Journal of Information Systems Engineering and Management
2025, 10(3s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Perceptions of AI-Driven Dynamic Pricing Strategies and Their Financial Impact on Vietnamese Tourism Companies

Thi Thanh Nhan Nguyen[1], Thi Kim Thanh Nguyen[2*]
[1]*Dr, Hai Phong University, Vietnam, https://orcid.org/0009-0007-9026-2408*
[2]*Dr, Electric Power University, Vietnam, https://orcid.org/0009-0005-6743-094X*
[*]***Corresponding Author:*** *thanhntk@epu.edu.vn*

ARTICLE INFO

Received: 06 Oct 2024
Revised: 12 Dec 2024
Accepted: 22 Dec 2024

ABSTRACT

This study was conducted to answer the question of how artificial intelligence-based pricing systems affect customer satisfaction and the financial performance of Vietnamese travel agencies. The study was conducted to explore factors that enhance customer satisfaction and financial performance in travel agencies using artificial intelligence-based pricing strategies, with a specific focus on understanding the interaction between the effectiveness of perceived artificial intelligence systems, the extent to which artificial intelligence is applied, the trust of regulators, and perceptions of price fairness based on artificial intelligence. Using a linear structure model, we collected and analyzed survey data from 372 people to test five research hypotheses. The findings show that the perceived effectiveness of artificial intelligence systems, the level of application of artificial intelligence and the trust of managers significantly increase customer satisfaction, thereby positively impacting the financial performance of travel companies in Vietnam. However, the study did not find a statistically significant effect of perceptions of price fairness based on artificial intelligence on customer satisfaction. These results are important because they show that travel companies need to focus on the application of effective, adaptive and reliable artificial intelligence systems while addressing fairness concerns through transparency and effective communication with customers. The implications underscore how travel companies can improve the customer experience and achieve financial efficiencies by leveraging artificial intelligence technologies in their dynamic pricing strategies.

Keywords: AI, dynamic pricing strategy, financial performance, Vietnam

INTRODUCTION

The advancement and rapid adoption of Artificial Intelligence (AI) has transformed the dynamic pricing strategies of many industries globally, with significant implications for the tourism industry. Dynamic pricing, which involves real-time price adjustments based on factors such as demand, competition, and customer behavior is increasingly supported by AI to enhance decision-making and profitability (Huang & Rust, 2018). Around the world, companies such as airlines, hotel chains, and online travel agencies have leveraged AI-driven pricing systems to optimize revenue management, respond to market changes, and personalize pricing strategies for customers (Wamba et al., 2017). These systems use large amounts of data and machine learning algorithms to provide real-time accuracy, reliability, and responsiveness that manual pricing strategies cannot achieve (Chong et al., 2018).

In Vietnam, the tourism industry is an important contributor to the economy, accounting for a significant proportion of GDP and employment. However, the industry faces its own challenges, including unstable customer demand, fierce market competition, and seasonal fluctuations in tourist arrivals. AI-driven dynamic pricing provides solutions to these challenges by enabling Vietnamese travel companies to maximize revenue, improve operational efficiency, and offer competitive rates. For example, dynamic pricing can help hotels adjust prices during peak travel seasons while remaining competitive during periods of low customer demand. Furthermore, AI systems can combine customer preferences, shopping behavior and market trends to create value for both businesses and their customers (Davenport & Ronanki, 2018).

AI's role in improving efficiency, equity, and profitability is especially important in the tourism sector. AI-based pricing systems are designed to improve efficiency by automating decision-making processes, reducing operating costs, and improving response times to market changes (Bughin et al., 2018). Moreover, AI can promote fairness by ensuring objective pricing decisions and providing transparent explanations of price movements, which is essential to building customer trust (Xia et al., 2004). AI also contributes to increased profitability by enabling travel companies to implement revenue maximization strategies while maintaining customer satisfaction (Chung et al., 2020). However, the success of AI-driven pricing systems depends significantly on the awareness of managers who implement and monitor these technologies. Managers' perceptions of the efficiency, fairness, and reliability of AI systems as well as their willingness to adopt such technologies play an important role in shaping their impact on business outcomes (Rai & Sambamurthy, 2006).

The study of perceptions of AI-driven dynamic pricing strategies and their financial impact on tour operators has attracted the attention of academics in recent years. Studies have highlighted AI's transformational role in optimizing pricing strategies to improve business outcomes, including customer satisfaction and financial performance. For instance, Huang & Rust (2018) demonstrated that AI-powered systems significantly improve price accuracy and responsiveness helping organizations adapt to fluctuations in demand. Similarly, Chong et al. (2018) and Wamba et al. (2017) emphasize that the application of AI in dynamic pricing improves profitability by enabling real-time price adjustments and reducing operational inefficiencies. However, while several studies conducted have explored the benefits of AI-driven pricing strategies, they have mainly focused on developed markets such as the United States, Europe, and East Asia (Chung et al., 2020; Bughin et al., 2018). These studies often look at industries such as aviation, e-commerce, and hospitality, where AI pricing systems are widely deployed and researched. For example, Davenport & Ronanki (2018) studied how AI-powered dynamic pricing has transformed revenue management practices in global hotel chains and airlines.

Although the above studies provide valuable insights, there are still limited studies in the Vietnamese context on how Vietnamese travel agency managers perceive these technologies. Existing studies on the application of AI in dynamic pricing have mainly focused on developed markets, leaving a significant gap in understanding its application and effectiveness in emerging economies (Phung et al., 2025). Thus, this study was conducted exploring the perceptions of Vietnamese tourism agency managers about AI-driven dynamic pricing strategies. Specifically, the study aims to investigate how managers' perceptions of AI efficiency, fairness, adoption, and trust affect customer satisfaction with AI-driven pricing systems. In addition, the study also seeks to examine the relationship between customer satisfaction and the financial performance of AI-driven pricing systems. By addressing these objectives, this study aims to provide valuable insights into the implementation and impact of AI pricing technologies in Vietnam's tourism industry. In addition, this study will enrich the theory and practice of AI adoption in developing countries, serving as a foundation for future research in similar contexts.

THEORETICAL BASIS AND LITERATURE REVIEW

Theoretical basis

This study on perceptions of AI-driven dynamic pricing strategies and their financial impact on Vietnamese tourism companies is based on the following five foundational theories. These theories provide a framework for understanding management perceptions, customer satisfaction, and financial performance in the context of AI adoption.

Technology Acceptance Model (TAM): The Technology Acceptance Model, introduced by Davis (1989), explains how users come to accept and use technology. It posits that two key factors - perceived usefulness and perceived ease of use - determine an individual's intention to adopt a technology. This research examines managers' perceptions of AI-driven pricing strategies, including their effectiveness and ease of adoption. TAM provides a foundation for exploring how these perceptions influence the adoption of AI-powered systems in tourism companies. For instance, if managers perceive AI as easy to use and beneficial for pricing decisions, they are more likely to embrace it.

Expectation-Confirmation Theory (ECT): Expectation-Confirmation Theory, proposed by Oliver (1980), explains how user satisfaction is derived. It suggests that satisfaction is a function of the confirmation of initial expectations against actual performance. If a system performs as expected or better, users are likely to feel satisfied. This theory is essential for understanding how managerial expectations about the effectiveness and fairness of AI pricing systems influence their satisfaction with these technologies. It also helps explain how perceived customer satisfaction with AI pricing impacts financial performance, as satisfied customers are more likely to engage in repeat business.

Equity Theory: Equity Theory, introduced by Adams (1963), focuses on fairness and justice in decision-making and relationships. It suggests that individuals evaluate fairness by comparing their inputs and outcomes with others. If perceived inequities exist, dissatisfaction follows. The study explores the perceived fairness of AI-driven pricing systems as a key factor influencing customer satisfaction. Managers may believe that fair pricing (e.g., avoiding price discrimination or exploitation) builds customer trust and loyalty. This theory underpins the hypothesis that fairness perceptions impact customer satisfaction and, ultimately, financial outcomes.

Resource-Based View (RBV): The Resource-Based View, popularized by Barney (1991), posits that a firm's competitive advantage is derived from utilizing valuable, rare, inimitable, and non-substitutable resources. Technology, such as AI, is considered a strategic resource that enhances firm performance. AI-driven pricing systems are treated as a strategic resource in this study. Managers' perceptions of the adoption level of AI systems reflect how tourism companies in Vietnam are leveraging this resource to gain a competitive edge, improve efficiency, and boost financial performance.

Customer Satisfaction Theory: Customer Satisfaction Theory, rooted in the works of Cardozo (1965) and later refined by Parasuraman et al. (1988), emphasizes that customer satisfaction depends on the perceived value of a product or service relative to customer expectations. Higher satisfaction leads to loyalty and financial benefits for companies. This theory is critical for understanding the mediating role of customer satisfaction in the relationship between AI pricing systems and financial performance. Managers' perceptions of how AI pricing influences customer satisfaction (e.g., through effectiveness, fairness, and trustworthiness) directly impact the financial outcomes of tourism companies.

EXPERIMENTAL STUDY

Perceived effectiveness of AI in pricing and customer satisfaction with AI-based pricing

The perceived effectiveness of AI in pricing refers to the extent to which managers believe AI-powered pricing systems can achieve desired outcomes, such as optimizing pricing strategies, improving decision-making, and responding to market demands in real-time. Effectiveness is a critical factor influencing the adoption and success of AI technologies, as it reflects the ability of AI systems to deliver tangible benefits for businesses and their customers (Davis, 1989; Bughin et al., 2018).

The perceived effectiveness of AI in pricing significantly enhances customer satisfaction with AI-powered pricing strategies. Research indicates that AI-driven pricing algorithms can optimize pricing based on real-time data and consumer behavior, leading to more personalized and competitive pricing strategies that resonate with customers (Gatera, 2024; Venigandla, 2023). This personalization fosters a deeper connection between consumers and brands, as tailored offers and recommendations increase the likelihood of purchase, thereby enhancing overall customer satisfaction (Yang et al., 2021). Furthermore, the ability of AI to analyze large datasets allows for dynamic pricing adjustments, which not only improves revenue but also aligns prices with customer expectations, further boosting satisfaction levels (Bag et al., 2021; Wang, 2024). As companies increasingly adopt AI technologies in their pricing strategies, the positive correlation between perceived effectiveness and customer satisfaction becomes more pronounced, suggesting that effective AI implementation can lead to improved consumer experiences and loyalty (Sharma, 2022).

H1: Perceived effectiveness of AI in pricing has a positive impact on perceived customer satisfaction with AI-powered pricing.

Perception of AI-Based Price Fairness and Customer Satisfaction with AI-Based Price

Perceived fairness of AI-based pricing refers to the extent to which customers and managers believe that AI-powered pricing systems deliver equitable, transparent, and unbiased pricing decisions. Fairness is a critical factor in shaping customer satisfaction, as customers tend to evaluate pricing not only based on the price itself but also on whether the pricing process aligns with their sense of justice and equity (Xia et al., 2004). Similarly, managers who perceive AI pricing systems as fair are likely to believe that these systems foster customer trust and satisfaction.

Simanjuntak highlights that price fairness is a critical determinant of customer satisfaction among college students using mobile services, indicating a strong correlation between perceived fairness and satisfaction levels (Simanjuntak, 2023). Similarly, research by F and Haryanto corroborates this by demonstrating that price fairness positively influences customer satisfaction and, consequently, loyalty in the hospitality sector (F & Haryanto, 2021). Githiri further supports this notion, asserting that customers who perceive restaurant prices as fair exhibit higher satisfaction and loyalty intentions (Githiri, 2018). Additionally, Setiawan et al. emphasize that both service quality and price fairness significantly impact customer satisfaction in the airline industry, reinforcing the importance of fairness perceptions in enhancing customer experiences (Setiawan et al., 2020). Collectively, these findings illustrate that perceived fairness in pricing strategies, particularly in AI applications, plays a pivotal role in fostering customer satisfaction.

H2: Perceived fairness of AI-based pricing has a positive impact on perceived customer satisfaction with AI-powered pricing.

The extent to which AI is applied to pricing and the level of customer satisfaction with AI-powered pricing

The adoption level of AI in pricing refers to the degree to which businesses integrate and utilize AI-powered systems in their pricing strategies. This includes the extent to which AI is applied to collect and analyze data, predict demand, optimize pricing, and deliver personalized pricing solutions. Higher levels of AI adoption indicate greater reliance on advanced algorithms and machine learning models to make data-driven pricing decisions, which can enhance efficiency, accuracy, and customer satisfaction (Huang & Rust, 2018).

AI-driven systems, such as chatbots and virtual assistants, have been shown to improve user experience, with approximately 85% of customer satisfaction attributed to these technologies in ticket booking systems (Shankar, 2024). Furthermore, AI's ability to personalize pricing based on customer preferences leads to increased satisfaction and loyalty, as evidenced by studies in the hospitality sector (Gatera, 2024). Price fairness also plays a crucial role; research indicates that customers perceive fair pricing as a key determinant of their satisfaction and loyalty (F & Haryanto, 2021; Kawatu, 2023). Additionally, AI's capacity to analyze data and optimize pricing strategies contributes to a more tailored customer experience, reinforcing the positive impact of AI on customer satisfaction in the travel industry (Zahra, 2023). Overall, the strategic application of AI in pricing not only meets customer expectations but also fosters long-term loyalty.

H3: AI adoption level in pricing has a positive impact on perceived customer satisfaction with AI-powered pricing.

Management's confidence in the AI system and customer satisfaction with AI-powered pricing

Managerial trust in AI systems refers to the confidence managers have in the reliability, transparency, and effectiveness of AI-powered tools in performing specific tasks, such as pricing decisions. Trust in AI is a critical factor influencing its adoption and success, as it determines how managers perceive the system's ability to deliver intended outcomes without unintended consequences (Mayer et al., 1995; Rai et al., 2019). When managers trust AI systems for pricing, they are more likely to believe that these systems will enhance customer experiences and satisfaction by providing accurate, fair, and data-driven pricing solutions.

Research indicates that trust is a critical determinant of customer loyalty, which is mediated by customer satisfaction (Susanto, 2024). This relationship suggests that when customers perceive AI systems as trustworthy, their satisfaction with pricing strategies improves, leading to increased loyalty towards the agency. Furthermore, the perception of AI's usefulness and ethical considerations, such as transparency and privacy, also play vital roles in fostering trust among users (Majrashi, 2024).

Furthermore, the emotional labor exhibited by tour leaders and guides can further influence customer perceptions of trust in AI systems, as positive interactions enhance overall satisfaction (Chang et al., 2022). Thus, the interplay between trust in AI, customer satisfaction, and the emotional dynamics within the service environment creates a robust framework for understanding how AI-assisted pricing can positively impact customer experiences in the tourism sector.

H4: Managerial trust in AI systems has a positive impact on perceived customer satisfaction with AI-powered pricing.

Customer satisfaction with prices supported by AI and perceived financial performance of prices supported by AI

Perceived customer satisfaction with AI-powered pricing refers to the extent to which customers believe that AI-driven pricing systems meet or exceed their expectations in terms of fairness, accuracy, personalization, and transparency. High levels of customer satisfaction are associated with positive customer perceptions of value and trust, which can directly influence their purchasing behavior, loyalty, and overall experience with a company (Parasuraman et al., 1988; Xia et al., 2004). When customers perceive AI-powered pricing as satisfactory, this satisfaction can translate into tangible benefits for the business, such as increased sales, repeat purchases, and improved customer retention, all of which contribute to financial performance.

Perceived financial performance of AI-powered pricing refers to the extent to which managers believe that implementing AI systems in pricing contributes to key financial outcomes, such as revenue growth, profitability, and cost efficiency. Research shows that customer satisfaction is a crucial driver of financial success, as satisfied customers are more likely to engage in repeat business, provide positive word-of-mouth referrals, and exhibit higher levels of brand loyalty (Anderson et al., 1994). In the context of AI-powered pricing, when customers view pricing systems as fair, transparent, and responsive to their needs, they not only purchase more but also develop stronger relationships with the brand, enhancing long-term financial performance.

The link between customer satisfaction and financial performance has been well established in the marketing and strategy literature. For example, Anderson et al. (1994) found that firms with higher customer satisfaction tend to outperform competitors financially due to higher customer retention and reduced price sensitivity. Similarly, Rust et al. (2004) highlighted that investments in improving customer experiences, such as through AI-driven personalized pricing, directly contribute to financial returns by fostering stronger customer relationships. In the context of AI-powered pricing, the positive perception of customer satisfaction can reinforce managerial beliefs that these systems are instrumental in achieving superior financial outcomes.

Moreover, AI-powered pricing systems are often designed to optimize both customer satisfaction and financial performance by delivering value to customers while maximizing profitability for the business (Huang & Rust, 2018). Managers who perceive customers as being satisfied with AI-powered pricing are likely to attribute financial success, such as revenue growth and profitability, to the implementation of these systems. This connection highlights the interdependence between customer satisfaction and financial performance, reinforcing the importance of delivering positive customer experiences through AI-powered pricing strategies.

H5: Perceived customer satisfaction with AI-powered pricing has a positive impact on the perceived financial performance of AI-powered pricing.

RESEARCH METHODOLOGY

The article uses SPSS 22 and AMOS 20 to test the linear structure model to answer the following questions: What are the perceptions of Vietnamese tourism company managers regarding AI-driven dynamic pricing systems? How do perceptions of AI effectiveness, fairness, adoption level, and trust influence perceived customer satisfaction with AI-powered pricing? How does perceived customer satisfaction with AI pricing systems impact the financial performance of tourism companies?

For optimal results, the authors conducted a validation process including: Following Anderson & Gerbing (1988), the linear structural model analysis process includes: (i) Scale test: Overall Cronbach's alpha coefficient > 0.7 and corrected item-total correlation > 0.3; (ii) Exploratory Factor Analysis (EFA): Appropriateness of the measure with 0.5≤ Kaiser-Meyer-Olkin (KMO) ≤ 1, Bartlett's test of sphericity with a significance level (Sig) ≤ 0.05, factor extraction variance > 50%, Eigenvalues > 1, factor loadings require > 0.5 (Hair et al., 1998); (iii) Confirmatory Factor Analysis (CFA): The model is considered suitable when the Chi-square test has a P value > 0.05. However, the disadvantage of Chi-square is that it depends on the size of the research sample. The larger the sample size, the larger the Chi-quare, thereby reducing the suitability of the model. Therefore, in addition to P-value, the standards used are CMIN/df, in some practical studies, people distinguish between 2 cases: CMIN/df < 5 (with sample N > 200); or CMIN/df < 3 (when N < 200), the model is considered suitable (Kettinger et al., 1995). In this study, because the research sample of the graduate student N = 372 > 200, the article will use the standards of Kettinger et al. (1995), accepting CMIN/df < 5; GFI, TLI, CFI > 0.9; RMSEA < 0.08, the case of RMSEA < 0.05 according to Steiger (1990) is considered very good. In addition, according to Zikmund et al. (2000), if GFI < 0.9, the model's suitability to market data is also acceptable. According to Awang (2012) and Forza & Filippini (1998), the model is acceptable if the values 0.8 < TLI, CFI < 0.9, CMIN/df < 5, RMSEA ≤ 0.08. (iv) Structural equation modeling (SEM).

The research model is shown in Figure 1, with the economic equation of the study corresponding to the model as:

PCS = f (PEAI, PFAI, AIAL, MTAI) (1)

PFP = f (PCS) (2)

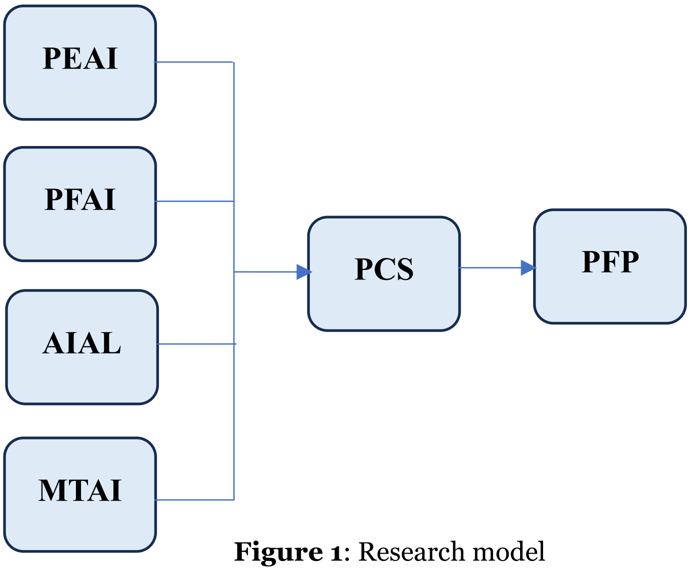

Figure 1: Research model

Source: Construction by the Authors

Variables in the PLS-SEM quantitative model are measured using a 5-level Likert scale (Likert, 1932), the scale is constructed in 5 levels, with the number 1 describing total disagreement, the number 2 disagreeing, the number 3 being a neutral rating, the number 4 agreeing, the number 5 strongly agreeing. The number of scales measuring the variables of this study is built on the basis of the foundation theory and the research overview, shown in Table 1 as follows:

Table 1. Scales and variables in the research model

No.	Code	Survey question content	Source
I	***Perceived Effectiveness of AI (PEAI)***		
1	PEAI1	AI-driven pricing systems provide accurate and effective pricing recommendations.	Chong et al. (2018)
2	PEAI2	AI technology improves the efficiency of our company's pricing strategies.	Wamba et al. (2017)

3	PEAI3	Using AI in pricing has enhanced our ability to respond quickly to market changes.	Huang & Rust (2018)
II	***Perceived Fairness of AI (PFAI)***		
4	PFAI1	AI pricing models are perceived by customers as fair and unbiased.	Xia et al. (2004)
5	PFAI2	AI-driven pricing systems provide transparent explanations for price differences.	Bolton et al. (2003)
6	PFAI3	AI-powered pricing ensures equitable treatment of all customer segments.	Kahneman et al. (1986)
III	***AI Adoption Level (AIAL)***		
7	AIAL1	Our company uses AI systems for dynamic pricing to maximize revenue.	Davenport & Ronanki (2018)
8	AIAL2	AI is fully integrated into our pricing strategies and decision-making processes.	Ransbotham et al. (2017)
9	AIAL3	Our company has invested significant resources in adopting AI-based pricing technologies.	Bughin et al. (2018)
IV	***Managerial Trust in AI (MTAI)***		
10	MTAI1	I trust the AI pricing system to make accurate and reliable pricing decisions.	Gursoy et al. (2019)
11	MTAI2	AI pricing systems align with our company's goals and values.	Rai & Sambamurthy (2006)
12	MTAI3	I believe AI pricing systems prioritize the company's performance and customer satisfaction equally.	Madsen & Gregor (2006)
V	***Perceived Customer Satisfaction with AI-Pricing (PCS)***		
13	PCS1	AI-driven pricing enhances customer satisfaction by offering competitive prices.	Huang & Rust (2018).
14	PCS2	Customers perceive value in the prices set by AI systems.	Chung et al. (2020)
15	PCS3	AI-based pricing systems improve customer trust, leading to greater satisfaction.	L et al. (2019)
16	PCS4	Customers are satisfied with the transparency of prices set by AI systems.	Xia et al. (2004)
VI	***Perceived Financial Performance of AI-Pricing (PFP)***		
17	PFP1	AI-powered pricing has contributed to significant revenue growth for our company.	Chong et al. (2018)
18	PFP2	AI systems have improved our company's profitability by optimizing pricing decisions.	Wamba et al. (2017)
19	PFP3	AI-driven pricing has reduced operational costs associated with manual pricing processes.	Davenport & Ronanki (2018)
20	PFP4	The use of AI in pricing has strengthened our company's competitive position in the market.	Ransbotham et al. (2017)

Source: Authors' synthesis based on the theoretical framework

The model comprises 6 scales and 20 observed variables

In addition, to ensure the study sample size in SEM analysis, based on the recommendations of Bentler & Chou (1987) proposed a ratio of 5 to 10 surveys for each survey question. Kline (2023) recommends a minimum sample size of 200 for any SEM analysis or 10 cases per one observation, whichever is greater. Accordingly, the minimum sample size in this study is n = 10*i (i is the number of observed variables in the model), corresponding to this study, the sample size will be 10*20 = 200 votes. In order to improve the reliability of the survey information, the study selects the largest sampling for the model according to one of the above principles.

The target audience of this study includes managers from tourism companies in Vietnam, including restaurants, hotels, tour operators, and tour operators, who are involved in pricing decisions. These managers have the knowledge and experience to provide insights into the use and impact of AI-powered pricing systems in their organization. To ensure the relevance of the data, intentional sampling methods are used. This method ensures that all participants have firsthand experience with AI-powered pricing systems, which is important for addressing research questions.

The questionnaire consists of two parts, the first part includes demographic information such as, gender, age group, education level, job position, years of experience, type of travel company. The second part includes the PEAI, PFAI, AIAL, MTAI, PCS, PFP variables and the corresponding scales. First of all, the questionnaire will undergo a pre-examination with a small sample of 2 experts and 2 academics in the industry to ensure clarity, reliability and relevance to research objectives. Feedback from this inspection will be incorporated to refine the survey instrument. The final survey will be distributed both online and in person to maximize participation. Online surveys are administered through Google Drive, while in-person surveys are conducted in the workplace.

Data collection period from March 12, 2024 to July 16, 2024. The research results are based on 372 valid responses, ensuring sufficient data to conduct statistical analysis. The authors cleaned the data, entered the survey data into an excel spreadsheet before running the model using SPSS 22 and AMOS 20 software.

During the data collection process, this study strictly adheres to research ethics and ensures the anonymity and privacy of all participants. Participants were fully informed about the purpose of the study, how their data would be used, participation in the survey was entirely voluntary, with no pressure or obligation placed on respondents to complete the questionnaire.

RESULTS AND DISCUSSION

Descriptive statistical analysis

The majority of the respondents are male (58.1%), while female respondents account for 41.9%, indicating a slight gender imbalance with more male managers participating in the survey. The largest age group is 30–39 years old (36.8%), followed by those below 30 years old (30.1%). Managers aged 40–49 years make up 20.4%, and those aged 50 and above account for 12.6%, suggesting that most respondents are early- to mid-career professionals. In terms of education, most respondents hold a bachelor's degree (60.8%), while 23.1% have a master's degree. A smaller proportion has a high school diploma or equivalent (9.7%), and only 6.5% have a doctorate, indicating that the sample is relatively well-educated with an emphasis on undergraduate and graduate qualifications. The respondents occupy diverse roles, with Marketing Managers representing the largest group (33.3%), followed by Operations Managers (28.5%) and Pricing Managers (26.1%). General Managers account for 12.1%, reflecting their smaller involvement in day-to-day pricing decisions. Regarding experience, most respondents have 5–10 years of experience (37.1%), followed by those with 11–15 years (30.6%). Managers with less than 5 years of experience account for 22.0%, while those with more than 15 years make up the smallest group (10.2%), indicating that the majority are seasoned professionals with significant industry experience. Respondents also represent various tourism company types, with the hotel sector comprising the largest group (38.2%), followed closely by travel agencies (36.0%). Tour operators account for 25.8%, reflecting a balanced distribution across different tourism-related companies.

Table 2. Characteristics of survey subjects

No.	Demographic Information		Person	Percentage(%)
1	Gender	Male	216	58.1
		Female	156	41.9
2	Age Group	Below 30	112	30.1
		30–39	137	36.8
		40–49	76	20.4
		50 and above	47	12.6
3	Educational Qualification	High school diploma or equivalent	36	9.70
		Bachelor's degree	226	60.8
		Master's degree	86	23.1
		Doctorate	24	6.50
4	Job Title/Position	General Manager	45	12.1
		Pricing Manager	97	26.1
		Marketing Manager	124	33.3
		Operations Manager	106	28.5
5	Experiences	Less than 5 years	82	22.0
		5–10 years	138	37.1
		11–15 years	114	30.6
		More than 15 years	38	10.2
6	Type of Tourism Company	Hotel	142	38.2
		Travel agency	134	36.0
		Tour operator	96	25.8

Source: Compiled from the survey results

Assess the reliability of the scale

3.2 Testing the reliability of the scale by Cronbach's Alpha reliability coefficient: Cronbach's alpha coefficient is a statistical test of the degree of coherence and correlation between observed variables in the scale. The results of the reliability analysis of the scale are detailed in Table 3 below.

Table 3. Scale analysis results for variables in the SEM model

Variable	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
***Perceived Effectiveness of AI (PEAI)*:α = 0.809**				
PEAI1	3.54	0.922	0.683	0.733
PEAI2	3.96	0.894	0.544	0.781
PEAI3	3.59	0.834	0.664	0.745
***Perceived Fairness of AI (PFAI)*:α = 0.783**				
PFAI1	3.28	1.129	0.533	0.764
PFAI2	3.47	1.037	0.720	0.656
PFAI3	3.93	0.845	0.480	0.780
***AI Adoption Level (AIAL)*:α = 0.776**				
AIAL1	3.16	1.027	0.596	0.717
AIAL2	2.84	1.010	0.589	0.718
AIAL3	3.23	1.246	0.533	0.750
***Managerial Trust in AI (MTAI)*:α = 0.869**				
MTAI1	3.81	0.992	0.737	0.825
MTAI2	3.73	0.928	0.745	0.823
MTAI3	3.73	1.032	0.795	0.799
***Perceived Customer Satisfaction with AI-Pricing (PCS)*: α = 0.817**				
PCS1	2.83	1.188	0.708	0.740
PCS2	2.69	1.359	0.757	0.708
PCS3	2.72	1.348	0.723	0.726
PCS4	2.98	1.285	0.592	0.782
***Perceived Financial Performance of AI-Pricing (PFP):* α = 0.816**				
PFP1	3.17	0.864	0.629	0.734
PFP2	3.41	0.821	0.698	0.739
PFP3	3.57	0.871	0.679	0.747
PFP4	3.53	0.805	0.560	0.802

Source: Statistical analysis using SPSS 22 software

After testing the reliability of the scales, the observed variables all had Cronbach's Alpha coefficients greater than 0.6 and the total variable correlation coefficient greater than 0.3, no observed variables were excluded from the scale, proving that the observed variables well reflected the concept proposed in the study and qualified for further analysis.

Exploratory factor analysis

The study used the extraction method with Principal Component Analysis rotation in EFA analysis (Gerbing & Anderson, 1988) with a load factor of ≥ 0.5 (Hair et al., 1998) for all variables. Table 4 shows that KMO coefficient = 0.835 > 0.5, Bartlett's Test = 0.000 < 0.05, so factor analysis is suitable.

Table 4. Test the KMO index

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.835	
Bartlett's Test of Sphericity	Approx. Chi-Square	3087.124
	df	415
	Sig.	0.000

Source: Report extracted from SPSS 22 software

Next, the factor matrix table after rotation will be considered, the analysis results show that the observed variables have been gathered into 6 groups of variables with the order of the observed variables being kept the same compared to the originally built variables, the factor load factors are greater than 0.5, so these 6 groups of variables ensure the convergence value and differentiation value. The initial theoretical model was unchanged and had practical implications (Table 5).

Table 5. Rotated Component Matrix[a]

Pattern Matrix[a]	Component					
	1	2	3	4	5	6
PEAI2	.919					
PEAI1	.904					
PEAI3	.858					
PCS3		.933				
PCS4		.907				
PCS2		.678				
PCS1		.651				
PFAI2			.887			
PFAI1			.881			
PFAI3			.812			
PFP1				.802		
PFP2				.796		
PFP4				.694		
PFP3				.665		
AIAL1					.919	
AIAL2					.882	
AIAL3					.742	
MTAI2						.883
MTAI1						.761
MTAI3						.649

Eigenvalues = 1.012
Total variance extracted = 63.286%

Extraction Method: Principal Component Analysis.

Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 6 iterations.

Source: Statistics using SPSS 22 software

Table 5 also shows that, the coefficient Eigenvalue = 1.012 > 1 represents the part of variation explained by each factor, the drawn factor is the best summary of the information. Total variance Extraction Sums of Squared Loadings (Cumulative %) = 63.286% > 50%. This proves that 5 independent factors explain 63.286% of the research model.

CFA and PLS-SEM analysis

Confirmatory factor analysis (CFA) was used to test the model fit and reliability of the final scale. The results of Confirmatory Factor Analysis and the estimation of the Partial Least Squares Structural Equation Modeling are illustrated in the Figure 2.

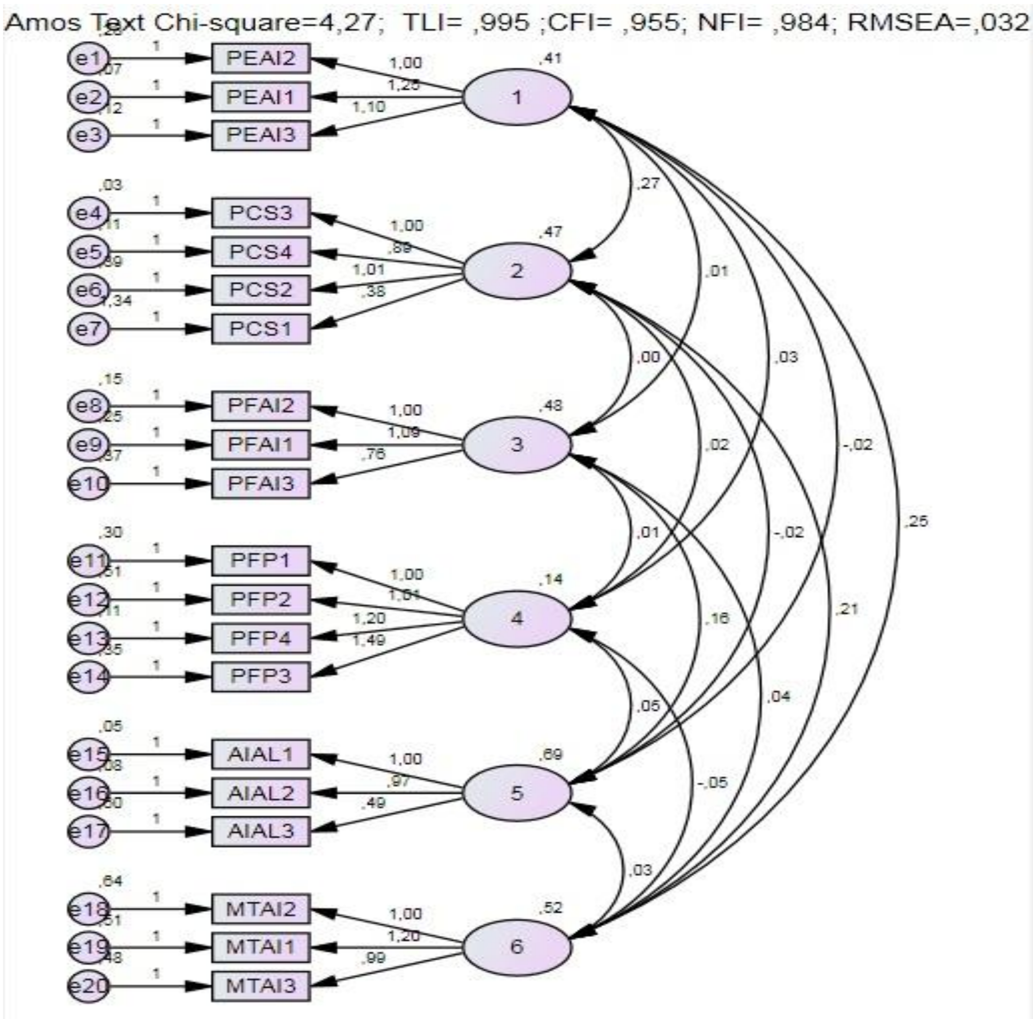

Figure 2. Summary of confirmatory factor analysis

Source: Data analyzed by the authors using AMOS 20 software

The results of the confirmatory factor analysis indicate that the adjusted Chi-squared value divided by degrees of freedom (Cmin/df) is 4.27, which is in the range ≤ 5. TLI value = 0.995, greater than 0.9; CFI value =

0.955 and greater than 0.9; NFI value = 0.984, greater than 0.9; and RMSEA value = 0.032, which is less than 0.05. Therefore, it can be concluded that the integrated model is suitable for market data as it meets the test criteria.

The study uses a linear structure model (SEM) to test the model and research hypotheses, the results are shown in Figure 3.

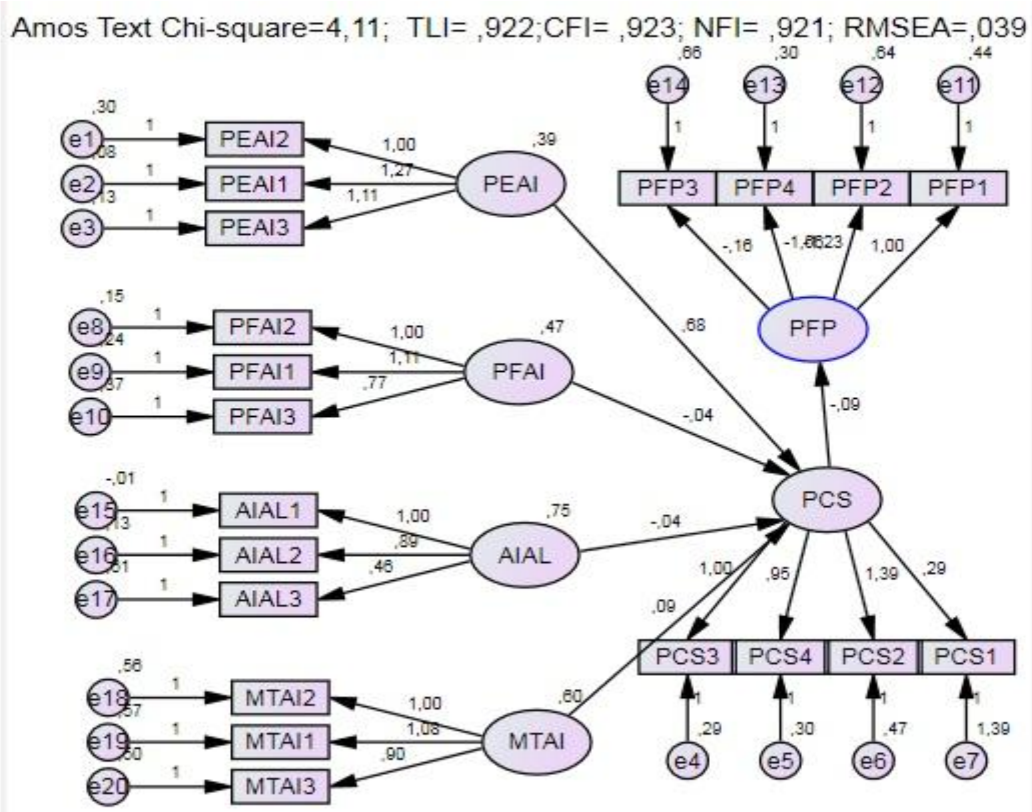

Figure 3. Results of model regression estimation

Source: Data analyzed by the authors using AMOS 20 software

The results from Figure 3 show that the adjusted Chi-squared value divided by degrees of freedom (Cmin/df) is 4.11 in the range of ≤ 5. The TLI = 0.922 value is greater than 0.9; the CFI = 0.923 value exceeds 0.9; the NFI = 0.921 value exceeds 0.9; and the RMSEA = 0.039, which is less than 0.05. Thus, it can be seen that the model is suitable for real data because it meets the accreditation criteria.

The following table 6 presents the results of hypothesis testing, the significance level of the estimated coefficients: P ≤ 0.05; the confidence level ≥ 95%. The factors included in the model are statistically significant and the hypotheses are accepted.

Table 6. Hypothesis test results

Hypothesis	Impact			Estimate	S.E.	C.R.	P	Label
H1	PCS	<---	PEAI	0.681	0.061	11.182	***	Accept
H2	PCS	<---	PFAI	0.036	0.029	1.234	0.217	**Refuted**
H3	PCS	<---	AIAL	0.076	0.021	1.694	0.002	Accept
H4	PCS	<---	MTAI	0.090	0.028	3.180	0.028	Accept
H5	PFP	<---	PCS	0.094	0.089	1.050	0.034	Accept

Source: Statistics obtained by using AMOS 20 software

The study's findings provide valuable insights into the relationships between AI-related factors and their impact on customer satisfaction and financial performance. The results confirm that Perceived Effectiveness of AI has the strongest positive and significant impact on Perceived Customer Satisfaction, with an estimate of 0.681 ($P < 0.001$), highlighting the critical role of AI systems' effectiveness in enhancing customer experiences. However, Perceived Fairness of AI does not significantly influence PCS, as indicated by its low estimate of 0.036 ($P = 0.217$), suggesting that fairness may not be a primary driver of satisfaction in this context or that it requires further exploration. AI Adoption Level shows a positive and significant impact on PCS, with an estimate of 0.076 ($P = 0.002$), indicating that higher levels of AI integration contribute to improved customer satisfaction. Managerial Trust in AI also significantly affects PCS, with an estimate of 0.090 ($P = 0.028$), underscoring the importance of managerial confidence in AI systems to optimize their implementation and effectiveness. Finally, PCS significantly impacts Perceived Financial Performance, with an estimate of 0.094 ($P = 0.034$), demonstrating that customer satisfaction with AI-pricing systems translates into tangible financial benefits, such as increased revenue and profitability. Overall, the findings strongly support the proposed research model, emphasizing the critical roles of PEAI, AIAL, and MTAI in driving customer satisfaction, which in turn positively influences financial performance. These results highlight the importance of leveraging AI technologies effectively, fostering managerial trust, and prioritizing customer satisfaction to maximize financial outcomes in AI-driven systems.

The results of this study reveal that the perceived effectiveness of artificial intelligence has the strongest positive and significant impact on perceived customer satisfaction. This finding highlights the critical role of artificial intelligence systems' effectiveness in shaping customer satisfaction. When customers perceive artificial intelligence-driven pricing systems as effective, they are more likely to value the accuracy, reliability, and efficiency of pricing decisions, which enhances their overall satisfaction. This aligns with prior research, such as Davis (1989), which established that perceived usefulness - a concept closely tied to effectiveness - is a key factor in user acceptance and satisfaction. Similarly, Venkatesh & Davis (2000), Yang et al. (2021), Bag et al. (2021), Wang (2024) found that technologies perceived as effective are more likely to be adopted and positively evaluated by users. Furthermore, studies like those by Parasuraman et al. (2005) suggest that perceived effectiveness directly impacts trust and satisfaction, especially in technology-driven interactions. However, other research, such as Binns et al. (2018), emphasizes that while effectiveness is critical, factors like transparency and fairness may also influence satisfaction, suggesting a more nuanced relationship. The findings of this study confirm that prioritizing the development and communication of effective artificial intelligence systems is essential for organizations aiming to improve customer satisfaction and maintain a competitive edge.

The research results demonstrate that the level of artificial intelligence adoption positively and significantly affects customer satisfaction. This finding suggests that higher levels of artificial intelligence adoption reflect better integration and optimization of these systems within organizational processes, which enhances customer interactions and overall satisfaction. As organizations progressively adopt artificial intelligence, they are likely to benefit from improved efficiency, accuracy, and personalization in their services, ultimately leading to better customer experiences. This result aligns with previous research highlighting the incremental benefits of artificial intelligence adoption. For example, studies such as those by Rai et al. (2019), Shankar (2024), Gatera (2024) emphasize that organizations adopt artificial intelligence in a phased and strategic manner experience enhanced operational efficiency and customer engagement over time. Similarly, Brynjolfsson & McAfee (2017) argue that the full potential of artificial intelligence is often realized only after organizations restructure their workflows and processes to integrate the technology effectively. These findings underscore the importance of gradual and thoughtful adoption of artificial intelligence to maximize its impact on customer satisfaction.

The study also found that management confidence in artificial intelligence positively and significantly affects customer satisfaction. This result highlights the critical role of managers' trust in artificial intelligence systems in driving their effective implementation and use, ultimately improving customer satisfaction. When managers trust artificial intelligence systems, they are more likely to champion their adoption, allocate resources for their optimization, and ensure their proper integration into organizational processes. This trust fosters confidence in the system's capabilities, leading to more efficient operations and better customer experiences. Previous research supports this finding by emphasizing the importance of managerial trust in technology adoption. For instance, studies by Schoorman et al. (2007) and Susanto (2024) suggest that trust in technology can reduce resistance to adoption and encourage proactive usage, thereby enhancing performance outcomes. Similarly, Ransbotham et al.

(2017), Chang et al. (2022) highlight that managerial trust in artificial intelligence fosters a culture of innovation, enabling organizations to leverage artificial intelligence capabilities effectively for customer-centric improvements. These findings underscore that managerial trust is not only a driver of artificial intelligence adoption but also a critical factor in ensuring that these systems are used in ways that maximize customer satisfaction. Building trust at the managerial level is thus essential for successful artificial intelligence initiatives.

The study results also show that customer satisfaction significantly and positively impacts perceived financial performance. This finding underscores the critical link between customer satisfaction and financial outcomes, particularly in the context of AI-driven pricing systems. When customers are satisfied with such systems, they are more likely to exhibit loyalty, repeat purchasing behavior, and positive word-of-mouth, all of which contribute to improved financial performance, including increased revenue and profitability. This result aligns with prior research that consistently identifies customer satisfaction as a key driver of financial success. For instance, Anderson et al. (1994), Gatera (2024) demonstrated that high levels of customer satisfaction improve customer retention, which in turn enhances financial performance metrics like profitability and market share. Similarly, Homburg et al. (2005), Suryawan (2024), Monterey & Borbon (2021) found a direct and positive relationship between customer satisfaction and revenue generation, emphasizing that satisfied customers are more willing to pay premium prices and remain loyal even in competitive markets. In the context of AI, systems that deliver accurate and fair pricing foster trust and satisfaction, ultimately boosting financial outcomes. These findings reinforce the idea that investing in customer satisfaction, particularly through advanced AI technologies, is not only a customer-centric strategy but also a financially lucrative one.

However, the results of the study found that perceptions of AI's fairness did not have a significant impact on perceptions of customer satisfaction. This result suggests that customers may not consider fairness as a key determinant of their satisfaction with AI-based pricing systems or that travel agencies in Vietnam do not effectively communicate aspects related to the fairness of these systems. Although fairness is often considered an important factor in customer reviews, its impact depends on the context of the research. In Vietnam, customers often know little about how AI systems make pricing decisions, because pricing is a relatively new concept in Vietnam, so customers may not evaluate or prioritize fairness in pricing models. Customers often focus more on pricing outcomes (e.g., affordability and value) rather than process fairness or transparency, making fairness a less important factor in their satisfaction. Moreover, Vietnamese customers in the tourism industry are often price sensitive. They may prioritize low prices or perceived value over fairness. The results of this study show a difference from previous studies that emphasized that perceptions of fairness have a greater impact in situations where customers experience clear transparency or feel directly affected by pricing decisions. For example, F & Haryanto (2021), Githiri (2018) demonstrate that price equity positively affects customer satisfaction in the hospitality sector. Similarly, Setiawan et al. (2020) emphasize that both service quality and price fairness significantly impact customer satisfaction in the airline industry, reinforcing the importance of perceptions of fairness in enhancing the customer experience. Findings from this study highlight the need for organizations to proactively promote transparency and educate customers about equity mechanisms in AI-based pricing systems to enhance their relevance in driving satisfying outcomes.

CONCLUSION AND RECOMMENDATIONS

The study provides valuable insights into the factors that drive customer satisfaction in the context of the application of artificial intelligence-based pricing systems and their subsequent impact on financial performance. The findings highlight the critical role of artificial intelligence's cognitive performance, artificial intelligence's ability to learn, and managers' trust in artificial intelligence in enhancing customer satisfaction. These factors emphasize the importance of designing artificial intelligence systems that not only work well, but also demonstrate the ability to adapt and create trust for managers because these factors together contribute to a positive customer experience. Furthermore, the study confirms the positive and significant impact of customer satisfaction on the financial performance of travel companies in Vietnam, which suggests that satisfied customers are more likely to drive revenue and profit growth of travel companies through loyalty and repeat use of services. However, this study did not find a statistically significant impact of perceptions of AI-based price fairness on customer satisfaction. This finding reflects the fact that customers of travel agencies in Vietnam often focus more on pricing outcomes (e.g., affordability and value) rather than the fairness or transparency of the process making fairness a less important factor in their satisfaction.

Based on the research results, the authors propose some recommendations for tourism companies, specifically as follows:

First, travel companies should focus on improving the perceived efficiency of artificial intelligence systems by ensuring that their pricing algorithms provide accurate, reliable, and efficient results tailored to the unique preferences of Vietnamese and international visitors. For example, pricing systems should take into account domestic travel trends, such as the surge in demand for domestic travel during the April 30 and Lunar New Year holidays or Lunar New Year or long weekends. Companies should also ensure that these systems provide flexible pricing options that reflect real-time changes in the actual needs of travelers, such as for flights, hotels, or tour packages, while maintaining consistency to avoid losing customers with sharp price fluctuations.

Second, fostering regulators' confidence in artificial intelligence systems is critical to the effective implementation of dynamic pricing based on artificial intelligence. Managers in travel agencies may hesitate to rely on artificial intelligence due to ignorance or fear of losing control over pricing decisions. To address this, companies should invest in targeted training programs aimed at equipping managers on how artificial intelligence systems work and their specific benefits for the tourism industry in Vietnam. For example, managers should be trained how artificial intelligence can predict customer booking patterns, optimize prices during peak seasons, and improve revenue management. Clearly communicating these benefits along with case studies of successful AI adoption in the tourism sector can build trust and encourage managers to support these systems internally.

Third, to maximize the potential of artificial intelligence, travel agencies in Vietnam need to integrate these systems seamlessly into their organizational processes. Artificial intelligence should not be seen as an isolated tool but as an integral part of the customer journey. For example, AI-powered chatbots and recommendation systems need to be paired with pricing tools to provide personalized travel recommendations to customers based on their interests, travel history, and income. Collaboration between departments such as marketing and sales can help ensure that artificial intelligence systems are effectively aligned with corporate goals, such as improving customer engagement and increasing repeat bookings. Integrating artificial intelligence with existing platforms such as mobile apps or booking websites will also enhance customer convenience and satisfaction.

Finally, travel agencies must increase transparency and fairness communication as perceptions of fairness have a significant impact on customer trust. Vietnamese travelers are becoming more aware of pricing practices and may be skeptical of prices driven by artificial intelligence if they feel they lack transparency. Companies should communicate clearly how their pricing system works, such as by providing information on how prices are determined and ensuring customers understand factors such as demand, availability, and timing. Providing tools like price tracking systems or notifications of fare changes can give customers even more peace of mind that prices are objective, fair, and consistent. In addition, companies should establish feedback channels, such as surveys or customer service hotlines, where travelers can share pricing concerns or seek clarification on pricing-related inquiries.

CONFLICT OF INTEREST

No potential conflict of interest was reported by the author

REFERENCES

[1] Adams, J. S. (1963). Toward an understanding of inequity. *Journal of Abnormal and Social Psychology*, 67(5), 422–436. https://doi.org/10.1037/h0040968

[2] Anderson, E. W., Fornell, C., & Lehmann, D. R. (1994). Customer satisfaction, market share, and profitability: Findings from Sweden. *Journal of Marketing*, 58(3), 53–66.

[3] Anderson, J.C., Gerbing, D.W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, 103(3), 411-423.

[4] Awang, Z. (2012). Research methodology and data analysis (second edition). UiTM Press.

[5] Bag, S., Srivastava, G., Bashir, M., Kumari, S., Giannakis, M., & Chowdhury, A. (2021). Journey of customers in this digital era: understanding the role of artificial intelligence technologies in user engagement and conversion. *Benchmarking an International Journal*, 29(7), 2074-2098.

[6] Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120. https://doi.org/10.1177/014920639101700108

[7] Bentler, P. M., & Chou, C. P. (1987). Practical issues in structural modeling. *Soc. Methods Res*. 16, 78–117. https://doi.org/10.1177/0049124187016001004

[8] Binns, R., Veale, M., Van Kleek, M., & Shadbolt, N. (2018). 'It's reducing a human being to a percentage': Perceptions of justice in algorithmic decisions. Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, 1–14. https://doi.org/10.1145/3173574.3173951

[9] Bolton, L. E., Warlop, L., & Alba, J. W. (2003). Consumer perceptions of price (un)fairness. *Journal of Consumer Research*, 29(4), 474–491. https://doi.org/10.1086/346244

[10] Brynjolfsson, E., & McAfee, A. (2017). Machine, platform, crowd: Harnessing our digital future. W.W. Norton & Company.

[11] Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlström, P., & Trench, M. (2018). AI adoption advances, but foundational barriers remain. McKinsey Quarterly. Retrieved from https://www.mckinsey.com

[12] Bughin, J., Seong, J., Manyika, J., Chui, M., & Joshi, R. (2018). Notes from the AI frontier: Modeling the impact of AI on the world economy. McKinsey Global Institute. Retrieved from https://www.mckinsey.com

[13] Cardozo, R. N. (1965). An experimental study of customer effort, expectation, and satisfaction. *Journal of Marketing Research*, 2(3), 244–249.

[14] Chong, A. Y. L., Bai, R., & Tan, M. (2018). Predicting consumer product demands via big data: The roles of online promotional marketing and price bundling. *International Journal of Production Research*, 56(1–2), 494–505. https://doi.org/10.1080/00207543.2017.1401238

[15] Chong, A. Y. L., Li, B., Ngai, E. W. T., & Ch'ng, E. (2018). Predicting online product sales via online reviews, sentiments, and promotion strategies: A big data architecture and neural network approach. *International Journal of Operations & Production Management*, 38(3), 665–690.

[16] Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, 117, 587–595.

[17] Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108–116. Retrieved from https://hbr.org

[18] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. https://doi.org/10.2307/249008

[19] F, B. and Haryanto, B. (2021). Strategy for enhancing kai argo pahrayangan customers' loyalty. *Research Society and Development*, 10(1), e33010111656. https://doi.org/10.33448/rsd-v10i1.11656

[20] Forza, C., & Filippini, R. (1998). TQM impact on quality conformance and customer satisfaction: a causal model. *International journal of production economics*, 55(1), 1-20.

[21] Gatera, A. (2024). Role of artificial intelligence in revenue management and pricing strategies in hotels. *Journal of Modern Hospitality*, 3(2), 14-25. https://doi.org/10.47941/jmh.1957

[22] Gerbing, D. W., & Anderson, J. C. (1988). An updated paradigm for scale development incorporating unidimensionality and its assessment. *Journal of Marketing Research*, 25(2), 186–192. https://doi.org/10.1177/002224378802500207

[23] Githiri, M. (2018). An examination of the relationship between perceived price fairness on customer satisfaction and loyalty in kenyan star-rated restaurants. *International Journal of Scientific Research and Management,* 6(10). https://doi.org/10.18535/ijsrm/v6i10.em06

[24] Gursoy, D., Chi, C. G., & Chi, O. H. (2019). Effects of artificial intelligence (AI) on customer satisfaction and experience. *International Journal of Hospitality Management*, 89, 102540. https://doi.org/10.1016/j.ijhm.2020.102540

[25] Hair, J. F., Anderson, R. E., Tatham, R. L. and Black, W. C. (1998). Multivariate data analysis. (5th ed.). Prentice-Hall, New Jersey.

[26] Heskett, J. L., Jones, T. O., Loveman, G. W., Sasser, W. E., Jr., & Schlesinger, L. A. (1994). Putting the service-profit chain to work. *Harvard Business Review*, 72(2), 164–174.

[27] Homburg, C., Koschate, N., & Hoyer, W. D. (2005). Do satisfied customers really pay more? A study of the relationship between customer satisfaction and willingness to pay. *Journal of Marketing,* 69(2), 84–96. https://doi.org/10.1509/jmkg.69.2.84.60760

[28] Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, 21(2), 155–172. https://doi.org/10.1177/1094670517752459

[29] Kahneman, D., Knetsch, J. L., & Thaler, R. (1986). Fairness as a constraint on profit seeking: Entitlements in the market. *The American Economic Review*, 76(4), 728–741. Retrieved from https://www.jstor.org/stable/1806070

[30] Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1986). Fairness and the assumptions of economics. *The Journal of Business*, 59(4), S285–S300. https://doi.org/10.1086/296367

[31] Kawatu, F. (2023). The analysis of price fairness and servicescape on customer satisfaction at up creative space and coffee manado. *Jurnal Emba Jurnal Riset Ekonomi Manajemen Bisnis Dan Akuntansi*, 11(3), 535-544. https://doi.org/10.35794/emba.v11i3.49574

[32] Kettinger, W. J., Lee, C. C., & Lee, S. (1995). Global measures of information service quality: A cross-national study. *Decision Sciences*, 26(5), 569-588.

[33] Kline, R. B. (2023). Principles and practice of structural equation modeling (5th ed.). Guilford Press.

[34] Likert, R. (1932). A technique for the measurement of attitudes. *Archives of Psychology*, 22(140), 1–55.

[35] Lu, L., Cai, R., & Gursoy, D. (2019). Developing and validating a service robot integration willingness scale. *International Journal of Hospitality Management*, 80, 36–51. https://doi.org/10.1016/j.ijhm.2019.01.005

[36] Madsen, S., & Gregor, S. (2006). Measuring human-computer trust. In Proceedings of the International Conference on Design Science Research in Information Systems and Technology (pp. 1–11).

[37] Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, 20(3), 709–734.

[38] Nunnally, J. C. (1978). Psychometric theory. New York: McGraw-Hill.

[39] Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research*, 17(4), 460–469.

[40] Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. *Journal of Retailing*, 64(1), 12–40.

[41] Parasuraman, A., Zeithaml, V. A., & Malhotra, A. (2005). E-S-QUAL: A multiple-item scale for assessing electronic service quality. *Journal of Service Research*, 7(3), 213–233.

[42] Peterson, R. A. (1994). A meta-analysis of Cronbach's coefficient alpha. *Journal of Consumer Research*, 21(2), 381–391. https://doi.org/10.1086/209405

[43] Phung, V. H., Pham, H. H., & Tran, B. M. (2025). The Effect of Pricing Strategies on Client Retention Rates for Small to Medium-Sized Auditing Firms. *International Review of Management and Marketing*, *15*(1), 31-45.

[44] Rai, A., & Sambamurthy, V. (2006). The growth of interest in trust in information systems: Opportunities for future research. *MIS Quarterly*, 30(4), 373–375.

[45] Rai, A., Constantinides, P., & Sarker, S. (2019). Next-generation digital platforms: Toward human–AI hybrids. *MIS Quarterly*, 43(1), iii–ix. https://doi.org/10.25300/MISQ/2019/13755

[46] Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping business with artificial intelligence. *MIT Sloan Management Review*, 59(1), 1–9.

[47] Rust, R. T., Moorman, C., & Dickson, P. R. (2002). Getting return on quality: Revenue expansion, cost reduction, or both? *Journal of Marketing*, 66(4), 7–24.

[48] Schoorman, F. D., Mayer, R. C., & Davis, J. H. (2007). An integrative model of organizational trust: Past, present, and future. *Academy of Management Review*, 32(2), 344–354.

[49] Setiawan, E., Wati, S., Wardana, A., & Ikhsan, R. (2020). Building trust through customer satisfaction in the airline industry in indonesia: service quality and price fairness contribution. *Management Science Letters*, 1095-1102. https://doi.org/10.5267/j.msl.2019.10.033

[50] Shankar, G. (2024). Application of chatbots and virtual assistants in ticket booking system. *Int Res J Adv Engg Mgt*, 2(05), 1605-1608. https://doi.org/10.47392/irjaem.2024.0221

[51] Sharma, R. (2022). Corporate social responsibility and customer satisfaction: role of artificial intelligence. *Acta Universitatis Bohemiae Meridionalis*, 25(2), 162-174.

[52] Simanjuntak, R. (2023). Customer perceptions of mobile telecommunication providers in determining satisfaction and loyalty: focusing on college students. *Gema Wiralodra*, 14(3), 1047-1060. https://doi.org/10.31943/gw.v14i3.576

[53] Steiger, J. H. (1990). Structural model evaluation and modification: An interval estimation approach. *Multivariate behavioral research*, 25(2), 173-180.

[54] Venigandla, K. (2023). Leveraging ai-enhanced robotic process automation for retail pricing optimization: a comprehensive analysis. *Journal of Knowledge Learning and Science Technology Issn* 2959-6386 (Online), 2(2), 361-370.

[55] Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186–204.

[56] Wamba, S. F., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2017). How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. International *Journal of Production Economics*, 165, 234–246. https://doi.org/10.1016/j.ijpe.2014.12.031

[57] Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, 70, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

[58] Wang, L. (2024). Leveraging emerging technologies in pricing strategies and consumer behavior: case studies from china's innovative markets. *ijetaa*, 1(6), 6-12.

[59] Xia, L., Monroe, K. B., & Cox, J. L. (2004). The price is unfair! A conceptual framework of price fairness perceptions. *Journal of Marketing*, 68(4), 1–15.

[60] Yang, X., Hao-wen, L., Ni, L., & Li, T. (2021). Application of artificial intelligence in precision marketing. *Journal of Organizational and End User Computing*, 33(4), 209-219.

[61] Zahra, A. (2023). Assessing customer satisfaction in ai-powered services: an empirical study with smartpls. *International Transactions on Artificial Intelligence* (Italic), 2(1), 81-89. https://doi.org/10.33050/italic.v2i1.432

[62] Zikmund, W. G., Babin, B. J., Carr, J. C., & Griffin, M. (2000). Business research methods (Vol. 6). Dryden Press.