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Research Paper

Behavioral intention of Chinese users to use DeepSeek for medical tourism

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Abstract

This study investigates the behavioral intentions of Chinese users toward adopting DeepSeek - an open-source large language model (LLM) - in the context of medical tourism. Using structural equation modeling, we analyzed data collected from 502 Chinese users experienced with DeepSeek to explore how various psychological, social, and practical factors influence user adoption. Results highlight that utilitarian motivation, hedonic motivation, hedonic value, and price value significantly shape users' attitudes and adoption intentions. Additionally, habit and social influence emerge as critical predictors of behavioral intention. Theoretically, the findings provide a comprehensive understanding of user acceptance behavior toward AI-driven medical tourism applications. Practically, the insights guide healthcare providers, tourism businesses, and policymakers in effectively leveraging AI technologies by enhancing emotional appeal, ensuring competitive pricing, and tailoring culturally relevant digital experiences for sustainable medical tourism growth in Asia. This study contributes theoretically by integrating three established models and provides practical insights for developers and healthcare providers to enhance AI-enabled medical tourism platforms in the Asian context.

Keywords: Medical tourism, behavioral intention, DeepSeek, UTAUT2, Theory of Planned Behavior, China.

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Introduction

Artificial Intelligence (AI) is transforming healthcare, tourism, and e-commerce by enabling personalized and context-aware services (Carvalho and Ivanov, 2024; Khennouche et al., 2024). In medical tourism, generative AI platforms such as DeepSeek enhance diagnosis support, hospital comparison, and personalized travel planning, improving decision-making and service personalization. User attitude remains a key predictor of behavioral intention, with perceived benefits strongly influencing AI adoption (Sun et al., 2025; Hossain and Rahman, 2023). Cognitive, emotional, and social factors - trust, social influence, and perceived control - significantly shape AI healthcare adoption (Akram et al., 2021; Alam et al., 2023; Seow et al., 2021; Meng et al., 2023; Hossain, 2025).

Technology adoption has been widely explained using the Unified Theory of Acceptance and Use of Technology (UTAUT, UTAUT2, and UTAUT3), validated across mobile payments, AI-enabled education, and tourism (Venkatesh et al., 2012; Kumar et al., 2023; Arora et al., 2023). UTAUT3 extends previous models by incorporating trust and personal innovativeness, making it particularly relevant for AI-driven services. Generative AI represents a major shift in service delivery by enabling human-like interactions, yet its integration with established adoption theories in medical tourism remains underexplored. The Stimulus–Organism–Response (SOR) framework explains how AI stimuli shape users' cognitive and emotional states, subsequently influencing behavioral responses (Hossain and Rahman, 2022). Integrating SOR with UTAUT3 and the Theory of Planned Behavior (TPB) therefore offers a comprehensive explanation of AI adoption.

Within TPB, perceived behavioral control (PBC) reflects individuals' perceived capability to perform a behavior and has consistently predicted technology adoption across multiple contexts (Yuen et al., 2020; Chen and Chen, 2021). Similarly, utilitarian value - the functional benefits users derive from a service - strongly influences attitudes and behavioral intentions in digital platforms (Chen et al., 2020; Fauzi and Sheng, 2020). However, previous studies have largely focused on general consumer technologies such as mobile payments, ride-sharing, and e-commerce, while AI-enabled medical tourism remains insufficiently investigated (Venkatesh et al., 2012; Kumar et al., 2023; Fauzi and Sheng, 2020; Meng et al., 2023; Ivanov et al., 2024). Moreover, existing research rarely integrates UTAUT3, TPB, and SOR to explain how cognitive, emotional, value-based, and control-related factors jointly influence AI adoption (Hossain and Rahman, 2022; Fachrurrozie et al., 2023; Yuen et al., 2020).

Despite growing interest in AI-supported medical tourism, existing studies mainly emphasize technological capabilities rather than the psychological mechanisms driving adoption (Hassan and Bellos, 2022; Bathla et al., 2024). Furthermore, empirical evidence from China remains limited despite its distinctive technology adoption patterns and health-seeking behaviors (Chen and Chen, 2021; Li and Zhang, 2024). This study addresses these gaps by integrating UTAUT3, TPB, and SOR to examine Chinese users' adoption of DeepSeek for medical tourism. It proposes a unified model explaining how AI stimuli influence perceived behavioral control, utilitarian and hedonic values, attitudes, and behavioral intentions, thereby extending technology adoption theory and providing practical insights for AI-enabled medical tourism (Seow et al., 2021; Wong and Sa'aid Hazley, 2021; Hossain and Rahman, 2022; Chen et al., 2020; Sun et al., 2025).

Literature Review

Technology Adoption in Tourism: Evolving Theories, Generative AI

UTAUT3 has gained traction in mobile learning (Khan et al., 2022) and virtual communication (Gupta et al., 2023), yet remains underexplored in generative AI adoption for medical tourism. Meta-analyses confirm habit, personal innovativeness, and price value drive behavioral intentions (Khan et al., 2022), but their implications in AI-mediated health tourism decisions remain unexamined. Hospitality and tourism research has explored generative AI tools like ChatGPT (Dwivedi et al., 2024), addressing challenges such as AI hallucinations (Christensen et al., 2024) and digital divides (Zeng et al., 2023). However, these studies remain conceptual, with few empirical investigations from established behavioral theory perspectives. TPB has been applied to international medical tourists (Meng et al., 2023) and AI users in higher education (Ivanov et al., 2024), but its integration with UTAUT3 and SOR remains absent in this domain. Mariani et al. (2022) call for theoretical cross-fertilization in AI adoption research, emphasizing comprehensive models accounting for emotional and cognitive drivers. Given rising interest in AI-assisted services and medical tourism complexities, bridging these gaps requires investigating Chinese users' behavioral intentions toward generative AI platforms like DeepSeek through an integrated UTAUT3–TPB–SOR framework.

Antecedents of Intention to Use Technology: Perceived Behavioral Control, Utilitarian Value, and Attitude

Research confirms PBC as a positive predictor of behavioral intention in technology adoption, though context-dependent. Yuen et al. (2020) found facilitating conditions significantly influence PBC, affecting autonomous vehicle adoption intention. Chen and Chen (2021) similarly found PBC predicts intention and reinforces habit, sustaining technology use. However, Fachrurrozie et al. (2023) reported PBC did not significantly predict halal food purchase intention, indicating behavioral variability. Perez et al. (2023) demonstrated hedonic motivation enhances PBC by improving perceived ease of use and enjoyment in NFT gaming contexts, positively influencing usage intention.

Utilitarian value - practical and functional benefits - is another key determinant of technology use intention. Utilitarian value mediates purchase intention in food delivery, with perceived usefulness shaping users' intentions (Chen et al., 2020). Fauzi and Sheng (2020) found personal innovativeness impacts ride-hailing continuance intention through perceived utilitarian and hedonic value, with demographic factors moderating this relationship. Evelina et al. (2020) and Sadiq et al. (2021) suggest utilitarian value often has stronger effects than hedonic value on satisfaction and continuance intention. However, Fukui and Tan (2024) found hedonic and price values may be more influential than utilitarian considerations in 5G smartphone adoption. Thus, utilitarian value is foundational yet its relative importance varies by context and product.

Attitude remains one of the most consistent predictors of technology use intention across TAM, UTAUT, and SOR frameworks. Positive attitudes shaped by perceived playfulness and convenience increase ChatGPT continuance intention (Sun et al., 2025). Favorable attitudes mediate price value and experience effects on behavioral intentions in tourism and virtual reality applications (Qian and Li, 2024; Le et al., 2024). Nevertheless, Ropret Homar and Knežević Cvelbar (2024) caution an attitude-intention gap exists in some domains, particularly environmental behaviors where intention does not always lead to actual use. These findings reinforce that while attitude strongly predicts intention, social influence, PBC, and situational variables remain critical in determining whether intention results in adoption.

Although prior studies have applied UTAUT3, TPB, and SOR independently, few have examined their integration in AI-enabled medical tourism platforms (Seow et al., 2021; Wong and Sa'aid Hazley, 2021). Recent investigations highlight generative AI's transformative potential while identifying challenges like ethical concerns, digital inequality, and human-touch trade-offs (Cham et al., 2025). By linking habit, personal innovativeness, price value, PBC, and hedonic and utilitarian values to DeepSeek adoption, this study provides a context-specific theoretical perspective (Hossain and Rahman, 2022; Chen et al., 2020; Sun et al., 2025; Yuen et al., 2020). This approach demonstrates how cognitive, emotional, and social factors jointly influence attitudes and behavioral intentions in high-involvement, AI-mediated medical tourism services, bridging generative AI research with behavioral adoption frameworks.

Hypotheses Development

Antecedents of Perceived Behavioral Control (PBC)

Several prior studies have integrated UTAUT2 and TPB to explore behavioral intention determinants. Yuen et al. (2020) confirmed that habit, hedonic motivation, and price value influenced behavioral intentions via attitudes, while TPB variables - attitude, subjective norm, and perceived behavioral control - significantly predicted SAV adoption intention. Fachrurrozie et al. (2023) applied both frameworks to halal food purchases via mobile platforms, finding TPB constructs strong predictors but UTAUT2 variables (hedonic motivation, price value, habit) insignificant, highlighting industry and cultural variability. In workplace behavior, habit formation in energy-saving was significantly influenced by attitude and PBC, with behavioral intention mediating this relationship (Chen and Chen, 2021), supporting habit as both outcome and contributor to perceived control. Perez et al. (2023) combined TPB with HMSAM in NFT gaming, finding hedonic motivation strongly predicted PBC and was central to behavioral intention and immersion, reinforcing emotional gratification's significance in digital adoption. Sun and Wang (2020) demonstrated attitude, subjective norms, and PBC significantly predicted green product purchase intentions via social media, while price consciousness negatively affected intentions, validating TPB's relevance and price value's nuanced role. Drawing from this research, the following hypotheses are proposed regarding DeepSeek for medical tourism:

H1a Habit (HB) has a positive effect on Perceived Behavioral Control (PBC) in using DeepSeek for medical tourism purposes.

H1b Hedonic Motivation (HEM) has a positive effect on Perceived Behavioral Control (PBC) in using DeepSeek for medical tourism purposes.

H1c Price Value (PV) has a positive effect on Perceived Behavioral Control (PBC) in using DeepSeek for medical tourism purposes.

Antecedents of Hedonic Value (HV)

Hedonic motivation consistently enhances hedonic value across technology adoption contexts. Akram et al. (2021) demonstrated hedonic motivation positively impacts customer engagement and online purchase intention by increasing enjoyment. Meet et al. (2022) and Gunawan et al. (2022) similarly found hedonic motivation significantly influences user satisfaction and positive experiences.

Effort expectancy also contributes to hedonic value. When users perceive system effort as manageable, their hedonic experience improves (Alam et al., 2023; Meet et al., 2022). Availability of Medical Facilities (MF) plays a critical role in medical tourism decisions. Service accessibility and quality positively influence user attitudes and satisfaction (Chen et al., 2020; Gunawan et al., 2022). Performance Expectancy (PEE) - users' belief that DeepSeek effectively achieves medical tourism goals - enhances satisfaction and enjoyment (Gunawan et al., 2022; Meet et al., 2022). Price Value (PV) - perception that benefits justify costs - enhances emotional satisfaction (Alam et al., 2023; Meet et al., 2022). Finally, Perceived Behavioral Control (PBC) increases users' confidence and emotional engagement, leading to more positive emotional outcomes and greater enjoyment (Chen et al., 2020). Based on these insights, the following hypotheses are proposed:

H2a Hedonic Motivation (HEM) positively influences Hedonic Value (HV) when using DeepSeek for medical tourism.

H2b Effort Expectancy (EFE) positively influences Hedonic Value (HV) when using DeepSeek for medical tourism.

H2c Availability of Medical Facilities (MF) positively influences Hedonic Value (HV) when using DeepSeek for medical tourism.

H2d Performance Expectancy (PEE) positively influences Hedonic Value (HV) when using DeepSeek for medical tourism.

H2e Price Value (PV) positively influences Hedonic Value (HV) when using DeepSeek for medical tourism.

H2f Perceived Behavioral Control (PBC) positively influences Hedonic Value (HV) when using DeepSeek for medical tourism.

Antecedents of Utilitarian Value (UV)

Effort expectancy positively influences utilitarian value by shaping users' perceptions of reasonable effort. Chen et al. (2020) found that when consumers believe a platform demands manageable effort, they attribute higher utilitarian value to it. Hedonic motivation, though traditionally associated with enjoyment, also enhances perceived usefulness. Akram et al. (2021) and Fukui and Tan (2024) reported that pleasurable experiences can increase perceptions of practical benefits. Social influence further reinforces utilitarian value through social endorsement. Chen et al. (2020) and Fukui and Tan (2024) emphasize that social acceptance highlights a platform's utility.

Personal innovativeness significantly enhances utilitarian value. Fauzi and Sheng (2020) demonstrated that users with higher personal innovativeness perceive greater practical benefits from innovative services. Price value, reflecting a favorable cost-benefit trade-off, consistently increases perceived usefulness (Alam et al., 2023; Fukui and Tan, 2024). Finally, perceived behavioral control strengthens utilitarian value by boosting users' sense of capability and control (Chen et al., 2020). Based on these insights, we propose the following hypotheses.

H3a Effort Expectancy (EFE) positively influences Utilitarian Value (UV) when using DeepSeek for medical tourism.

H3b Hedonic Motivation (HEM) positively influences Utilitarian Value (UV) when using DeepSeek for medical tourism.

H3c Social Influence (SI) positively influences Utilitarian Value (UV) when using DeepSeek for medical tourism.

H3d Personal Innovativeness (PEI) positively influences Utilitarian Value (UV) when using DeepSeek for medical tourism.

H3e Price Value (PV) positively influences Utilitarian Value (UV) when using DeepSeek for medical tourism.

H3f Perceived Behavioral Control (PBC) positively influences Utilitarian Value (UV) when using DeepSeek for medical tourism.

Value Effects on Attitude

Hedonic value positively influences users' attitudes by providing pleasurable and enjoyable experiences that shape favorable perceptions. Wen et al. (2022) demonstrated hedonic motivation significantly contributes to positive attitudes, increasing continuance intention for food delivery apps. Mohammed and Ferraris (2021) found hedonic value enhances user attitudes in social media participation during crises, reinforcing enjoyment's role in forming positive behavioral attitudes. Utilitarian value - perceived practical and functional benefits - is also a key attitude determinant. Chen et al. (2020) showed utilitarian value significantly shapes positive consumer attitudes toward food delivery platforms, driving usage intentions. Nystrand and Olsen (2020) further supported that utilitarian eating values strongly and positively affect consumer attitudes, suggesting practical benefits are primary drivers of favorable attitudes. Perceived Behavioral Control (PBC) - users' confidence in effectively using a service - has a well-established positive effect on attitude toward use. Wen et al. (2022) confirmed PBC positively affects attitudes toward continued app use, while Mohammed and Ferraris (2021) similarly found PBC a significant predictor of positive attitudes. Sadiq et al. (2021) highlighted PBC's dual role in shaping attitudes and behavioral intentions in extended TPB models, reinforcing perceived control's importance in attitude formation. In light of these findings, the following hypotheses are proposed:

H4a Hedonic Value (HV) positively influences Attitude Toward Use (ATT) of DeepSeek for medical tourism.

H4b Utilitarian Value (UV) positively influences Attitude Toward Use (ATT) of DeepSeek for medical tourism.

H4c Perceived Behavioral Control (PBC) positively influences Attitude Toward Use (ATT) of DeepSeek for medical tourism.

Attitude on Behavioral Intention

Prior research consistently demonstrates that users' attitudes toward a technology or service significantly shape their behavioral intentions to use it. For example, Sun et al. (2025) found that positive attitudes, influenced by perceived usefulness and ease of use, strongly enhance students' intentions to continue using ChatGPT for educational purposes. Similarly, Le et al. (2024) showed that customer attitudes formed through positive online experiences significantly predict behavioral intentions toward virtual reality tours, emphasizing the attitudinal impact on intention even under situational constraints like social distancing. Although Ropret Homar and Knežević Cvelbar (2024) noted an attitude-behavior gap in tourism contexts, their findings still underscore the general positive association between attitude and intention to engage in sustainable behaviors. Moreover, Qian and Li (2024) confirmed that tourists' positive attitudes, framed as Price Value and place identity, directly enhance their behavioral intentions in rural tourism. Together, these studies support the proposition that a favorable attitude toward using DeepSeek in medical tourism will increase users' behavioral intention to adopt the platform.

H5 Attitude Toward Use (ATT) positively influences Behavioral Intention (BI) to use DeepSeek for medical tourism.

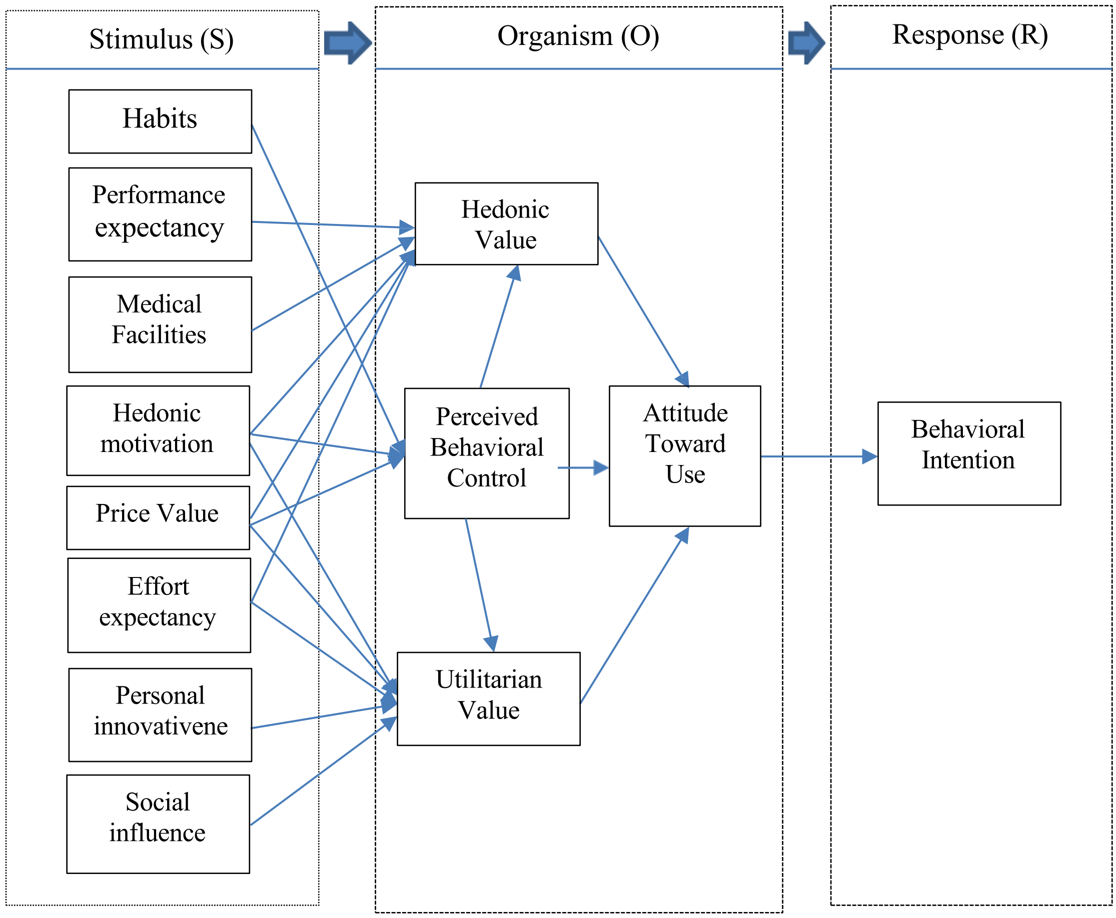
Theoretical Framework

This study integrates UTAUT2/3, TPB, and SOR to examine behavioral intention toward adopting DeepSeek for medical tourism. UTAUT2 (Venkatesh et al., 2012) incorporates consumer-oriented constructs - hedonic motivation, price value, and habit - capturing intrinsic motivation and cost-benefit considerations. Building on UTAUT2, this study further incorporates Personal Innovativeness and Hedonic Value following UTAUT3 trends (Khan et al., 2022; Gupta et al., 2023), accounting for user-specific psychological factors in AI-enabled medical tourism platforms. TPB (Meng et al., 2023; Ivanov et al., 2024) complements UTAUT2/3 by emphasizing PBC and attitudes as central behavioral intention determinants, with empirical support in medical tourism and generative AI adoption contexts (Meng et al., 2023; Ivanov et al., 2024).

SOR (Hossain and Rahman, 2022; Hossain et al., 2018) provides process logic linking external stimuli to internal cognitive/emotional states and behavioral responses. External stimuli - performance expectancy, social influence, habit, and price value from UTAUT2/3 - affect users' internal evaluations (hedonic and utilitarian values) in the organism stage. These evaluations mediate stimuli's influence on attitudes and PBC, which drive behavioral intention as specified in TPB. Prior studies demonstrate SOR's utility in digital and health contexts, showing how affective and cognitive processing mediates behavioral outcomes (Hossain et al., 2018; Hossain and Rahman, 2022).

Integrating these models offers a hierarchical, process-oriented framework (Figure 1) capturing adoption determinants: UTAUT2/3 explains perceived platform features and social cues; SOR details psychological evaluation of stimuli; and TPB links evaluations to intentional behavior. This integration combines rational, emotional, and social drivers into a coherent framework, enabling nuanced understanding of AI adoption in high-stakes, emotionally charged, socially influenced medical tourism decisions. The approach avoids conceptual redundancy while highlighting how stimuli, internal evaluations, attitudinal and control mechanisms collectively shape behavioral intention, providing a strong theoretical basis for analyzing user cognition and behavior in AI-enabled medical tourism.

Figure 1: Proposed framework



Methodology

This study aims to examine the key factors influencing the behavioral intention of Chinese users to adopt DeepSeek for medical tourism. A quantitative approach was employed to collect data from Chinese participants who had previously used DeepSeek to research or plan medical tourism. The data collection process took place between April 10 and May 25, 2025, through a self-administered online survey. The survey was created using a Chinese online survey tool WenJuanXing, and the link was distributed across various WeChat groups to reach a broad base of Chinese users interested in international healthcare services.

A total of 628 responses were initially collected. However, to ensure the relevance and reliability of the data, only respondents who indicated that they had used DeepSeek for medical tourism purposes were included in the final analysis. This filtering process resulted in a final dataset comprising 502 valid responses. All questionnaire items were initially developed in English and then translated into Simplified Chinese by bilingual experts. The survey instrument included 13 constructs, each measured by multiple items derived and adapted from previously validated scales in the context of health technology and behavioral studies. A 5-point Likert scale (ranging from 1 = Strongly Disagree to 5 = Strongly Agree) was used to assess participants' agreement with each item. Appendix 1 lists all constructs, their respective measurement items, and the academic sources from which they were drawn.

Demographic details are summarized in Table 1. Most respondents were aged 25–34 years (42.23%), over 48% held at least an undergraduate degree, and 60.96% were employed full-time. All participants confirmed prior DeepSeek experience for medical tourism purposes. Data were analyzed using SmartPLS 4 for partial least squares structural equation modeling (PLS-SEM), selected for its robustness in handling complex models and suitability for exploratory technology acceptance research. Analysis involved two stages: assessing the measurement model for reliability and validity, and evaluating the structural model to test hypotheses and determine path relationships (Hair et al., 2019).

Table 1: Profile of the respondents

Category	Frequency	Percentage (%)
Age		
Under 18 years old	3	0.60
18-24 years old	56	11.16
25-34 years old	212	42.23
35-44 years old	135	26.89
45-54 years old	73	14.54
55 years and above	23	4.58
Gender		
Female	276	54.98
Male	226	45.02
Education Level		
High school and below	26	5.18
College	52	10.36
Undergraduate	242	48.21
Master	129	25.70
PhD and above	53	10.56
Current occupation		
Unemployed	8	1.59
Student	58	11.55
Part-time job	60	11.95
Freelancing	63	12.55
Full-time job	306	60.96
Retire	7	1.39
DeepSeek usage experience for medical tourism		
Yes	502	100%

Results

Measurement Model Evaluation and Model Fit

The measurement model was assessed to confirm construct reliability and validity. As shown in Table 2, all constructs exhibited strong internal consistency with Cronbach's alpha and composite reliability exceeding the 0.7 threshold (Hair et al., 2019). AVE values ranged from 0.69 to 0.79, demonstrating adequate convergent validity.

Discriminant validity was confirmed via Fornell-Larcker criterion and HTMT ratios (Table 3). Square roots of AVE exceeded inter-construct correlations, fulfilling Fornell-Larcker conditions, while all HTMT values were below 0.9. VIF values for all indicators were below 3, indicating no multicollinearity. Model fit statistics indicated good fit (SRMR = 0.06, <0.08 acceptable). Bootstrapping with 3000 iterations ensured robust path coefficient estimation.

Table 2: Measurement model assessment

	Items	VIF	Outer Loadings	Cronbach's Alpha	rho_A	CR	AVE
ATT				0.91	0.91	0.93	0.73
	ATT1	2.45	0.85				
	ATT2	2.34	0.85				
	ATT3	2.45	0.86				
	ATT4	2.41	0.85				
	ATT5	2.37	0.84				
BI				0.89	0.9	0.92	0.69
	BI1	2.14	0.83				
	BI2	1.99	0.81				
	BI3	2.2	0.83				
	BI4	2.26	0.86				
	BI5	2.24	0.84				
EFE				0.88	0.88	0.91	0.73
	EFE1	2.24	0.87				
	EFE2	2.15	0.85				
	EFE3	2.15	0.84				
	EFE4	2.09	0.84				
HB				0.83	0.83	0.9	0.74
	HB1	1.94	0.86				
	HB2	1.86	0.86				
	HB3	1.84	0.86				
HEM				0.88	0.88	0.92	0.73
	HEM1	2.26	0.86				
	HEM2	2.25	0.86				
	HEM3	2.16	0.85				
	HEM4	2.22	0.86				
HV				0.9	0.9	0.93	0.77
	HV1	2.48	0.87				
	HV2	2.56	0.87				
	HV3	2.51	0.88				
	HV4	2.45	0.88				

	Items	VIF	Outer Loadings	Cronbach's Alpha	rho_A	CR	AVE
MF				0.86	0.87	0.9	0.7
	MF1	1.89	0.82				
	MF2	1.94	0.82				
	MF3	2.03	0.85				
	MF4	2.16	0.87				
PBC				0.87	0.87	0.91	0.72
	PBC1	2.14	0.84				
	PBC2	2.1	0.85				
	PBC3	1.95	0.83				
	PBC4	2.2	0.86				
PEE				0.89	0.89	0.92	0.75
	PEE1	2.4	0.87				
	PEE2	2.22	0.86				
	PEE3	2.33	0.87				
	PEE4	2.48	0.86				
PEI				0.87	0.87	0.91	0.72
	PEI1	1.89	0.82				
	PEI2	2.14	0.85				
	PEI3	2.22	0.86				
	PEI4	2.23	0.86				
PV				0.87	0.87	0.92	0.79
	PV1	2.35	0.9				
	PV2	2.13	0.87				
	PV3	2.29	0.89				
SI				0.88	0.88	0.92	0.73
	SI1	2.37	0.86				
	SI2	2.13	0.86				
	SI3	2.13	0.84				
	SI4	2.28	0.87				
UV				0.87	0.87	0.91	0.72
	UV1	2.1	0.85				
	UV2	2.08	0.85				
	UV3	2.16	0.86				
	UV4	2.06	0.84				

Note: ATT = Attitude Toward Use; BI = Behavioral Intention; EFE = Effort Expectancy; HB = Habit; HEM = Hedonic Motivation; HV = Hedonic Value; MF = Medical Facilities; PBC = Perceived Behavioral Control; PEE = Performance Expectancy; PEI = Personal Innovativeness; PV = Price Value; SI = Social Influence; UV = Utilitarian Value; VIF = Variance Inflation Factor; CR = Composite Reliability; AVE = Average Variance Extracted.

Table 3: Discriminant validity

	ATT	BI	EFE	HB	HEM	HV	MF	PBC	PEE	PEI	PV	SI	UV
Fornell-Larcker Criterion													
ATT	0.85												
BI	0.31	0.83											
EFE	0.41	0.43	0.85										
HB	0.45	0.34	0.4	0.86									
HEM	0.50	0.37	0.42	0.42	0.86								
HV	0.49	0.36	0.46	0.40	0.47	0.88							
MF	0.45	0.38	0.42	0.40	0.42	0.46	0.84						
PBC	0.43	0.32	0.37	0.41	0.44	0.44	0.38	0.85					
PEE	0.45	0.34	0.37	0.44	0.47	0.46	0.40	0.40	0.87				
PEI	0.42	0.31	0.31	0.36	0.41	0.39	0.39	0.33	0.41	0.85			
PV	0.55	0.38	0.44	0.47	0.51	0.52	0.48	0.45	0.48	0.39	0.89		
SI	0.36	0.36	0.33	0.30	0.34	0.30	0.37	0.31	0.29	0.35	0.33	0.86	
UV	0.43	0.37	0.43	0.40	0.45	0.48	0.38	0.42	0.42	0.45	0.49	0.39	0.85
Heterotrait - Monotrait Ratio (HTMT)													
ATT													

	ATT	BI	EFE	HB	HEM	HV	MF	PBC	PEE	PEI	PV	SI	UV
BI	0.34												
EFE	0.46	0.49											
HB	0.52	0.39	0.47										
HEM	0.56	0.42	0.48	0.49									
HV	0.54	0.40	0.52	0.47	0.53								
MF	0.51	0.43	0.47	0.47	0.49	0.52							
PBC	0.49	0.37	0.43	0.48	0.50	0.50	0.43						
PEE	0.50	0.38	0.42	0.51	0.53	0.51	0.46	0.45					
PEI	0.47	0.35	0.36	0.43	0.47	0.44	0.45	0.37	0.47				
PV	0.62	0.43	0.51	0.55	0.58	0.58	0.56	0.52	0.55	0.45			
SI	0.41	0.41	0.37	0.36	0.39	0.34	0.42	0.36	0.33	0.40	0.38		
UV	0.49	0.42	0.49	0.47	0.52	0.54	0.44	0.47	0.48	0.52	0.57	0.44	

Note: ATT = Attitude Toward Use; BI = Behavioral Intention; EFE = Effort Expectancy; HB = Habit; HEM = Hedonic Motivation; HV = Hedonic Value; MF = Medical Facilities; PBC = Perceived Behavioral Control; PEE = Performance Expectancy; PEI = Personal Innovativeness; PV = Price Value; SI = Social Influence; UV = Utilitarian Value.

Assessment of Structural Model: Path Coefficients and Significance

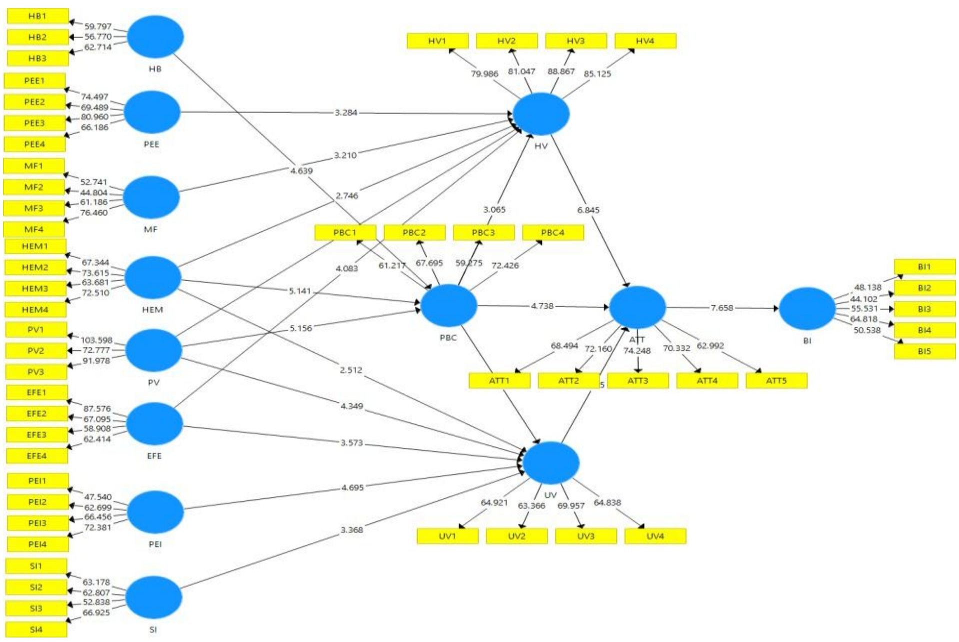
The structural model assessment results presented in Table 4 reveal that all hypothesized paths are statistically significant, with p-values less than 0.05, leading to the acceptance of all tested hypotheses. In detail (see figure 2), the predictors of Perceived Behavioral Control (PBC) - Habit (HB), Hedonic Motivation (HEM), and Price Value (PV) - all showed positive and significant effects, with path coefficients of 0.20 ($t = 4.63$), 0.23 ($t = 5.14$), and 0.24 ($t = 5.19$), respectively (H1a, H1b, H1c accepted). Similarly, Hedonic Value (HV) was significantly influenced by multiple factors: HEM ($\beta = 0.13$, $t = 2.78$), Effort Expectancy (EFE) ($\beta = 0.17$, $t = 4.22$), Availability of Medical Facilities (MF) ($\beta = 0.14$, $t = 3.22$), Performance Expectancy (PEE) ($\beta = 0.15$, $t = 3.28$), PV ($\beta = 0.18$, $t = 4.04$), and PBC ($\beta = 0.13$, $t = 3.11$), confirming hypotheses H2a through H2f. For Utilitarian Value (UV), significant positive effects were observed from EFE ($\beta = 0.15$, $t = 3.60$), HEM ($\beta = 0.11$, $t = 2.56$), PBC ($\beta = 0.12$, $t = 2.81$), Social Influence (SI) ($\beta = 0.13$, $t = 3.28$), Personal Innovativeness (PEI) ($\beta = 0.20$, $t = 4.76$), and PV ($\beta = 0.20$, $t = 4.41$), supporting hypotheses H3a through H3e. Further, Hedonic Value (HV), Utilitarian Value (UV), and PBC significantly predicted Attitude (ATT) toward the behavior, with path coefficients of 0.30 ($t = 6.94$), 0.20 ($t = 4.63$), and 0.22 ($t = 4.82$), respectively (H4a, H4b, H4c accepted). Finally, Attitude (ATT) was a significant predictor of Behavioral Intention (BI), with a path coefficient of 0.31 and a t-statistic of 7.72, confirming hypothesis H5.

Table 4: Structural model assessment

Hypothesis Paths	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Decision
H1a:HB -> PBC	0.20	0.20	0.04	4.63	0.00	Accepted
H1b: HEM -> PBC	0.23	0.24	0.05	5.14	0.00	Accepted
H1c:PV -> PBC	0.24	0.24	0.05	5.19	0.00	Accepted

Hypothesis Paths	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Decision
H2a: HEM -> HV	0.13	0.13	0.04	2.78	0.01	Accepted
H2b: EFE -> HV	0.17	0.17	0.04	4.22	0.00	Accepted
H2c:MF -> HV	0.14	0.14	0.04	3.22	0.00	Accepted
H2d: PEE -> HV	0.15	0.15	0.04	3.28	0.00	Accepted
H2e:PV -> HV	0.18	0.18	0.05	4.04	0.00	Accepted
H2f: PBC -> HV	0.13	0.13	0.04	3.11	0.00	Accepted
H3a: EFE -> UV	0.15	0.14	0.04	3.60	0.00	Accepted
H3b: HEM -> UV	0.11	0.11	0.04	2.56	0.01	Accepted
H3c: SI -> UV	0.13	0.13	0.04	3.28	0.00	Accepted
H3d:PEI -> UV	0.20	0.20	0.04	4.76	0.00	Accepted
H3e: PV -> UV	0.20	0.20	0.05	4.41	0.00	Accepted
H3f: PBC -> UV	0.12	0.12	0.04	2.81	0.00	Accepted
H4a: HV -> ATT	0.30	0.30	0.04	6.94	0.00	Accepted
H4b: UV -> ATT	0.20	0.20	0.04	4.63	0.00	Accepted
H4c: PBC -> ATT	0.22	0.22	0.05	4.82	0.00	Accepted
H5: ATT -> BI	0.31	0.31	0.04	7.72	0.00	Accepted

Figure 2: Bootstrapping outputs



Critical Reflection on the Uniformly Supported Hypotheses

The structural model's support for all proposed hypotheses necessitates careful interpretation beyond simple confirmation. A critical examination of effect sizes, methodological rigor, and theoretical scope is essential to contextualize these findings meaningfully. It is crucial to distinguish between statistical significance and substantive influence. Analysis of the path coefficients (β) and total effects reveals a clear hierarchy among predictors. Price Value (PV) and Perceived Behavioral Control (PBC) exhibited the strongest total effects on the model's endogenous variables, affirming their central role in a high-involvement, cost-sensitive domain like medical tourism. In contrast, paths such as Social Influence (SI) → Utilitarian Value (UV) ($\beta = 0.13$) and Habit (HB) → PBC ($\beta = 0.20$), while statistically significant, demonstrated more modest effects. This differential impact suggests that for Chinese users evaluating AI for medical tourism, rational assessments of cost and self-efficacy are primary, while social norms and established routines serve as secondary reinforcing factors.

Common method bias (CMB) is acknowledged in this cross-sectional design. We employed procedural remedies - respondent anonymity and validated scales. Harman's single-factor test indicated the first unrotated factor explained 33.07% of variance, well below the 50% threshold. Combined with strong discriminant validity (HTMT < 0.90), CMB is unlikely the primary driver of positive results. Consistent hypothesis support confirms the integrated UTAUT3–TPB–SOR framework's strong explanatory power. However, this coherence reveals a limitation: the model captures mainly facilitative factors. Omission of potential inhibitors - perceived risk, data privacy concerns, algorithmic distrust - may have contributed to uniformly positive results. Future research should incorporate these constructs for a more complete assessment of AI adoption drivers and barriers. The model's fit reflects successful theoretical synthesis rather than lack of critical testing. Findings reveal a clear influence hierarchy, with utilitarian and control-related factors paramount, offering practical guidance for platform design and establishing foundations for exploring boundary conditions, moderating variables, and inhibitory factors.

Discussion

Structural Model Analysis

The findings (Table 4) provide strong empirical support for the proposed model. First, Habit, Hedonic Motivation, and Price Value significantly enhance PBC. This suggests repeated use, emotional rewards, and perceived cost-benefit jointly empower users' confidence and control - extending prior research on routine and value perceptions in shaping perceived control. Hedonic Value, influenced by emotional motivation, Effort Expectancy, and Performance Expectancy, underscores the multifaceted nature of health value formation, with both intrinsic and external factors contributing to value judgments. Utilitarian Value emerges as critical, shaped by Effort Expectancy, Social Influence, and Personal Innovativeness, highlighting how practical benefits and social context affect value perceptions. Personal Innovativeness and Price Value substantially impact utilitarian value, aligning with growing awareness of sustainability and social responsibility in consumer decisions. Attitude is robustly influenced by Hedonic Value, Utilitarian Value, and PBC, demonstrating affective and cognitive evaluations collectively shape attitudes. The significant attitude-behavioral intention link confirms attitude's central role in driving intention, consistent with established behavioral theories. Overall, results validate the integrative framework, emphasizing the importance of addressing health-related motivations and environmental considerations in fostering positive behavioral intentions.

Direct and Indirect Effects on Behavioral Intention

The indirect effects analysis (Appendix 3) reveals a clear hierarchy among predictors. Price Value (PV) and Perceived Behavioral Control (PBC) exhibit the strongest indirect effects on Attitude (ATT) and Behavioral Intention (BI), underscoring their central role in the behavioral framework. Hedonic Motivation (HEM) also shows notable indirect effects across multiple outcomes (ATT, BI, HV, and UV), reflecting its broad influence on both cognitive and motivational aspects of behavior. Other constructs - including Effort Expectancy (EFE), Habit (HB), Availability of Medical Facilities (MF), Performance Expectancy (PEE), Personal Innovativeness (PEI), and Social Influence (SI) - contribute smaller but still significant indirect effects, confirming their supporting roles within the extended causal network. When total effects - which combine direct and indirect influences - are considered, Attitude remains the most powerful predictor of Behavioral Intention, reinforcing its centrality in the behavioral process. PV and PBC exhibit substantial total effects across multiple outcomes, reflecting their pervasive influence throughout the model. Environmental constructs like EFE and PEI similarly demonstrate meaningful total effects on HV, UV, ATT, and BI, illustrating how environmental perceptions and motivations interconnect with individual attitudes and intentions. Overall, these findings highlight that the predictors operate both directly and through mediated pathways to affect attitude and behavioral intention, revealing a complex interplay of emotional, cognitive, and environmental factors driving behavioral outcomes as summarized in Appendix 3.

Conclusion

The analysis reveals a coherent behavioral intention model where Attitude Toward Use (ATT) serves as the central mediator, integrating effects from hedonic value (HV), utilitarian value (UV), and perceived behavioral control (PBC). Effort Expectancy, habit, intrinsic motivation, price considerations, and social influence shape attitudes and value perceptions, driving DeepSeek adoption intention. Effort Expectancy indirectly promotes positive attitudes by enhancing hedonic and utilitarian perceptions. Habits strengthen PBC, reinforcing confidence and encouraging adoption. Hedonic Motivation and Price Value exert broad effects on perceived enjoyment, control, and usefulness, highlighting both emotional and rational evaluations in technology acceptance. Trust in Medical Facilities (MF), though less influential, remains important for hedonic value perceptions - likely due to the high-stakes nature of medical tourism decisions. Social Influence primarily drives utilitarian perceptions, emphasizing peer recommendations' role in shaping utility beliefs. Personal Innovativeness significantly affects utilitarian value, suggesting early adopters should be targeted with innovative features. These results underscore the necessity for DeepSeek to provide an easy-to-use, enjoyable, valuable platform, building user trust and supporting habitual engagement. The multifaceted influences highlight the interplay between cognitive evaluations, affective responses, and social factors in AI-enabled medical tourism adoption.

Theoretical Implications

This study makes several theoretical contributions. First, by integrating UTAUT2/3, TPB, and SOR, it forms a comprehensive framework capturing user decision-making in high-stakes, emotionally charged contexts. Second, it verifies and extends habit's significance as a key behavioral intention precursor within AI-mediated healthcare, suggesting routine AI system use can become automatic when perceived as user-friendly and productive. Third, validating personal innovativeness as an antecedent of hedonic and utilitarian value highlights individual-trait perspectives within TPB and UTAUT, underscoring intrinsic motivation and technology readiness in consumer adoption.

Fourth, empirically identifying hedonic and utilitarian value as mediators extends SOR's application to digital health platforms, demonstrating that emotional and price value are cognitively experienced before affecting intention - explaining the "organism" element in SOR. Fifth, incorporating hedonic value - relatively disregarded in digital health literature - reveals users' perception of hedonic benefits and affective engagement's role in AI service adoption over time. Finally, confirming the mediating role of attitude toward use and perceived behavioral control - central TPB components - shows these variables bridge stimulus and behavioral response. These findings underscore that intention is shaped not by rational evaluation alone but by perceived ease of control and emotional orientation toward the platform. This multi-theoretical integration offers a comprehensive behavioral model, contributing to theory development and future research design in digital health and medical tourism contexts.

Practical Implications

The practical implications of this study are directly informed by the strongest predictors of adoption behavior. The results indicate that Attitude Toward Use (ATT, $\beta = 0.31$, $p < 0.001$), Hedonic Value (HV, $\beta = 0.09$, $p < 0.001$), and Perceived Behavioral Control (PBC, $\beta = 0.09$, $p < 0.001$) are the dominant factors driving users' intention to adopt DeepSeek for medical tourism. These findings suggest that developers and healthcare platforms should prioritize fostering positive user attitudes and confidence alongside functional performance. Ensuring that the platform provides a pleasant, emotionally satisfying experience - through engaging visuals, enjoyable browsing, and culturally adapted content - can enhance Hedonic Value and strengthen users' attitudes.

Price Value (PV, $\beta = 0.05$, $p < 0.001$) and Utilitarian Value (UV, $\beta = 0.06$, $p < 0.001$) also exert significant influence, indicating that users remain sensitive to both perceived affordability and practical usefulness. Platforms should therefore offer clear cost-benefit information, tiered pricing options, and transparent comparisons with traditional medical tourism alternatives. Habit (HB) and Hedonic Motivation (HEM), while smaller predictors, still contribute to adoption, highlighting the value of features that encourage repeated engagement, such as personalized recommendations, reminders, and loyalty rewards. The significant effects of Perceived Behavioral Control and Attitude further suggest that reducing barriers to entry - through streamlined onboarding, multi-language support, tutorials, and responsive virtual assistants - can enhance user confidence and strengthen adoption intention. Finally, although constructs such as Performance Expectancy (PEE), Personal Innovativeness (PEI), Social Influence (SI), and Medical Facilities (MF) show comparatively smaller effects, they still play a supportive role. Clear demonstrations of medical accuracy, endorsements from peers or professionals, and listings from reputable healthcare providers can subtly reinforce adoption decisions. Collectively, these insights provide actionable guidance for developers, marketers, healthcare institutions, and policymakers to design AI-enabled medical tourism platforms that align with both the emotional and practical expectations of users, thereby improving adoption rates and user satisfaction.

Limitations and Future Research Directions

Despite its contributions, this study has several limitations. First, the sample is limited to Chinese users with prior DeepSeek experience, constraining generalizability. Future research should conduct cross-cultural comparisons to explore adoption variations across national and cultural contexts. Second, reliance on self-reported survey data may introduce social desirability or recall bias. Subsequent studies could employ longitudinal or experimental designs, or incorporate behavioral usage data, to validate and extend findings. Third, focusing on a single platform limits generalizability to other AI-based medical tourism solutions. Comparative studies across multiple platforms could provide richer insights into platform-specific and industry-wide adoption patterns. Fourth, the current model captures primarily facilitative factors; future studies should incorporate inhibitors - perceived risk, data privacy concerns, algorithmic distrust - to provide a more balanced understanding. Additionally, examining moderating variables and testing the model in diverse cultural or healthcare contexts would enhance generalizability and practical relevance. Trust, perceived risk, and service quality - not included in the current model - may significantly affect user behavior and should be integrated in future research. Finally, behavioral intention is inherently dynamic; longitudinal research could explore how user attitudes and intentions evolve with continued use, platform updates, or changing external conditions in the global healthcare landscape.

Practical Implications for Asian Business

This study provides actionable insights for Asian tourism and healthcare businesses seeking to attract Chinese medical tourists, highlighting how AI-enabled platforms like DeepSeek can influence adoption behavior. The strongest drivers of behavioral intention - Attitude Toward Use ($\beta = 0.31$, $p < 0.001$), Hedonic Value ($\beta = 0.09$, $p < 0.001$), and Perceived Behavioral Control ($\beta = 0.09$, $p < 0.001$) - suggest that platforms must deliver both functional benefits and positive user experiences. Performance expectancy and utilitarian value emerge as key factors for efficiency and reliability, emphasizing that AI platforms should act as trustworthy facilitators of decision-making, supporting smooth and informed medical tourism choices. For Asian healthcare providers, this means investing in AI capabilities that not only present accurate medical information but also streamline the entire decision journey from initial research to post-treatment follow-up, thereby reducing uncertainty and building confidence in cross-border healthcare decisions.

Integrating hedonic motivation and hedonic value into the experience is crucial; emotionally appealing features - such as immersive content, culturally adapted wellness activities, or post-operative recovery experiences - enhance user engagement and promote favorable attitudes, which can drive word-of-mouth and reinforce competitive differentiation. Asian tourism boards and medical institutions should collaborate to co-create content that showcases not just clinical excellence but also the holistic wellness journey, incorporating elements of local culture, cuisine, and leisure activities that appeal to Chinese sensibilities. This emotional engagement transforms medical tourism from a purely transactional healthcare decision into a meaningful life experience, increasing the likelihood of repeat visits and positive referrals within Chinese social networks.

Habitual usage underscores the importance of creating long-term engagement ecosystems, such as AI health monitoring subscriptions, personalized recovery check-ins, and loyalty programs, transforming the customer relationship from transactional to interactive and increasing lifetime value. Asian healthcare providers should view DeepSeek not merely as an acquisition tool but as a platform for ongoing patient relationship management, offering continuous value through health tracking, appointment reminders, and wellness content that keeps the provider top-of-mind between medical visits. This approach aligns with the growing trend of Chinese consumers seeking integrated, continuous healthcare solutions rather than episodic interventions.

The positive effects of price value highlight the necessity for transparent, detailed cost information, personalized cost-benefit analyses, and clear communication of financial advantages, which can reduce perceived risk and enhance perceived fairness. Asian medical tourism destinations often compete on cost advantages; however, this study suggests that value perception extends beyond price alone to encompass the full spectrum of benefits relative to investment. Providers should leverage DeepSeek to offer comparative cost calculators, treatment outcome projections, and total cost of care estimates that account for travel, accommodation, and ancillary expenses, enabling users to make fully informed financial decisions.

Social influence, though smaller, remains significant in collectivist cultures; fostering digital trust through verified reviews, social media content, collaboration with medical KOLs (Key Opinion Leaders), and shareable AI-generated summaries can enhance confidence and adoption. Asian businesses should strategically partner with trusted influencers and medical professionals who can authentically endorse their services within Chinese digital ecosystems, leveraging platforms like WeChat, Xiaohongshu, and Douyin to amplify reach and credibility.

Finally, eliminating friction points - through localized interfaces, Mandarin support, integration with WeChat Pay/Alipay, and assistance with visas - strengthens perceived behavioral control and facilitates platform adoption. Altogether, these findings demonstrate that Asian healthcare and tourism providers must combine technological capability, cultural understanding, emotional engagement, transparency, and social trust into a seamless user journey to remain competitive in the growing Chinese medical tourism market. To operationalize these insights, businesses should prioritize investments in user experience design, localized content creation, and strategic partnerships with technology platforms like DeepSeek, recognizing that competitive advantage in this sector increasingly depends on digital excellence and cultural resonance rather than clinical capabilities alone.

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Appendix

Appendix 1: Measurement constructs, items, and sources used in the study

Constructs	Items	Sources
Habits (HB)	**HB1**: Using DeepSeek for medical tourism has become a routine for me. **HB2**: I automatically think of DeepSeek when I need information about medical treatments abroad. **HB3**: I frequently use DeepSeek without needing to consciously decide.	Kurniawan et al. (2024); de Blanes Sebastián et al. (2023)
Performance expectancy (PEE)	**PEE1**: DeepSeek enhances my ability to make informed decisions about medical tourism. **PEE2**: I find DeepSeek useful for achieving better medical outcomes through tourism. **PEE3**: DeepSeek helps improve my efficiency when researching international healthcare providers. **PEE4**: Using DeepSeek increases my confidence in selecting a suitable medical destination.	Kurniawan et al. (2024); de Blanes Sebastián et al. (2023)
Medical Facilities (MF)/ Facilitating Conditions	**MF1**: The quality of medical facilities shown on DeepSeek influences my decision to use it. **MF2**: I trust the information about hospital facilities provided on DeepSeek. **MF3**: DeepSeek features reputable medical institutions that meet my expectations. **MF4**: I believe DeepSeek includes high-standard healthcare providers for medical tourism.	Kurniawan et al. (2024); Strzelecki (2024)
Hedonic motivation (HEM)	**HEM1**: I enjoy using DeepSeek when searching for medical tourism options. **HEM2**: Using DeepSeek is entertaining and emotionally rewarding. **HEM3**: I find pleasure in discovering new medical travel opportunities through DeepSeek. **HEM4**: Exploring medical tourism via DeepSeek makes the process more enjoyable.	Kurniawan et al. (2024); Strzelecki (2024)

Constructs	Items	Sources
Price Value (PV)	**PV1**: DeepSeek offers good value for the cost of medical tourism planning. **PV2**: I find the cost-benefit of using DeepSeek for medical tourism research to be worthwhile. **PV3**: The services provided by DeepSeek justify any expenses involved in using it.	Kurniawan et al. (2024); Strzelecki (2024)
Effort expectancy (EFE)	**EFE1**: Learning to use DeepSeek for medical tourism is easy for me. **EFE2**: I find DeepSeek user-friendly when searching for healthcare options. **EFE3**: Navigating through DeepSeek is effortless. **EFE4**: It is easy for me to become skillful at using DeepSeek for medical tourism.	de Blanes Sebastián et al. (2023); Strzelecki (2024)
Personal innovativeness (PEI)	**PEI1**: I am usually among the first to try new health-tech platforms like DeepSeek. **PEI2**: I like experimenting with innovative tools for planning medical travel. **PEI3**: I enjoy using new technologies even if they are unfamiliar at first. **PEI4**: I am open to adopting novel digital solutions like DeepSeek for healthcare.	Strzelecki (2024)
Social influence (SI)	**SI1**: People important to me think I should use DeepSeek for medical tourism. **SI2**: My family and friends support my use of DeepSeek for international healthcare. **SI3**: I am influenced by social media or peer recommendations about using DeepSeek. **SI4**: I would feel more confident using DeepSeek if others I know also used it.	de Blanes Sebastián et al. (2023); Strzelecki (2024)
Hedonic Value (HV)	**HV1:** I enjoy browsing DeepSeek for medical tourism options. **HV2:** Using DeepSeek for medical tourism research is a fun experience. **HV3:** I feel excited when exploring DeepSeek's content on medical tourism. **HV6:** I feel emotionally involved when using DeepSeek.	Rodríguez-Ardura et al. (2024); Akram et al. (2024)
Perceived Behavioral Control (PBC)	**PBC1:** I feel capable of using DeepSeek effectively to research medical tourism. **PBC2:** I have the resources needed to use DeepSeek for exploring medical tourism options. **PBC3:** I have the knowledge required to use DeepSeek for researching medical tourism. **PBC4:** I believe I have full control over using DeepSeek to find information about medical tourism.	Botha and Wiese (2024); Polyportis (2023)
Utilitarian Value (UV)	**UV1:** DeepSeek helps me effectively plan my medical tourism. **UV2:** I find DeepSeek to be a practical tool for comparing treatment providers.	Rodríguez-Ardura et al. (2024); Akram et al. (2024)

Constructs	Items	Sources
	UV3: Using DeepSeek improves the quality of my healthcare decisions.	
	UV7: DeepSeek offers great value when it comes to organizing medical tourism.	
Attitude Toward Use (ATT)	**ATT1:** Using DeepSeek for researching medical tourism is a good idea.	Sun et al. (2025); Akram et al. (2024)
	ATT2: I have a positive attitude toward using DeepSeek for medical tourism.	
	ATT3: I think using DeepSeek to find medical tourism options is beneficial.	
	ATT4: I like the idea of using DeepSeek for medical tourism.	
	ATT5: I feel favorable toward DeepSeek as a platform for medical tourism.	
Behavioral Intention (BI)	**BI1:** I am likely to rely on DeepSeek when planning future medical tourism.	Kurniawan et al. (2024); Strzelecki (2024)
	BI2: I intend to use DeepSeek regularly to stay informed about treatment options abroad.	
	BI3: I plan to recommend DeepSeek to others interested in medical tourism.	
	BI4: I am committed to using DeepSeek for researching and comparing treatment providers.	
	BI5: I will continue exploring medical tourism through DeepSeek over the next year.	

Appendix 2: Harman's single-factor test – Component variance explained

Component	Explained Variance (%)	Cumulative Variance (%)
Factor1	33.06791	33.06791
Factor2	5.343576	38.41149
Factor3	4.442883	42.85437
Factor4	3.914309	46.76868
Factor5	3.652547	50.42123
Factor6	3.551613	53.97284
Factor7	3.311229	57.28407
Factor8	3.236863	60.52093
Factor9	3.015858	63.53679
Factor10	2.965409	66.5022
Factor11	2.784213	69.28641
Factor12	2.543071	71.82948
Factor13	2.140494	73.96998
Factor14	1.087321	75.0573
Factor15	1.052203	76.1095
Factor16	1.040637	77.15014
Factor17	0.998671	78.14881
Factor18	0.945837	79.09465
Factor19	0.935029	80.02968
Factor20	0.901931	80.93161
Factor21	0.883587	81.81519
Factor22	0.851888	82.66708
Factor23	0.824645	83.49173
Factor24	0.803035	84.29476

Component	Explained Variance (%)	Cumulative Variance (%)
Factor25	0.784346	85.07911
Factor26	0.776658	85.85577
Factor27	0.763334	86.6191
Factor28	0.718609	87.33771
Factor29	0.698893	88.0366
Factor30	0.67872	88.71532
Factor31	0.676554	89.39188
Factor32	0.664406	90.05628
Factor33	0.644298	90.70058
Factor34	0.622957	91.32354
Factor35	0.616576	91.94011
Factor36	0.594937	92.53505
Factor37	0.587514	93.12257
Factor38	0.562868	93.68543
Factor39	0.548565	94.234
Factor40	0.534095	94.76809
Factor41	0.524964	95.29306
Factor42	0.52121	95.81427
Factor43	0.48473	96.299
Factor44	0.473273	96.77227
Factor45	0.457983	97.23025
Factor46	0.442335	97.67259
Factor47	0.435822	98.10841
Factor48	0.419539	98.52795
Factor49	0.406994	98.93494
Factor50	0.405314	99.34026
Factor51	0.334834	99.67509
Factor52	0.324908	100

Appendix 3: Indirect and total effects

Paths	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Total indirect effect					
EFE -> ATT	0.08	0.08	0.02	5.15	0.00
EFE -> BI	0.02	0.03	0.01	4.07	0.00
HB -> ATT	0.06	0.06	0.01	3.73	0.00
HB -> BI	0.02	0.02	0.01	3.1	0.00
HB -> HV	0.03	0.03	0.01	2.68	0.01
HB -> UV	0.02	0.02	0.01	2.34	0.02
HEM -> ATT	0.13	0.13	0.02	5.8	0.00
HEM -> BI	0.04	0.04	0.01	4.35	0.00
HEM -> HV	0.03	0.03	0.01	2.56	0.01
HEM -> UV	0.03	0.03	0.01	2.49	0.01
HV -> BI	0.09	0.09	0.02	4.95	0.00
MF -> ATT	0.04	0.04	0.01	2.82	0.00
MF -> BI	0.01	0.01	0.01	2.53	0.01
PBC -> ATT	0.06	0.06	0.02	3.49	0.00
PBC -> BI	0.09	0.09	0.02	4.87	0.00
PEE -> ATT	0.04	0.04	0.01	2.91	0.00
PEE -> BI	0.01	0.01	0.01	2.62	0.01

Paths	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
PEI -> ATT	0.04	0.04	0.01	3.18	0.00
PEI -> BI	0.01	0.01	0.00	2.72	0.01
PV -> ATT	0.16	0.16	0.02	7.18	0.00
PV -> BI	0.05	0.05	0.01	5.08	0.00
PV -> HV	0.03	0.03	0.01	2.6	0.01
PV -> UV	0.03	0.03	0.01	2.41	0.02
SI -> ATT	0.03	0.03	0.01	2.68	0.01
SI -> BI	0.01	0.01	0.00	2.43	0.02
UV -> BI	0.06	0.06	0.02	3.71	0.00
Total effect					
ATT -> BI	0.31	0.31	0.04	7.72	0.00
EFE -> ATT	0.08	0.08	0.02	5.15	0.00
EFE -> BI	0.02	0.03	0.01	4.07	0.00
EFE -> HV	0.17	0.17	0.04	4.22	0.00
EFE -> UV	0.15	0.14	0.04	3.60	0.00
HB -> ATT	0.06	0.06	0.01	3.73	0.00
HB -> BI	0.02	0.02	0.01	3.10	0.00
HB -> HV	0.03	0.03	0.01	2.68	0.01
HB -> PBC	0.20	0.20	0.04	4.63	0.00
HB -> UV	0.02	0.02	0.01	2.34	0.02
HEM -> ATT	0.13	0.13	0.02	5.80	0.00
HEM -> BI	0.04	0.04	0.01	4.35	0.00
HEM -> HV	0.15	0.16	0.04	3.55	0.00
HEM -> PBC	0.23	0.24	0.05	5.14	0.00
HEM -> UV	0.14	0.14	0.04	3.26	0.00
HV -> ATT	0.30	0.30	0.04	6.94	0.00
HV -> BI	0.09	0.09	0.02	4.95	0.00
MF -> ATT	0.04	0.04	0.01	2.82	0.00
MF -> BI	0.01	0.01	0.01	2.53	0.01
MF -> HV	0.14	0.14	0.04	3.22	0.00
PBC -> ATT	0.28	0.28	0.04	6.80	0.00
PBC -> BI	0.09	0.09	0.02	4.87	0.00
PBC -> HV	0.13	0.13	0.04	3.11	0.00
PBC -> UV	0.12	0.12	0.04	2.81	0.00
PEE -> ATT	0.04	0.04	0.01	2.91	0.00
PEE -> BI	0.01	0.01	0.01	2.62	0.01
PEE -> HV	0.15	0.15	0.04	3.28	0.00
PEI -> ATT	0.04	0.04	0.01	3.18	0.00
PEI -> BI	0.01	0.01	0.00	2.72	0.01
PEI -> UV	0.20	0.20	0.04	4.76	0.00
PV -> ATT	0.16	0.16	0.02	7.18	0.00
PV -> BI	0.05	0.05	0.01	5.08	0.00
PV -> HV	0.21	0.21	0.05	4.69	0.00
PV -> PBC	0.24	0.24	0.05	5.19	0.00
PV -> UV	0.23	0.23	0.04	5.10	0.00
SI -> ATT	0.03	0.03	0.01	2.68	0.01
SI -> BI	0.01	0.01	0.00	2.43	0.02
SI -> UV	0.13	0.13	0.04	3.28	0.00
UV -> ATT	0.20	0.20	0.04	4.63	0.00
UV -> BI	0.06	0.06	0.02	3.71	0.00