the relationship between perceived RS quality and travel intentions, emerging as the most influential factor within the model. This study underscores the effectiveness of decision-making driven by perceived RS quality in the tourism context. These findings provide valuable insights for policymakers and system developers to improve RS quality, thereby attracting tourists, enhancing competitive advantages in the tourism industry.
Keywords: *AI, Decision-making, Recommendation system, Tourism, Travel intention.*

1. Introduction

In an era characterized by digital transformation, the tourism industry has been profoundly influenced by technological innovations, particularly recommendation systems. These systems, powered by artificial intelligence (AI) and big data, have revolutionized how travelers select destinations, plan itineraries, and make decisions. By providing personalized suggestions, recommendation systems have emerged as a pivotal tool for enhancing user experiences, fostering satisfaction, and ultimately shaping travel intentions. Despite their increasing prevalence, understanding the nuanced role these systems play in mediating travel intentions remains underexplored.

The primary objective of this research is to investigate the mediating effect of recommendation systems on travel intentions, with a focus on how they influence traveler decision-making processes. While previous studies have acknowledged the role of recommendation systems in promoting personalized travel experiences, there exists a significant research gap in understanding their psychological and behavioral impacts on travelers through the central role of perceived quality of RS and the mediating role of satisfaction on consumer travel intentions. This study aims to bridge this gap by exploring the interplay between recommendation systems, user satisfaction, and subsequent travel intentions. The study highlights the increasing reliance on technology and RS in the travel decision-making process. The importance of understanding how RS influences consumer travel intentions.

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Furthermore, the research addresses a critical gap in the literature: the integration of technological affordances, such as explainability and perceived trust in recommendation systems, into models of travel behavior. By doing so, the study contributes to a more comprehensive understanding of how advanced digital tools can shape consumer behavior in tourism. Additionally, it aligns with the growing need for sustainable tourism development by highlighting how technology can optimize resource utilization through informed decision-making. To accomplish this goal, the study will answer the following questions:

1. What factors influence perceived quality of RS in forming travel intentions?

2. What is the mediating role of satisfaction in the relationship between perceived quality of RS and travel intentions?

In light of the limited research on the role of recommendation systems in shaping travel intentions, this study holds significant theoretical and practical implications. It not only enriches the theoretical framework of travel behavior but also offers actionable insights for tourism stakeholders, including destination management organizations and technology developers, to design more effective, user-centric recommendation systems.

The following sections of the study will present the foundational theories related to the research topic, hypotheses, proposed research model, research methodology, results, and discussion. The final section will offer conclusions and managerial implications.

2. Literature Review and Research Model

2.1. The Technology Acceptance Model (TAM)

In the context of recommendation systems, the application of TAM can elucidate how these systems enhance user experiences and influence travel intentions. Examines perceived ease of use and usefulness in adopting RS. Yang et al. found that technological acceptance and readiness significantly impact flow experiences in virtual tourism, which subsequently affects users' intentions to visit destinations [1]. This indicates that when users perceive recommendation systems as easy to use and beneficial, they are more likely to engage with them and develop a positive intention to travel. Sari et al. further support this notion by demonstrating that understanding user acceptance through TAM is crucial for developing effective marketing strategies in tourism [2]. Their findings suggest that as users become more comfortable with technology, they are more likely to embrace digital tools that facilitate their travel planning, including recommendation systems.

The TAM serves as a valuable framework for understanding the acceptance of recommendation systems in tourism. By focusing on perceived ease of use, perceived usefulness, user satisfaction, and trust, stakeholders can enhance the effectiveness of these systems and positively influence travelers' intentions. As technology continues to evolve, leveraging TAM will be essential for developing user-centric recommendation systems that meet the needs of modern travelers.

2.2. The Information Systems Success Model (ISSM)

The Information Systems Success model, developed by [3] provides a comprehensive framework for evaluating the effectiveness of information systems, including recommendation systems in tourism. This model identifies several key dimensions that contribute to the success of information systems: system quality, information quality, service quality, use, user satisfaction, and net benefits. System quality refers to the technical performance and usability of the recommendation system. High system quality ensures that the system is reliable, user-friendly, and responsive to user needs. Research by Yan and Lee highlights that the quality of restaurant recommendation information on tourism websites significantly impacts user satisfaction and their intention to visit destinations [4]. This suggests that a well-designed recommendation system that functions effectively can lead to higher user satisfaction, which is crucial for fostering positive travel intentions. Information quality encompasses the accuracy, relevance, and timeliness of the recommendations provided. In tourism, where users often seek specific and reliable information, high information quality is essential. The study by Masri et al. emphasizes that the quality of information systems directly influences customer satisfaction and their intention to continue using e-tourism services [5]. When travelers receive accurate and relevant recommendations, their satisfaction increases, which in turn enhances their likelihood of engaging in travel activities.

2.3. The Stimulus-Organism-Response (SOR)

The Stimulus-Organism-Response model [6] has been widely used in tourism research to examine the relationships between various factors that influence tourist behavior and decision-making. The SOR model posits that environmental stimulus (S) can influence an individual's internal states (O), which in turn shape their behavioral responses (R) [7-9]. In the context of tourism, the stimuli can include various factors such as tourism policies, virtual reality technologies, user-generated content, service encounters, and destination marketing efforts [7, 8, 10, 11]. Furthermore, the references emphasize the importance of integrating the SOR model with other theoretical frameworks, such as the Technology Acceptance Model, Flow Theory, and Attitude-Behavior-Context Theory, to provide a more comprehensive understanding of tourist behavior [12, 13].

2.4. Recommendation Systems in Tourism

The development of recommendation systems in tourism has become increasingly sophisticated, leveraging various technologies and methodologies to enhance user experience and personalization. These systems aim to provide tailored suggestions based on individual preferences, behaviors, and contextual factors, thereby improving the overall travel experience. One of the foundational aspects of tourism recommendation systems is their ability to process and analyze large volumes of data. As noted by Kamal and Chatzigiannakis, managing extensive data sets is significant, necessitating systems that can deliver personalized recommendations based on user preferences and behaviors [14]. This is echoed by Hong et al., who emphasize that modern recommender systems utilize explicit and implicit feedback from users to align tourism offerings with their needs [15]. Furthermore, Park and Kim highlight the importance of adapting descriptive information to meet diverse traveler categories, underscoring the necessity for context-aware systems that can cater to varying user demands [16].

Moreover, the emergence of real-time context-aware systems has revolutionized how recommendations are generated. Yoon and Choi present a model that adjusts recommendations based on real-time data, enhancing the relevance of suggestions for tourists [17]. This dynamic approach is crucial in the fast-paced tourism environment, where user preferences can shift rapidly. Additionally, the work of Frikha et al. emphasizes the role of semantic user profiles in improving recommendation accuracy by aligning suggested activities with users' historical preferences [18].

2.5. The Influence of Technological Factors on Perceived Quality of RS

The perceived quality of recommendation systems is influenced by several interrelated factors, including information quality, system quality, trust, perceived usefulness, and personalization. Each of these elements plays a critical role in shaping user experiences and satisfaction with recommendation systems, particularly in contexts such as e-commerce and tourism.

Information quality refers to the accuracy, relevance, and timeliness of the data provided by the recommendation system. High-quality information enhances user satisfaction and trust in the system, as users are more likely to rely on recommendations that are perceived as credible and useful [19]. System quality encompasses the technical performance of the recommendation system, including its usability, reliability, and responsiveness. Research by Zhang and Cao indicates that both information quality and system quality significantly impact user satisfaction and their intention to continue using the system [20]. Similarly, Karajizadeh et al. emphasize that usability is a critical aspect of system quality that influences user engagement and satisfaction in clinical decision support systems, which can be extrapolated to other domains, including tourism [21].

Trust is a vital component in the acceptance and effectiveness of recommendation systems. Users are more likely to engage with a system if they trust the information it provides. Özdemir and Nacar highlight that perceived trust positively influences users' intentions to purchase and engage with recommendations [22, 23]. Furthermore, perceived usefulness is defined as the degree to which a user believes that using a particular system enhances their performance is a significant predictor of user acceptance. Mican and Sitar-Tăut found that the perceived usefulness of personalized recommendations directly influences users' purchase intentions, reinforcing the importance of delivering relevant and effective suggestions [24].

Personalization is another crucial factor that enhances the perceived quality of recommendation systems. Systems that provide tailored recommendations based on individual user preferences and behaviors are more likely to be perceived as valuable and useful. Research by Laban and Araujo indicates that personalization techniques significantly affect users' perceptions of conversational recommender systems, suggesting that users appreciate recommendations that feel customized to their needs [25]. This aligns with findings from Knijnenburg, et al. [26] who argue that personalization not only improves the relevance of recommendations but also enhances user satisfaction and trust in the system [26].

Personalization in recommendation systems involves customizing the recommendations based on user-specific data, such as past interactions, preferences, and social influences. Research by Zhang and Liu indicates that personalized recommendations are crucial for matching users with products that align with their tastes, thereby enhancing user satisfaction and loyalty [27]. This is further supported by Golbeck, who emphasizes that personalized ratings derived from trusted sources can provide users with recommendations that better reflect their individual preferences, especially in cases where they may disagree with average ratings [28]. The ability to provide relevant and personalized suggestions is a key determinant of a recommendation system's perceived usefulness. Therefore, the following hypotheses are proposed:

H_1: Information positively influences the perceived quality of RS.

H_2: System positively influences the perceived quality of RS.

H_3: Trust positively influences the perceived quality of RS.

H_4: Usefulness positively influences the perceived quality of RS.

H_5: Personalization positively influences the perceived quality of RS.

H_6: Personalization positively influences the perceived of Usefulness.

2.6. Perceived quality of RS and Satisfaction

Perceived quality encompasses several dimensions, including the accuracy of recommendations, the relevance of suggested items, and the overall user experience with the system. Research by Kim et al. indicates that when recommendation systems provide items that align closely with user preferences, satisfaction levels tend to increase significantly [29]. However, the study also highlights that if a system consistently recommends similar items, user satisfaction may decrease despite high accuracy. This suggests that a balance between accuracy and diversity is essential for maintaining user engagement and satisfaction.

In a similar vein, He emphasizes that merely improving the accuracy of recommendations is insufficient for enhancing user satisfaction. Instead, factors such as diversity and novelty must also be considered [30]. This aligns with the findings of Zhang, who notes that user satisfaction is not solely dependent on the accuracy of recommendations but also on how well the system supports decision-making through diverse and novel suggestions [31]. Thus, perceived quality in recommendation systems is a composite measure that includes not only accuracy but also the variety and novelty of recommendations. Therefore, the following hypothesis is proposed:

H_7: Perceived quality of RS positively influences the Satisfaction

2.7. Perceived quality of RS and Travel Intention

The perceived quality of recommendation systems plays a significant role in influencing travel intentions. This relationship can be understood through various dimensions of perceived quality, including system quality, information quality, and user satisfaction, which collectively shape travelers' attitudes and intentions to engage in tourism activities.

Research by Jung et al. indicates that both system quality and information quality significantly influence users' behavioral intentions to utilize mobile technologies for travel planning [32]. This finding suggests that when travelers perceive a recommendation system as high-quality, they are more likely to intend to travel based on the suggestions provided.

The influence of perceived quality of recommendation systems on travel intentions can be further elucidated through the lens of the Theory of Planned Behavior (TPB). Wang et al. explored how perceived risk and age moderate the relationship between subjective norms and travel intentions, highlighting that positive perceptions of recommendation systems can enhance travelers' attitudes towards travel [33]. When users trust the quality of the recommendations, they are more likely to feel confident in their travel decisions, which can lead to increased travel intentions. Therefore, the following hypothesis is proposed:

H_8: Perceived quality of RS positively influences Travel Intention.

2.8. Satisfaction and Travel Intention

The relationship between user satisfaction with recommendation systems and travel intention is a critical area of study in tourism research. This relationship is influenced by various factors, including the perceived quality of the recommendation system, user trust, and the overall user experience.

User satisfaction is closely linked to the perceived quality of recommendation systems. High-quality recommendations that accurately reflect user preferences can significantly enhance satisfaction levels. For instance, Wibawa et al. found that the perceived quality of destination recommendations positively influences travelers' intentions to recommend those destinations to others [34]. This suggests that when users are satisfied with the recommendations they receive, they are more likely to express positive travel intentions, such as revisiting or recommending the destination to friends and family.

The context in which recommendations are made also influences user satisfaction and travel intentions. Neuburger and Egger emphasize that travel risk perception can lead to travel anxiety, which negatively affects travel intentions [35]. Therefore, recommendation systems that effectively address these concerns by providing relevant and reassuring information can enhance user satisfaction and, consequently, travel intentions.

Additionally, the role of electronic word-of-mouth (eWOM) cannot be overlooked. Yadav et al. highlight that the surge in travel experiences and information sharing on social media has led travelers to rely on eWOM for their travel decisions [9]. Positive eWOM can enhance user satisfaction with recommendation systems, further influencing travel intentions. When users perceive that others have had positive experiences based on recommendations, their own intentions to travel may increase. Therefore, the following hypothesis is proposed:

H_9: Satisfaction positively influences Travel Intention

By comprehensively reviewing the relevant literature and underlying theories, the authors identified a research gap related to the research topic. Based on this understanding, the authors developed a hypothesis and proposed a research model based on the integration of TAM, ISS, and SOR models (Figure 1).

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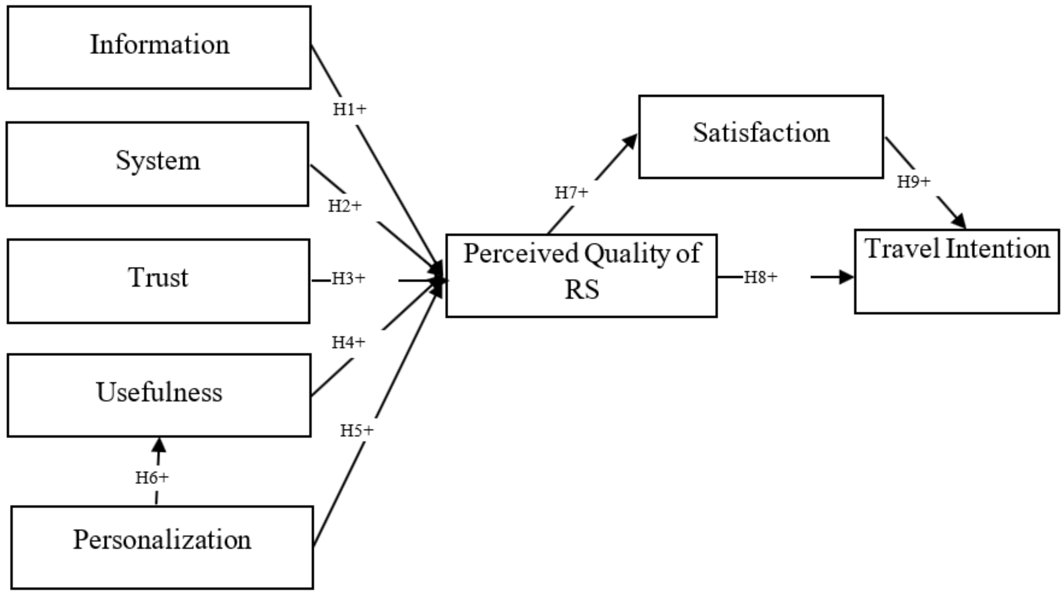

Figure 1.
Proposed research model.

3. Research Methods

3.1. Measurement Instruments and Data Collection

The measurement scales in this study are adapted from those used in previous research. Following a qualitative study, and based on the feedback and recommendations of experts, the scales will be adjusted to align with the research context. Appendix 1 presents the measurement scales inherited from previous studies.

Data was collected through online survey methods using convenience sampling. After more than two months of survey, more than 1,000 questionnaires were sent out via email and other communication channels, and after more than 2 months of sending, the number of responses received was 545 (response rate 55%). After cleaning and removing 22 invalid responses, the number of remaining questionnaires included in the official study was 523.

3.2. Data Analysis

The study adopts the Structural Equation Modeling (SEM) approach to test the proposed research model. SEM enables the simultaneous examination of multiple causal relationships between latent variables and observed variables, making it particularly effective for analyzing complex theoretical models with interactions among various factors [36]. SEM also provides model fit indices such as CFI, TLI, RMSEA, and chi-square/df, which are used to assess the alignment between the data and the theoretical model. Hence, the research team chose Covariance-Based SEM (CB-SEM) as the primary method to validate the model, with Maximum Likelihood Estimation employed for parameter estimation.

To test the reliability of the measurement scales and conduct Exploratory Factor Analysis (EFA), the study utilizes SPSS 26. Confirmatory Factor Analysis (CFA) and Average Variance Extracted (AVE) are applied to evaluate the measurement model, with the support of AMOS software.

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4. Research Results

4.1. Profile of the Sample

The statistical results of the research sample show that female demographics account for 59% of the sample, male demographics account for 41%, Regarding age distribution, people under 18 years old account for 4%, from 18 to 30 years old account for 61%, from 30 to 50 years old account for 25% and people over 50 years old account for 10%.

Regarding occupation, the results show that respondents who are students account for 22%, followed by office workers with the highest proportion at 54%. Meanwhile, workers make up 15%, and other occupations constitute the smallest proportion at 8%.

For the question "*Are you satisfied quality of recommendation systems?*", the number of people answering Yes is 390, accounting for 75% and the number of people answering No is 133, accounting for 25%. Table 1 shows detailed statistics of the research sample.

Table 1.
Research sample size and structure.

Characteristics	Frequency	Percentage
Gender		
Male	215	41%
Female	308	59%
Age		
Under 18 years	22	4%
18 - 30 years	320	61%
30 - 50 years	129	25%
Over 50 years	52	10%
Occupation		
Student	115	22%
Office staff	285	54%
Worker	80	15%
Others	43	8%
Are you satisfied with the quality of recommendation systems?	390	75%
Yes	133	25%
No		

Source: Results from SPSS.

4.2. Assessment of Measurement Model

To assess the measurement model, the authors plan to evaluate the reliability of the scales and perform both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). An oblique rotation technique will be used to determine the convergent and discriminant validity of all variables included in the model. The reliability of the variables will be measured based on specific thresholds: Cronbach's Alpha coefficient and composite reliability should each meet or exceed the value of 0.7 [36].

Eight factors with 37 variables were analyzed. After assessing the reliability using Cronbach's alpha, the results indicated that all factors met the reliability criteria. Notably, the lowest alpha value was 0.80, corresponding to the minimum composite reliability (CR) value of 0.807. All these factors satisfy the technical requirements for conducting exploratory factor analysis (EFA).

For convergent validity, the AVE threshold is 0.5, and the minimum factor loading is 0.6 [37]. Following the EFA of 37 variables, the results indicated that two variables, TRS4 and PQRS2, had factor loadings below 0.5 and were therefore excluded from the model. The remaining 35 variables were used for the second EFA. The results of the variance analysis extracted using EFA for the scales are presented in a summary in Table 2.

Table 2.
Reliability and Validity Measures.

Variables	Items	Loading	∝	CR	AVE
Information (INF)	INF1	0.716	0.86	0.863	0.559
	INF2	0.812			
	INF3	0.827			
	INF4	0.643			
	INF5	0.724			
System (SYS)	SYS1	0.734	0.87	0.867	0.565
	SYS2	0.786			
	SYS3	0.746			
	SYS4	0.771			
	SYS5	0.693			
Trust (TRS)	TRS1	0.667	0.84	0.828	0.547
	TRS2	0.798			
	TRS3	0.704			
	TRS5	0.727			
Usefulness (PU)	PU1	0.703	0.84	0.843	0.573
	PU2	0.854			
	PU3	0.679			
	PU4	0.710			
Personalization (PP)	PP1	0.729	0.80	0.807	0.511
	PP2	0.696			
	PP3	0.715			
	PP4	0.727			
Perceived Quality of RS (PQRS)	PQRS1	0.719	0.85	0.840	0.567
	PQRS3	0.551			
	PQRS4	0.804			
	PQRS5	0.733			
Satisfaction (SAT)	SAT1	0.730	0.87	0.863	0.568
	SAT2	0.702			
	SAT3	0.787			
	SAT4	0.734			
	SAT5	0.753			
Travel Intention (TINT)	TINT1	0.653	0.85	0.851	0.588
	TINT2	0.671			
	TINT3	0.644			
	TINT4	0.832			

Source: Results from SPSS and AMOS.

The CFA analysis results indicate that the proposed model is appropriate, as evidenced by the overall goodness-of-fit indices: Chi-Square/df = 1.156 (<3), GFI = 0.938, CFI = 0.990 (>0.9), TLI = 0.989 (>0.9), and RMSEA = 0.022 (<0.08), all of which satisfy the required thresholds (Figure 2).

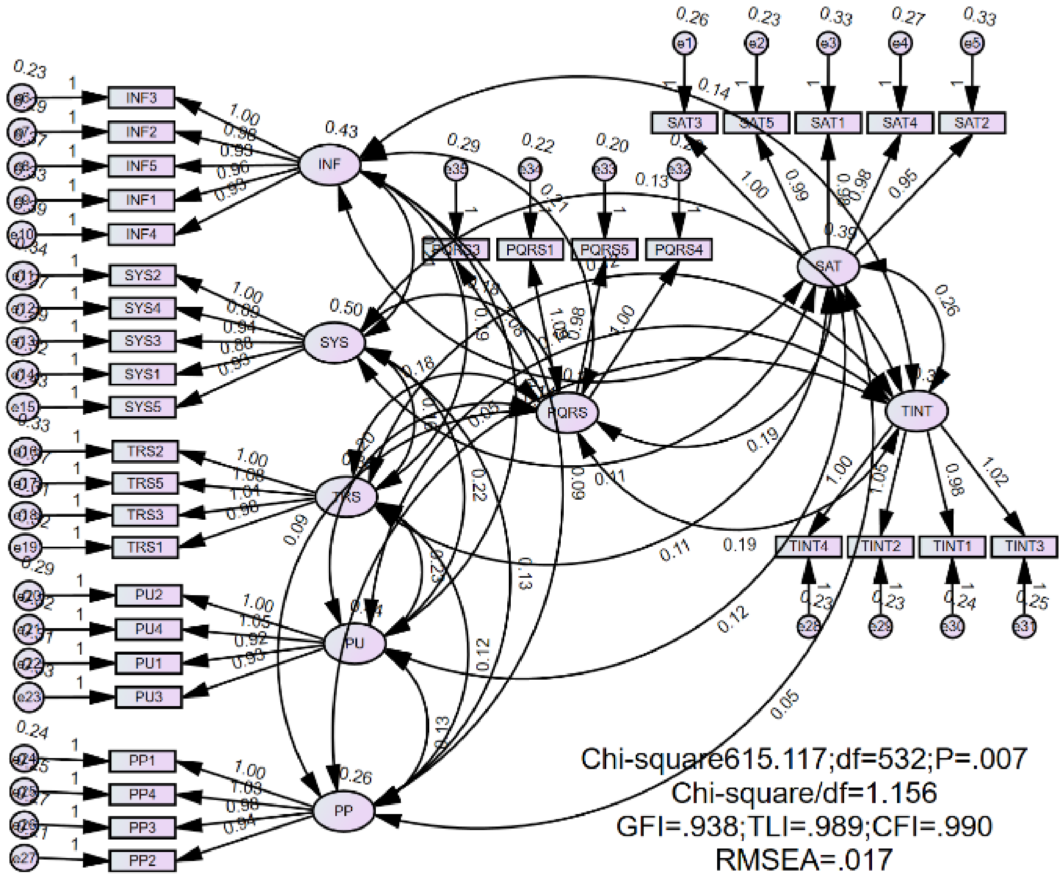

Figure 2.
CFA model.

Table 3 displays the results of the discriminant validity assessment, showing that the square root of AVE exceeds the correlation values in both rows and columns. Consequently, based on the Fornell-Larcker criteria [38], the research constructs in the theoretical model satisfy the discriminant validity requirements.

Table 3.
Discriminant validity test.

Items	SAT	INF	SYS	TRS	PU	PP	TINT	PQRS
SAT	0.754							
INF	0.330***	0.748						
SYS	0.254***	0.457***	0.752					
TRS	0.285***	0.467***	0.376***	0.739				
PU	0.288***	0.472***	0.463***	0.563***	0.757			
PP	0.162**	0.276***	0.361***	0.392***	0.387***	0.715		
TINT	0.742***	0.373***	0.319***	0.337***	0.357***	0.173**	0.767	
PQRS	0.595***	0.623***	0.499***	0.560***	0.577***	0.358***	0.643***	0.753

Source: Results from AMOS.

4.3. Structural Model and Hypotheses Test

A total of nine hypotheses were formulated to test the study's conceptual framework. The analysis results, shown in Figure 3, confirm that the model's overall fit indices meet the necessary technical standards: GFI = 0.937, TLI = 0.990 (>0.9), CFI = 0.991 (>0.9), and RMSEA = 0.017 (<0.08), all within acceptable thresholds.

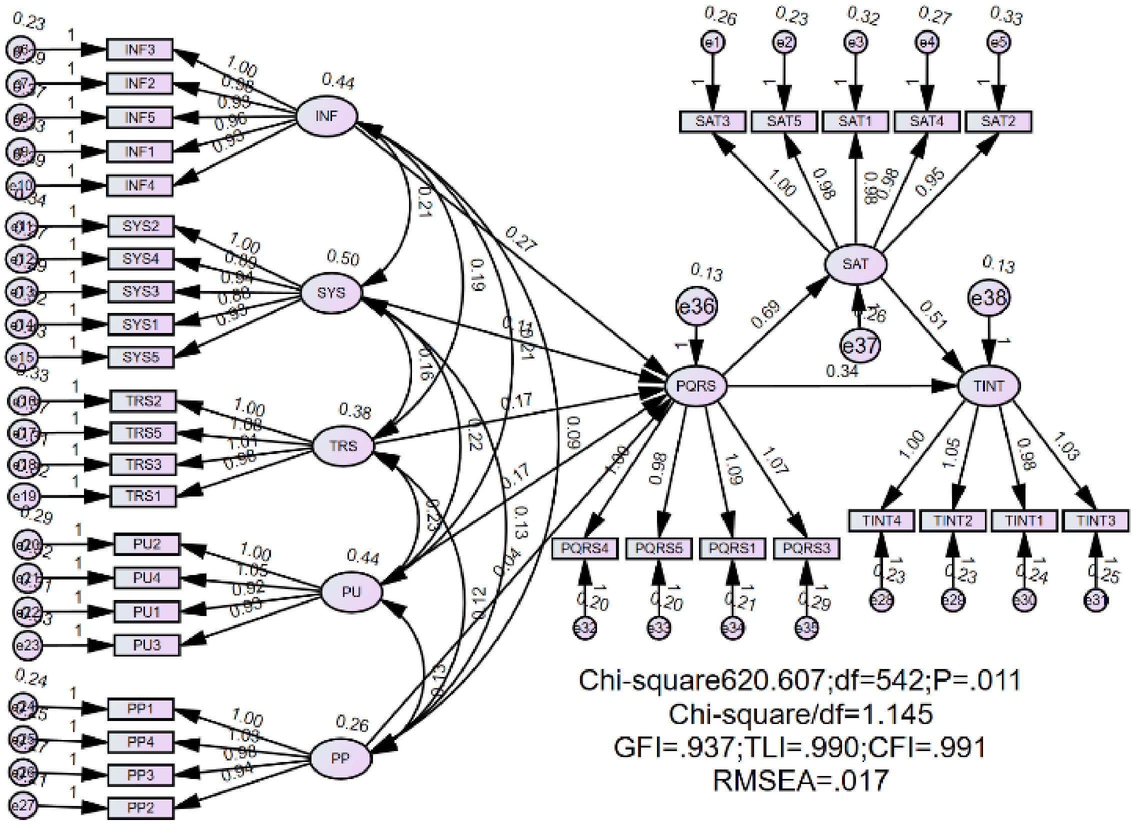

Figure 3.
Test research hypotheses using SEM.

The research findings indicate that the factors INF, SYS, TRS, PU, and PP positively influence PQRS. Furthermore, PQRS positively affect SAT and TINT, while SAT also has a positive impact on TINT (Table 4).

Table 4.
Regression weights of theoretical relationships.

Hyp	Relationship			Wei	S. E	C.R	p	Conc
H1	PQRS	<---	INF	0.274	0.041	6.673	***	Accepted
H2	PQRS	<---	SYS	0.115	0.036	3.192	0.001	Accepted
H3	PQRS	<---	TRS	0.178	0.044	4.021	***	Accepted
H4	PQRS	<---	PU	0.183	0.037	4.949	***	Accepted
H5	PQRS	<---	PP	0.020	0.058	0.344	0.731	Rejected
H6	PU	<---	PP	0.603	0.075	8.092	***	Accepted
H7	SAT	<---	PQRS	0.691	0.066	10.512	***	Accepted
H8	TINT	<---	PQRS	0.338	0.058	5.854	***	Accepted
H9	TINT	<---	SAT	0.515	0.052	9.920	***	Accepted

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5. Discussion

The findings of this study provide important insights into the dynamics of recommendation systems and their impact on perceived quality, satisfaction, and travel intentions. Information, System, and Trust Factors: The positive relationships between the perceived quality of recommendation systems and information ($\beta=0.274$, $p<0.001$), system ($\beta=0.115$, $p<0.01$), and trust ($\beta=0.178$, $p<0.001$) align with the findings of Zhang and Benyoucef (2016), who emphasized the role of trust and system functionality in shaping user satisfaction with recommendation systems. Furthermore, high quality information provided by the recommendation system, in terms of accuracy, completeness, and relevance, can enhance user trust and lead to positive behavioral intentions [20, 39].

System quality is another important factor that affects the perceived quality of recommendation systems. Factors such as system accessibility, flexibility, reliability, and timeliness have been shown to impact user satisfaction and revisit intentions [40, 41]. Well-designed and user-friendly recommendation systems can improve the overall user experience [40, 41].

Trust is a critical factor that influences the perceived quality of recommendation systems. Studies have found that users' trust in the recommendation system is a significant predictor of their satisfaction and loyalty [42]. Factors such as transparency, perceived reliability, and the system's ability to provide accurate and personalized recommendations can enhance user trust [42].

Usefulness and Perceived Quality: Usefulness ($\beta=0.183$, $p<0.001$) was also found to significantly contribute to the perceived quality of recommendation systems. This corroborates the study by Davis [43] which introduced the Technology Acceptance Model, highlighting perceived usefulness as a key determinant of technology adoption.

Personalization and Perceived Quality: Interestingly, personalization did not show a significant relationship with perceived quality ($\beta=0.02$, $p=0.731$), contrasting with findings by Fan and Poole [44] who identified personalization as critical for enhancing the user experience in e-commerce platforms. This discrepancy could be attributed to contextual differences in study designs or participant demographics. When users receive an excessive number of personalized recommendations, they may feel overwhelmed. This can result in dissatisfaction with the recommendation system, even if the system functions effectively. Users often have high expectations for personalized systems. If these expectations are not met, their perception of quality may be negatively affected. Additionally, some users may dislike being monitored or evaluated based on their behavior. This could lead to negative sentiments toward the recommendation system, regardless of whether it employs personalization.

Satisfaction and Travel Intention: Satisfaction was significantly influenced by the perceived quality of recommendation systems ($\beta=0.691$, $p<0.001$), supporting studies such as Kim, et al. [8] which demonstrated satisfaction as a mediator between system quality and user outcomes. Additionally, satisfaction positively impacted travel intention ($\beta=0.515$, $p<0.001$), consistent with the work of Shi and Lee [4] who explored satisfaction's role in predicting travel behavior. This highlights the role of RS quality in user perceptions, where higher RS quality significantly influences greater user satisfaction.

Direct impact of Perceived Quality of Recommendation Systems on Travel Intention: The direct relationship between perceived quality and travel intention ($\beta=0.338$, $p<0.001$) reflects findings by Elci, et al. [45] and Ali, et al. [46] who highlighted the effectiveness of high-quality recommendation systems in influencing consumer decision-making.

6. Conclusions

This study underscores the pivotal role of RS quality in shaping user satisfaction and travel intentions. Key findings indicate that factors such as information quality, system functionality, and trust significantly influence users' perceptions of RS quality. Additionally, the usefulness of these systems plays a crucial role in enhancing their perceived quality. Interestingly, personalization did not exhibit a significant relationship with perceived RS quality, suggesting that excessive or poorly implemented personalization may lead to user dissatisfaction.

Furthermore, user satisfaction emerged as a critical mediator, bridging the perceived quality of RS with travel intentions. The direct influence of RS quality on travel intention highlights the potential of well-designed recommendation systems to positively impact consumer behavior. These results offer valuable insights for improving RS design to better meet user expectations and foster positive outcomes in tourism and other domains, such as distribution science.

While this study provides important contributions, several limitations must be acknowledged. First, the study's findings may be context-specific, as the demographic and behavioral characteristics of participants could influence the results. Second, the rejection of personalization as a significant factor might be attributed to measurement tools or the specific implementation of personalization within the study's scope. Future research could refine these measurements or explore alternative models of personalization. Lastly, the cross-sectional nature of the data limits the ability to infer causal relationships, warranting further longitudinal studies to validate these findings.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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Appendix 1. Instruments development.

No	Variable	Code	Instruments	References
1	Information (INF)	INF1	The recommendations provided are accurate and relevant to my needs	[3, 47]
		INF2	The recommendation system provides comprehensive information to help make decisions	
		INF3	The recommendations are delivered promptly when needed	
		INF4	The information provided by the recommendation system is consistent across different scenarios	
		INF5	The recommendation system provides information that aligns with my preferences	

			and interests	
2	System (SYS)	SYS1	The recommendation system operates quickly and efficiently	[28, 48, 49]
		SYS2	The recommendation system is easy to navigate and use	
		SYS3	The recommendation system integrates well with other tools or platforms I use	
		SYS4	The system is stable and rarely causes crashes or encounters errors.	
		SYS5	The system responds promptly to my inputs or actions	
3	Trust (TRS)	TRS1	I trust the recommendation system because it demonstrates expertise i understanding my preferences.	[28, 48]
		TRS2	I trust the recommendation system because it performs consistently over time	
		TRS3	I trust the recommendation system because it provides clear explanations for it suggestions	
		TRS5	I trust that the recommendation system provides unbiased suggestions withou hidden agendas	
4	Usefulness (PU)	PU1	The recommendation system helps me achieve my goals effectively	[28, 48, 49]
		PU2	The system provides recommendations that are highly relevant to my needs	
		PU3	The recommendation system helps me make better decisions	
		PU4	The recommendations provided by the system are easy to apply in real situations	
5	Personalization (PP)	**PP1**	The recommendations provided by the system are tailored to my individua preferences and interests	
		PP2	The recommendation system adapts to my behavior over time to improve th relevance of suggestions	
		PP3	The system offers diverse recommendations while still matching my preferences	
		PP4	The system frequently updates my profile to improve personalization based o recent interactions	
6	Perceived Quality of RS (PQRS)	**PQRS1**	Manufacturers provide users with high quality recommendation systems in trave decision making	[28, 48, 50]
		PQRS3	Manufacturers always meet users' quality standards for recommendation system in travel decision making	
		PQRS4	Manufacturers' recommendation systems are very reliable in travel decisio making	
		PQRS5	Recommendation systems are suitable for use in travel decision making	
7	Satisfaction (SAT)	**SAT1**	I am satisfied with the overall quality of recommendations provided by the system	[51-53]
		SAT2	I am satisfied with how easy it is to interact with the recommendation system	
		SAT3	The recommendations I receive are useful for making decisions, which increase my satisfaction	
		SAT4	The quality of the recommendations exceeds my expectations	
		SAT5	I am consistently satisfied with the recommendations provided over time	
8	Travel Intention (TINT)	TINT1	The system provides recommendations that align with my travel preferences increasing my intention to travel.	
		TINT2	The recommendation system simplifies the travel planning process, making m more likely to plan a trip	
		TINT3	The recommendation system helps me decide where to travel	
		TINT4	I am likely to visit a destination recommended by the system	