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| RESEARCH ARTICLE

Form AI-generated information to tourist booking intention: an integrated TAM-SOR perspective

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| ABSTRACT

The rapid development of Generative Artificial Intelligence (GenAI) is transforming how travelers seek information and make travel decisions. Despite its growing adoption, limited research explains how AI-generated information translates into actual booking behavior in tourism. This study investigates the effects of GenAI search tools on tourists' booking intentions through an integrated framework combining the Technology Acceptance Model (TAM), Stimulus-Organism-Response (S-O-R) paradigm, and Cognitive Load Theory (CLT). Using a quantitative research design, data were collected through an online survey of 357 Vietnamese tourists who use GenAI for travel purposes. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to test the proposed framework and hypotheses. The findings indicate that Perceived AI Intelligence and Cognitive Load Reduction do not directly influence booking intentions. Instead, Perceived Value represents a central psychological mechanism, fully mediating the effect of AI intelligence and partially mediating the effect of perceived ease of use on booking intentions. Task Complexity also negatively moderates the relationship between cognitive load reduction and booking intentions. These results suggest that technological sophistication and cognitive relief alone are insufficient to stimulate booking behavior. Tourism marketers should therefore effectively emphasize meaningful value, actionable AI-generated information, and human support for complex and high-stakes travel planning decisions.

| KEYWORDS

Generative Artificial Intelligence, Travel Booking Intention, Perceived Value, Tourism Technology.

| ARTICLE INFORMATION

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1. Introduction

The main objective of this thesis is to explore how the potential generative artificial intelligence search tools are able to shape a way that travelers search for their information related to their journey, as well as to highlight the impact of these tools on customer's booking intention. Moreover, this dissertation also evaluates a comprehensive framework including three model: Technology Acceptance Model (TAM), Stimulus-Organism-Response (SOR), and Cognitive Load Theory (CLT). This investigation aims to identify the characteristics of AI search engines that may affect on traveller booking intentions, as well as evaluate whether tourists natural psychological mechanisms are genuinely alleviated by these tools, and finally highlight the moderating influence of Task Complexity on these interactions. By doing so, this research could address a gap in the current marketing literature by examining the impact of artificial intelligence generation on the digital consumer experience within the travel industry and offer meaningful insights for marketers aiming to enhance their comprehensive marketing strategy in a dynamic digital landscape.

To begin with, it is readily apparent that artificial intelligence is becoming increasingly prevalent, not only changing how businesses operation but also emerging in personal and even professional lives (Erin Chao Ling et al., 2025). Indeed, technology advanced such as chatbots or automated robots are widely used in almost service delivery at the initial stage (Bowen and Morosan, 2018). Therefore, the tourism industry is one of the main sectors affected by the continuous innovation of AI and customer search behavior through it.

In addition, it can be seen that advances in AI have presented an enormous opportunity for tourism companies and hotels. They can apply these advancements to promote their products and services to customers and influence travel behavior (I.

Tussyadiah & Miller, 2019). Moreover, the tourism industry has successfully evolved based on content-centricity (Chuang, 2023) and continuously enhances the traveler experience (Asif and Fazel, 2024; Salamzadeh et al., 2022). Therefore, marketers can track and evaluate these changes in customer search behavior, particularly changes in the purchase journey, and can easily propose the most appropriate marketing strategies for businesses operating in the tourism sector in general.

2. Litureture Review

2.1. The direct impact of stimuli elements on travel decision booking

Generative AI might be seen as a valuable advisor to users. To illustration in the fact that, Alter and Oppenheimer (2009) reviewed the literature on information processing fluidity and determined that when information is processed more smoothly, it is easily engender greater confidence in judgment and boost a robust tendency to act than perviously observed. This mechanishm could be classified as metacognitive. In trip booking scenarios, where users must make financial commitments under condition of incompllete or even non-transparent information via travel agent websites, therefore, it can be seen that the flow of information and transparentcy are regarded as critical factors that influence the decisions of users. With another perspective, Eppler and Mengis (2004) observed that a non-linear correlation between information volume and decision quality in their multifiled summary of research on information overload. Consequently, they illustrated that decisions are impaired when cognitive capability is exceeded. Moreover, it is irrefutable that the inherent capabilities of GenAI may directly bypass corporate review pcoesses and serve as a catalyst, enhancing user trust and significantly reinforcing the immedite inlination to complete their booking decision. Several research in the travel sector, which involves papers authored from Wong, Lian, and Sun (2023) and Stankov and Gretzel (2020), indicates that when AI generation provide aggregated, personalised, and contextually relevant itineraries, users can acknowledge the system's utility, leading to enhanced decision-naking efficacy.

H1: Perceived AI Intelligence has a direct positive effect on Travel Decision Booking.

It is undeniable that the simplicity of a system's operation plays a crucial role in consumer decision-making.Therefore, it can be argued convincingly that the perceived ease of use of a generative artificial intelligence (GenAI) platform not only serves as a prerequisite for perceived value, but also positively and directly impacts user travel decision booking.

This is illustrated by the fact that the theoretical foundation for this claim is firmly rooted in the Technology Acceptance Model (TAM) (Davis, 1989) and its later adaptations (Venkatesh & Davis, 2000; Venkatesh et al., 2003). In all these models, effort expectancy (also called ease of use) has consistently been considered as a direct determinant of behavioral intention. If an AI interface is intuitive, smooth, and seemingly mentally effortless, users might skip the extended evaluation process and proceed more directly to purchase-oriented behaviors through simple, frictionless interaction.

To illustrate with more compelling evident, recent empirical studies in the tourism and hospitality sector has strongly supported for this view. For instance, Al-Romeedy and Alharethi (2025) use an extended technology acceptance model to generative systems like ChatGPT and find that perceived ease of use is directly and significantly linked to travelers' booking intentions. Likewise, Wong, Lian and Sun (2023) and Pillai and Sivathanu (2020) both found that if AI-powered tools can provide a seamless and user-friendly travel planning experience, consumers are more likely to take the plunge and make bookings.

In summary, these results point to a fairly clear conclusion that a fictionless user experience acts as a powerful catalyst, directly driving positive booking intentions.

H2. AI Perceived Ease of Use is directly and positively associated with Travel Decision Booking.

2.2. The indirect impact of stimuli elements on travel decision booking

The prevalent of advanced technologies, particularly Generative Artificial Intelligence has begun to ease the cognitive effort users typically expend when processing informtation. One of the hightly artificial intelligent systems, such as ChatGPT, do not only more than retieve results tool, but interpret complex queries through natural langiage and present synthesized answers, which can notice that reduce the mental work required from users (Wong, Lian, & Sun, 2023). Furtheremore, at the certain point, when users perceive AI to be highly inferential and accurate, even somewhat "intelligent", they start to delegate part of the task over to the algorithm. Eventually, the analytical effort will be replaced by delegation. This leads to the fact that instead of carefully considering each option, users are offered immediate and automatic suggestions and often accept them without extended reflection (Gerlich, 2025).

From a theortical standpoint, it seems that the cognitive-load process that faciliates the connection between perceived intelligence and the decrease of effort is an easy procedure. In traditional search, majority of the burden is derived from the processing costs, including query disambiguation, source filtering, and content synthesis (Sweller et al., 2019; Stankov &

Gretzel, 2020). Hence, the tourist is more inclined to delegate processing to the system that they evaluate as intelligent. In light of this reasoning:

H3. Perceived AI Intelligence is positively associated with Cognitive Load Reduction.

This is when generative AI begins to perform exceptionally. Large language systems (LLMs) such as ChatGPT assess data, synthesise information, and provide tailored suggestions, thereby alleviating some of the cognitive burden that users would otherwise handle independently. The approach seems to be more streamlined and straightforward. However, GenAI can produce either subtle or visible errors, such as presenting incorrect information and falsifying information (Cappellani et al., 2024; Walters & Wilder, 2023; Sun et al., 2024). Thus, users must retain cognitive clarity in order to process information methodically and make appropriate decisions. When that balance is maintained in a controlled manner, activities such as booking reservations become far more manageable.

H4: Cognitive Load Reduction is positively associated with the Travel Decision Booking.

In order to properly comprehend how arrtificial intelligence has influenced on customer behavior in the travel industry, it is necessary to examine the psycological mechanisms that underlying the apparent cause and effect relationship. One of the most interesting claims is that reducing cognitive load affects user's final booking intentions and their perception of the intelligence of the AI. To begin with, the theoretical basis for this mediating variable is rooted in Cognitive Load Theory (CLT). Sweller, van Merriënboer, and Paas (2019) claim that human working memory has a limited capacity, particularly when people are asked to perform tasks requiring cognitive effort. A clear example of this is a trip. When comparing itineraries with numerous destinations, considering costs, and reading reviews and arranging schedules, users can easily become overloaded with information processing demands. But when consumers can engage with a generative artificial intelligence system that is seen to be very intelligent, capable of understanding complex situations, stitching together disjointed information, and offering clear recommendations, they are more likely to delegate some of that analysis to the AI system.

H4a: Cognitive Load Reduction mediates the relationship between Perceived AI Intelligence and Travel Decision Booking.

The role of Perceived Value

Perceived ease of use has long been treated as a strating point in explaning how users form value judgments, which was intergrated in the fundamental princiles of the TAM model (Davis, 1989). When a technological system can feel effortless, meaning that user do not heavy mental work with any complicated steps, they tend to extract more functional value from their experience. To demontrate, King & He(2006) found a consistent between perceived ease of use and perceived value in their meta-analysis of 88 studies of TAM model in various fields. Importantly, a similar parrtern appears in reasech focused on tourism. Schepers và Wetzels (2007) confirmed this relationship, showing that the mechanism remains true even as the contect becomes more specific.

The scenario is significantly more complicated when it comes to application in the rourist industry. Pillai and Sivathanu (2020), for instance, show that perceived ease of use has stronger impact on behavioural attitudes. Despite the fact that it is crucial, it is it not the most main driver. Additionally, a comparable insight comes from Wong, Lian and Sun (2023), who find that conversational fluency, which is highly connected with ease of use, has significant influencer in deciding how user feel about technologies such as ChatGPT.

Subsequently, users are just needed to provide a description of their disires and they are not expected to have any prior understanding of knowledege about navigation strutures or interface logic. This sort of seamless involvement, which was developed by Al-Romeedy and Alharethi (2026), allows passenger to enhace their queries in a way that is nearly perfectly natural. As a result, the perceived utility of the experience as well as the overall worth of the encounter are both increased.

As a connsequence, conversational GenAI has evolved to the extent where ease of use is now an expectaiton rather than distinguishing feature:

H5: AI Perceived Ease of Use is positively associated with Perceived Value

In the contemporary digital landscape, the efficacy of Artificial Intelligence has increasingly considered through the lens of consumer perception. One of the compelling argument can be made that the perceived intelligence of an AI system can fundamentally dictate the overall consumers derive from it. Zeithaml (1988) makes a useful distinction is that perceived value is not just a sum of service attributes, yet it runs at higher and reflective level. Furthermore, when perceived value is applied across a various of dimensions, an artificial intelligence agen that is more intelligent will exhibit the potential to improve each applied demension. Sweeney and Soutar's (2001) PERVAL scale indicates that perceived intelligence can enhances functional (Sheth, Newman, and Gross, 1991), emotional (Lin, Chi, and Gursoy, 2020), social, and monetary value.

Moreover, empirical work in tourism tends to support this view. Lalicic and Weismayer (2021), for instance, show a direct link between the perceived capability of an AI agent and its "use value", with participants noting that the system assisted them avoid ineffective choices and reveal ambiguous alternatives. Likewise, Wong, Lian and Sun (2023) report a positive relationship between perceived capability in generative AI such as ChatGPT and the usefulness of the travel outputs they produce. There is also quantitative evidence from Hu, Lu and Gong (2021), suggesting that perceived AI quality contributes meaningfully to perceived value, even after accounting for baseline trust.

In summary, it is logically and empirically evident that as a user's perception of an AI intelligence increases, there is a corresponding, positive increase in the cognitive, utilitarian, and hedonic value they associate with that system.

H6. *Perceived AI Intelligence is positively associated with Perceived Value.*

As users perceive vital benefits and fewer obstacles in interacting with AI, their behavioral intention to make a purchase substantially increases. There is a rationale for this reasoning, because the theoretical underpinning of this relationship is based on signal-based logic (Zeithaml, 1988) and multiple value frameworks (Sweeney & Soutar, 2001; Sheth, Newman, & Gross, 1991). This hypothesis proposes that if the consumer sees a lot of value in the GenAI tool, like having high functional, emotional and cognitive value in some context, their willingness to follow the GenAI recommendations is high. This is because these GenAI tool can offer accurate options to users, leading to seamless experiences and novel insight that would have previously required long periods of time for research and synthesis.

The investigation found that participants consistently reported that AI recommendations assisted them avoid poor choices and directed them to follow the suggested itineraries. Besides that, there is an identical pattern in the work of Wong, Lian, and Sun (2023). They discovered that when users perceive the ChatGPT results to be beneficial, they are more likely to rely on them for travel decisuons, and in some certain situations, they even allow the system to shape their judgements in more consistent way. Ultimately, within the extended TAM, Al-Romeedy and Alharethi (2025) empirically validated that when an AI system is regarded as a valued advisor rather than merely a tool, it directly stimulates the user's intention to complete their booking choice.It also seves as a factor to further strengthen the hypothesis:

H7: Perceived Value is positively associated with the Travel Decision Booking.

The simplicity of usage generative AI platforms has undeniablt applealing to users. Nevertheless, its influence on purchasing behavior is more accurately seen as an indirect way rather than an immediate catalyst. To be more explicit, it can be strongly argued that perceived value serves as a crucial mediating variable between customers' perceived ease of use of artificial intelligence and their final booking intentions. From this perspective, it is important to note that a user interface that is both smooth and user-friendly does not always result in consumers finally completing their buying decisions.Indeed, it fundamentally enhances the whole functional and emotional value of the service, which is the true catalyst driving consumers to complete bookings.

Furthermore, more current practical studies in tourist and artificial intelligence generation provided credence to this theoretical premise. In fact, quantitative research with large sample sizes, such as that conducted by Ku and Chen (2024) and Pillai and Sivathanu (2020), indicates the perceived ease of use influences behavioural intention mainly through the value users receive, including time efficiency, stress alleviation, and the identification of ideal travel routes. Likewise, Lee and Cha (2023) discovered that perceived value functioned as an almost perfect mediator in their study of artificial intelligence travel chatbots.

H7a: Perceived Value mediates the relationship between AI Perceived Ease of Use and Travel Decision Booking.

When it comes to artificial intelligence and tourism, this approach has been given a lot more empirical focus since 2021. After that, this framework was later validated quantitatively by Hu, Lu, and Gong (2021) in a study involving 405 participants. They found that customer perceived value accounted for a significant portion of booking intention, even after controlling for baseline trust. As a result, there were a significant number of respondents who said that the advice made by the AI assisted them in better trip planning and prevented them from making bad decisions.

Interstingly, the rise of generative AI has not weakened users' trust in technology, but on the contrary, it has established conditions that enhance and reinforce this mediating connection.To illustration the fact that, Pham and Tran (2024) noted that artificial intelligence (AI) generates a unique "perceived value" by presenting novel travel information that users were previously unaware they needed to enquire about, significantly influencing their behavioural intentions. Moreover, Ku and Chen (2024), through a study of 512 generative AI users, formally confirmed that perceived value significantly mediated the indirect effect of AI quality on users' final intentions.

H7b Perceived Value mediates the relationship between Perceived AI Intelligence and Travel Decision Booking.

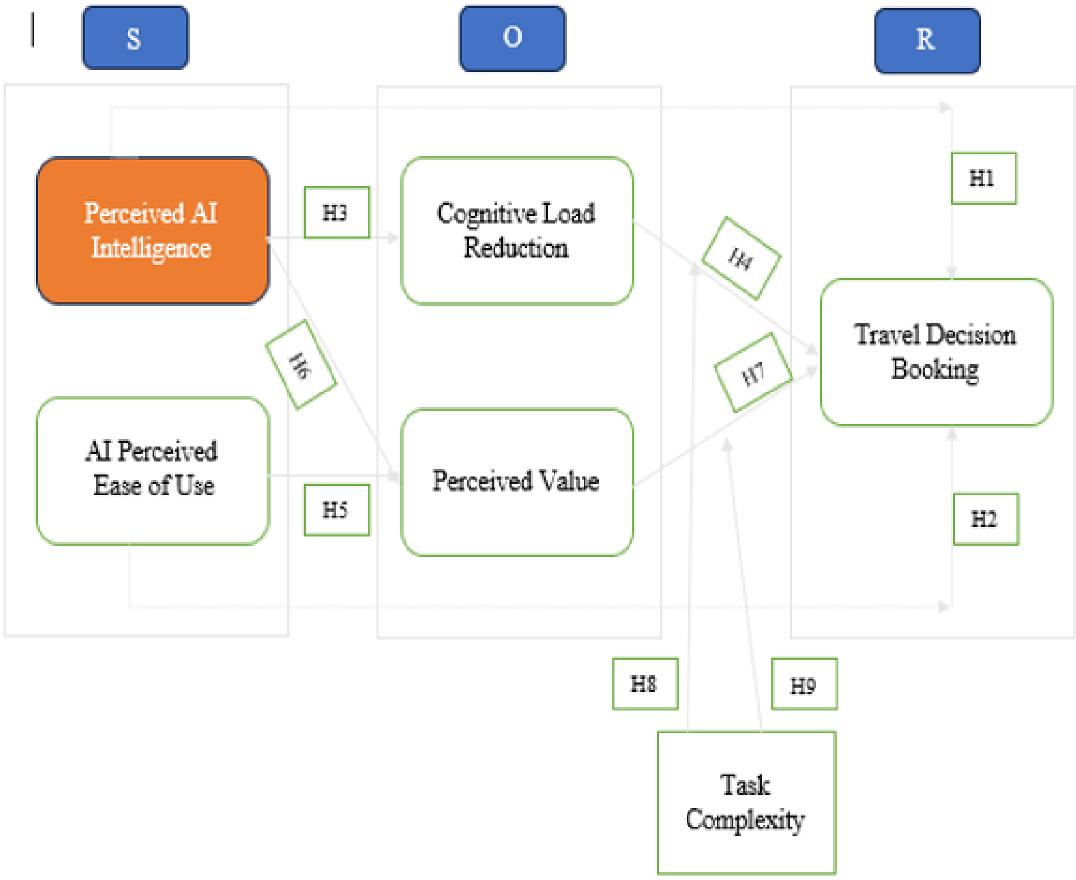
In the traveling sector, the travellers are able to manage the cognitive challenges of very easy and low risk travel activities, such as arranging travelling chores themselves. In such a situation, the decreased effort that AI offers may make it more convenient, but it is not likely to be a behaviour deciding element. However, detailed travel planning yields a different sort of story. It has been observed that coordinating schedules of multiple cities, knowing which modes of transport are possible across different countries and having to cope with plane cancellations is an important mental task. Most of such scenarios tend to take up a lot of time, and may cause regret or decision fatigue for the person. Therefore, under these conditions, the assistance provided by AI goes beyond being merely useful and becomes essential to the operation of the system. It is no longer enough to merely reduce cognitive effort for the sake of convenience but a vital operational requirement to maintain control over the decision-making process:

H8: Task Complexity moderates the relationship between Cognitive Load Reduction and Travel Decision Booking.

Despite the fact that the perceived value of artificial itelligence is often regarded as a strong predictor of customer behivor, but the impact of its on final purchase decisions tends to diinish as the complexity of the task increases. Regarding to previous technology adoption models, many scholars have pointed out that the psychological reason behind negative user's attitudes towards technologies lies in the intersecttion of perceived risk and anxiety related to its adoption (Pavlou ,2003; Hou and Zhang ,2017). In rountine transactions with low risk, consumers are likely to easily make decisions based on their own judgments and prior experiences. Under those conditions, the added value of AI may be helpful but not essential.

Futhermore, the transparency of artificial intelligence (AI) further contributes to exacerbating user anxieties about the technological adoption. Research by Singu et al. (2026) indicates that the "black box" aspect of AI heightens nevousness regarding the technology as tasks seem to become more difficult than ever. In the realm of travel, when individuals make intentions related to booking their journeys, which are often perceived as high risk, they often tend to exhibit hieghtened sensitivity and caution over the potential for algorithmic errors.

H9: Task Complexity moderates the relationship between Perceived Value and the Travel Decision Booking.



Conceptual Framework

3. Research Methodology

This dissertation adopts a quantitative research method and uses survey data to test the proposed hypothesis concerning the effects of factors into Stimulus-Organism-Response (SOR) theoretical framework. Specifically, the stimulus variables include perceived AI intelligence and AI perceived ease of use, which are expected to influence organism factors, including reduced cognitive effort and perceived value. Therefore, through the mediating variable of task complexity, the model clearly demonstrates the final impact on travel decision booking.

The target population for this dissertation consists of international tourists who have accessed Generative AI (GenAI) to gather information about travel, including checking flight or ticket prices, researching popular attractions in a particular location, or other complex tasks, such as trip planning. Notably, prior to the study, participants were required to have experience using GenAI, and the study used the PLS-SEM technique for data analysis, so the sampling strategy was carefully designed to produce objective and reliable data.

One of the commonly used methods in PLSSEM is the "*10-times rule*" that was put forth by Hair et al. (2011) to determine minimum required sample size. As per this rule, the sample size is required to be at least 10 times the greatest structural paths directed to any latent variable in the model (Kock & Hadaya, 2018). The independent variables: perceived AI intelligence, perceived ease of use, perceived value, and cognitive effort reduction; and the mediating variable: task complexity, were all found to influence the dependent variable of travel decision-making in this study. From this structure, the necessary sample size is 50 or more. The study aims about 300-400 valid responses to increase the statistical power and robustness of the study. This larger sample size should lead to more representative results and will be closer to good practice in research that use structural equation modelling (SEM).

Following the data collection process, the raw data were first screened, cleaned, and subjected to preliminary analysis to ensure their quality and suitability for further statistical analysis.Then the cleaned dataset was then analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). One of tools to use for it is SPSS that was employed for the preliminary statistical analyses, including data screening, reliability analysis, and exploratory factor analysis (EFA), while another one is SmartPLS that was used to estimate and evaluate the structural model.

As I see it, the order of these analytical operations is important in order to obtain accurate and reliable results. The initial analyses in SPSS provide a chance to detect potential problems, such as unreliable measurement items or unsuitable factor structures, at an early stage, before the estimation of the PLS-SEM model. This step will enhance the quality of the measurement model and give a more solid foundation for estimating the relationship between the latent constructs in SmartPLS.

4. Key Findings

4.1. Descriptive statistics

The number of samples for this thesis was originally 357 people. After screening, the final sample size was 357 people.

When you read the profile in Table 4.1, one thing is apparent. They're not just dabblers. 86.6% of the sample said they used AI daily, while 68.9% of the sample said they had been using AI for 12 months or longer. That is important to the interpretation of the results that follow: If the effort-reduction narrative is going to take hold anywhere, it should take hold here, with people who are accessing AI on a daily basis. The sample is young (93.6% under 45) and is educated (80.7% with bachelor's or higher). Women made up 56.9%. All the participants were residing in Vietnam, a market with a rapidly increasing tourism flow and rapid AI adoption (Central Statistics Office, 2026; VNAT, 2026).

The tools are grouped around a few names. ChatGPT finished first with 83.5% of the respondents, followed by Gemini with 61.9%, Perplexity with 33.9%, Claude with 20.7%, and Copilot with 17.9% (Multiple answers were permitted to the question). The activities people undertook with these tools were distributed throughout the planning process: asking for local recommendations (204 mentions), comparing accommodation or flights (188), creating or comparing itineraries (182), researching destinations (168), posing travel questions (102), and - importantly - actually booking travel (87). Thus, a real slice of this sample didn't halt at research. They transacted.

Table 4.1 Respondent profile (N = 357)

Characteristic	Category	n	%
Age	18-24	122	34.2
	25-34	117	32.8
	35-44	95	26.6
	45-54	10	2.8

Characteristic	Category	n	%
	55-64	13	3.6
Gender	Female	203	56.9
	Male	116	32.5
	Non-binary	14	3.9
	Prefer not to say	24	6.7
Education	Bachelor's degree	288	80.7
	Master's degree	46	12.9
	Secondary	23	6.4
Leisure trips / year	1	83	23.2
	2-3	258	72.3
	4-5	16	4.5
AI use frequency	Daily	309	86.6
	Weekly	23	6.4
	Monthly	16	4.5
	Rarely	9	2.5
AI use experience	Less than 6 months	3	0.8
	6-12 months	108	30.3
	1-2 years	133	37.3
	More than 2 years	113	31.7
Country of residence	Vietnam	357	100.0

Note. Percentages are of N = 357 and may not total 100 owing to rounding. Tool use and travel-activity items allowed multiple selections and are reported in the text.

4.2. Descriptive statistics

The item means tell a small story before any model is fitted. Booking intention sat highest, with a construct mean of 3.93 on the five-point scale, and perceived value came next at 3.82. Perceived AI intelligence was more reserved at 3.55, ease of use at 3.63, and cognitive load reduction at 3.68. Then there is task complexity, sitting alone at the bottom on 2.13. That last figure is not a footnote. It says most people in this sample were planning fairly simple trips when they used AI, and it will come back to bite the moderation hypotheses later. Full item-level statistics, alongside the outer loadings, appear in Table 4.2.

Table 4.2 Item descriptives and outer loadings

Item	Mean	SD	Outer loading
PAI1	3.538	1.085	0.801
PAI2	3.437	1.137	0.818
PAI3	3.473	1.189	0.796
PAI4	3.597	1.127	0.843
PAI5	3.566	1.141	0.845

Item	Mean	SD	Outer loading
PAI6	3.672	1.113	0.857
PEOU1	3.748	1.046	0.851
PEOU2	3.689	1.157	0.864
PEOU3	3.571	1.114	0.780
PEOU4	3.599	1.052	0.867
PEOU5	3.546	1.063	0.806
CLR1	3.759	1.101	0.849
CLR2	3.577	1.090	0.866
CLR3	3.711	1.160	0.887
PV1	3.916	0.895	0.775
PV2	3.815	1.003	0.791
PV3	3.843	1.027	0.783
PV4	3.866	0.962	0.811
PV5	3.647	1.062	0.828
TBD1	3.832	0.927	0.839
TBD2	4.022	0.848	0.923
TBD3	3.947	0.855	0.874
TC1	2.070	0.833	0.806
TC2	2.300	0.944	0.617
TC3	2.179	0.943	0.826
TC4	1.964	0.758	0.807

Note. All items measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). PAI = perceived AI intelligence; PEOU = perceived ease of use; CLR = cognitive load reduction; PV = perceived value; TBD = booking intention; TC = task complexity.

4.3. Measurement model

The constructs must first be earned, prior to being trusted, by the path coefficients. Outer loadings, composite reliability (CR) and average variance extracted (AVE) were used to assess the convergent validity. Nearly all loading exceeded the threshold of 0.708 (Hair et al., 2022), and all of these exceeded the threshold of significance of $p < 0.001$, with the t-values ranging from approximately 10 to 91 (in the bootstrap). One indicator was loaded with a value of 0.617, the other (TC2) was not. This is below the normal level. It was retained for two reasons: a) the model still satisfied its AVE criterion comfortably and b) discarding an item to achieve a decimal is not likely to produce a better model, and therefore it is not advisable to do so (Hair et al., 2022). All else was in good order.

Overall reliability was good. Cronbach's alpha ranged from 0.763 to 0.907, rho_A from 0.770 to 0.908, and CR from 0.851 to 0.929 - all past the 0.70 line. AVE for each was in a range from 0.591 to 0.773, which means that each construct accounted for more than half of the variance in each of its own items. The detail is in table 4.3.

Table 4.3 Construct reliability and convergent validity

Construct	Cronbach's α	rho_A	CR	AVE
CLR	0.836	0.836	0.901	0.753
PAI	0.907	0.908	0.929	0.684
PEOU	0.890	0.892	0.919	0.696
PV	0.858	0.861	0.898	0.637
TBD	0.852	0.854	0.911	0.773

Construct	Cronbach's α	rho_A	CR	AVE
TC	0.763	0.770	0.851	0.591

Note. All α ≥ 0.70, CR ≥ 0.70 and AVE ≥ 0.50, satisfying the criteria of Hair et al. (2022) for internal consistency and convergent validity.

Discriminant validity was judged two ways. The Fornell-Larcker criterion held: the square root of each construct's AVE, shown on the diagonal of Table 4.4, was larger than that construct's correlation with any other (Fornell and Larcker, 1981). The heterotrait-monotrait ratio (HTMT) told the same story more strictly (Henseler, Ringle and Sarstedt, 2015). The highest HTMT value was 0.859, between perceived AI intelligence and ease of use - high, and worth naming honestly, but still under the liberal 0.90 ceiling. Every other pair sat lower. The two constructs are related, as any traveller would expect; they are not the same thing.

Table 4.4 Discriminant validity - Fornell-Larcker criterion

	CLR	PAI	PEOU	PV	TBD	TC
CLR	**0.868**					
PAI	0.719	**0.827**				
PEOU	0.671	0.773	**0.834**			
PV	0.648	0.672	0.659	**0.798**		
TBD	0.482	0.454	0.499	0.661	**0.879**	
TC	-0.482	-0.449	-0.450	-0.457	-0.437	**0.769**

Note. Bold diagonal values are the square root of AVE. Off-diagonal values are inter-construct correlations.

Table 4.5 Discriminant validity - HTMT ratios

	CLR	PAI	PEOU	PV	TBD	TC
CLR	-					
PAI	0.823	-				
PEOU	0.775	0.859	-			
PV	0.755	0.754	0.747	-		
TBD	0.571	0.515	0.572	0.773	-	
TC	0.605	0.543	0.549	0.567	0.543	-

Note. All HTMT values fall below the 0.90 threshold (Henseler, Ringle and Sarstedt, 2015).

Collinearity was the last box to tick. Outer VIF values stayed under 5, topping out at 4.54 for PAI6, so indicator redundancy was not a problem (Hair et al., 2022). Inner VIF values for the substantive paths ranged from 1.44 to 3.20 - below the conservative 3.3 mark that Kock (2015) uses as a full-collinearity flag for common method bias. The two product terms carried higher inner VIFs (4.34 and 4.32), which is expected for interaction constructs and is not a sign of method contamination. On balance, common method bias is unlikely to be driving the results. As an approximate global fit check, the standardised root mean square residual (SRMR) was 0.071 for the saturated model, inside the 0.08 guideline (Hu and Bentler, 1999), and 0.082 for the estimated model - a whisker over the line, and reported here rather than hidden.

4.4. Structural model and hypothesis tests

Now the rent-paying part. The model accounted for a moderate variance and for this type of behavioural research, a respectable one. The R2 value for Booking intention was 0.479, indicating that the predictors explained about 48% of the variance in Booking intention. Perceived value obtained 0.500 and cognitive load reduction 0.517. The values and their adjusted equivalents are given in Table 4.6.

Table 4.6 Coefficient of determination (R^2)

Endogenous construct	R^2	R^2 adjusted
Cognitive load reduction (CLR)	0.517	0.516
Perceived value (PV)	0.500	0.497
Booking intention (TBD)	0.479	0.469

Note. Following Hair et al. (2022), R^2 values around 0.50 indicate moderate explanatory power in consumer behaviour research.

The direct paths are where the model begins to contradict its theory. They are presented in Table 4.7 along with their coefficients, t-values, p-values, effect sizes and verdict on each hypothesis. Take them in turn.

Perceived value drove booking intention hard ($\beta = 0.537$, $t = 7.634$, $p < 0.001$), with a medium effect size ($f^2 = 0.240$). This is the strongest structural relationship in the entire model; it supports H7 without qualification. Ease of use kept a modest but real direct grip on booking intention ($\beta = 0.128$, $t = 2.241$, $p = 0.025$), supporting H2, though the effect size was tiny ($f^2 = 0.011$). Perceived AI intelligence pushed value up ($\beta = 0.405$, $p < 0.001$, H6 supported) and pushed ease of use into value as well ($\beta = 0.345$, $p < 0.001$, H5 supported). And the strongest raw path of all was the one from perceived intelligence to cognitive load reduction, which was almost emphatic ($\beta = 0.719$, $t = 27.898$, $p < 0.001$, $f^2 = 1.070$). It's obvious that people felt the load was lighter with Smart-feeling AI.

Then the model becomes clumsy. H1 hypothesized that perceived intelligence would have a direct positive effect on booking intention. It did not. The coefficient was indeed negative but not significant ($\beta = -0.113$, $t = 1.732$, $p = 0.083$) and therefore H1 is rejected. What was more striking, however, is that cognitive-load reduction, the mechanism the whole cognitive-load limb was built to carry, was not on its own associated with booking intention at all ($\beta = 0.056$, $t = 0.885$, $p = 0.376$). AI not only saving you mental effort, but by itself, it did not get anyone closer to booking. Hold that thought.

Task complexity was a true variable, rather than a passive control. The more difficult they found it to plan the trip, the less willing they were to book on AI's word, and this effect was negative and significant ($\beta = -0.179$, $t = 3.686$, $p < 0.001$).

Table 4.7 Structural paths, effect sizes and direct-effect hypotheses

Hyp.	Path	β	t	p	f^2	Decision
H1	PAI → TBD	**-0.113**	1.732	0.083	0.008	**Not supported**
H2	PEOU → TBD	**0.128**	2.241	0.025 *	0.011	**Supported**
H3	PAI → CLR	**0.719**	27.898	0.000 ***	1.070	**Supported**
H4	CLR→TBD	**0.056**	0.885	0.376	0.003	**Not supported**
H5	PEOU → PV	**0.345**	6.604	0.000 ***	0.096	**Supported**
H6	PAI → PV	**0.405**	7.357	0.000 ***	0.132	**Supported**
H7	PV → TBD	**0.537**	7.634	0.000 ***	0.240	**Supported**
-	CLR → TBD	0.056	0.885	0.376	0.003	Non-significant
-	TC → TBD	**-0.179**	3.686	0.000 ***	0.043	Sig. (negative)
H8	TC × CLR → TBD	**-0.175**	2.392	0.017 *	0.022	**Supported †**
H9	TC × PV → TBD	**0.136**	1.841	0.066	0.016	**Not supported**

*Note. * $p < 0.05$, *** $p < 0.001$. β = standardised path coefficient; f^2 thresholds (Cohen, 1988): 0.02 small, 0.15 medium, 0.35 large. † H8 is statistically supported but the interaction is negative - see §4.5 and Chapter 8.*

The mediation tests, in Table 4.8, are where the model's real logic surfaces. Bootstrapped specific indirect effects with bias-corrected confidence intervals were used, and the mediation type read against Zhao, Lynch and Chen (2010). Perceived value carried both antecedents through to booking intention. Ease of use reached booking intention through value (indirect $\beta = 0.185$, $p < 0.001$, CI [0.124, 0.254]), and because the direct effect of ease of use also survived, this is complementary - partial - mediation, supporting H7a. Perceived intelligence reached booking intention through value too, and more powerfully (indirect $\beta = 0.217$, $p < 0.001$, CI [0.154, 0.301]). Here the direct effect was not significant, so value fully carries the relationship - indirect-only mediation in Zhao et al.'s terms - supporting H7b. The one mediation that failed was the cognitive-load route. The indirect effect of perceived intelligence on booking intention through cognitive load reduction was trivial and non-significant ($\beta = 0.041$, $t = 0.884$, $p = 0.377$), with a confidence interval straddling zero [−0.055, 0.127]. H4a is rejected.

Table 4.8 Mediation analysis (specific indirect effects)

Hyp.	Path	Indirect β	t	p	95% BC CI	Mediation / decision
H4a	PAI → CLR → TBD	**0.041**	0.884	0.377	[-0.055, 0.127]	**No mediation - not supported**
H7a	PEOU → PV → TBD	**0.185**	5.682	0.000	[0.124, 0.254]	**Complementary (partial) - supported**
H7b	PAI → PV → TBD	**0.217**	5.882	0.000	[0.154, 0.301]	**Indirect-only (full) - supported**

Note. BC CI = bias-corrected 95% confidence interval from 5,000 bootstrap subsamples. Mediation typology follows Zhao, Lynch and Chen (2010).

The moderation results close the chapter on a genuinely surprising note. Task complexity was tested as a mediator on two paths using the product-indicator approach (Aiken and West, 1991). On the cognitive-load route, the interaction was significant ($\beta = -0.175$, $t = 2.392$, $p = 0.017$), so H8 is statistically supported - task complexity does mediate the link between cognitive load reduction and booking intention. However, see the sign. It is negative. On a simple slope reading, when the trip was simple, easing mental effort nudged booking intention up (slope ≈ +0.23 at one standard deviation below the complexity mean); when the trip was complex, that same effort saving did nothing, and if anything worked against booking (slope ≈ −0.12 at one standard deviation above). The opposite of what the theory predicted - the theory said that AI's assistance should be more important when tasks become more difficult. The interaction was not significant on the value route ($\beta = 0.136$, $t = 1.841$, $p = 0.066$) and H9 is rejected at conventional levels. The rate of perceived value to booking intention was more or less the same for both the easy and hard trips. All verdicts have been gathered in Table 4.9.

Table 4.9 Summary of hypothesis testing

Hyp.	Statement	Result
H1	Perceived AI intelligence → booking intention (direct, +)	**Not supported**
H2	Perceived ease of use → booking intention (direct, +)	**Supported**
H3	Perceived AI intelligence → cognitive load reduction (+)	**Supported**
H4a	Cognitive load reduction mediates PAI → booking intention	**Not supported**
H5	Perceived ease of use → perceived value (+)	**Supported**
H6	Perceived AI intelligence → perceived value (+)	**Supported**
H7	Perceived value → booking intention (+)	**Supported**
H7a	Perceived value mediates PEOU → booking intention	**Supported**
H7b	Perceived value mediates PAI → booking intention	**Supported**
H8	Task complexity moderates CLR → booking intention	**Supported (opposite direction)**
H9	Task complexity moderates PV → booking intention	**Not supported**

Remove all the layers and the model has a message to say. Value converts. Effort savings, alone, do not. Six hypotheses stood; three fell; one held, with an internal contradiction; and the one that everyone assumes has been the beating heart of the appeal of AI-namely, that it reduces the mental burden-turned out to be a spectator in the matter of booking. The following chapters dissect that.

5. Conclusion

The paper explores the changing landscape of information search behaviour in travel planning, focusing on the adoption of Generative Artificial Intelligence (GenAI) and its impact on travel booking decisions. In order to achieve this objective, the study examines the empirical validity of an integrated framework that combines the Technology Acceptance Model (TAM), Stimulus-Organism-Response (S-O-R) model and Cognitive Load Theory (CLT) in the context of tourism. The empirical results offer significant support for the developed framework as well as several asymmetric relationships that contradict the conventional beliefs of AI-assisted consumer decision making. Of particular interest is the finding that Perceived Value (PV) was the most powerful direct determinant of travel booking decisions, while the other constructs were mainly indirect in their influence on travel booking decisions by having a direct impact on Perceived Value. Using these findings, the four research questions can be answered.

The results show that the impact of AI-related attributes on booking is mostly indirect. Hypothesis H1 was rejected as there is strong evidence that Perceived AI Intelligence (PAI) does not directly influence Travel Booking Decision. Rather, its impact is completely mediated by Perceived Value, which supports the full mediation posited in Hypothesis H7b. Perceived Ease of Use (PEU) has a direct significant effect on booking decision (H2), but the indirect effect on booking decision through Perceived Value (H7a) is greater. The results indicate that technology features are not enough to encourage buying. Instead, they act as value-enhancing features that influence users' general perceptions of the AI-assisted travel planning. So it's not the sophistication of the AI itself that ultimately urges travellers to take the actions that lead to a booking decision, but the benefits that AI provides.

The findings show that Perceived Value is the key psychological process in the suggested S-O-R model. It was found to have the highest direct impact on Travel Booking Decision of all endogenous constructs, thus proving the important role it played in moving the external technological stimuli to behaviour. The data shows that when travellers see value in the information AI provides, they're more likely to go through with a booking, such as better decision-making quality, convenience and more effective travel planning.

Cognitive Load Reduction (CLR) on the other hand did not show the same behavioural function. While it was significantly affected by Perceived AI Intelligence, it had no statistically significant direct effect on Travel Booking Decision. This result indicates that it is not enough to make people less cognitively demanding to motivate their booking behaviour. Rather, it seems as though visitors are considering if AI recommendations can offer them real value before they make a buying choice. The perceived usefulness and practical value of AI-assisted travel booking services, not the mere mental effort savings, is thus the key psychological factor in the proposed research framework for travel booking decisions.

The results partially respond to the third research question by showing that Task Complexity is a crucial boundary condition in AI-supported travel decision-making. Contrary to the conventional expectation that more complex tasks increase users' reliance on intelligent technologies, the empirical results reveal a significant negative moderating effect of Task Complexity on the relationship between Cognitive Load Reduction and Travel Booking Decision (H8). In addition, Task Complexity exerts a direct negative influence on booking decisions, indicating that travellers become less willing to make a booking as travel planning becomes more demanding.

There is evidence that the benefits of cognitive load reduction are contingent upon the nature of the travel task. For relatively straightforward travel arrangements, reducing cognitive effort appears to facilitate booking decisions by simplifying information processing. However, this positive effect diminishes as task complexity increases. It is likely that travellers planning more complicated trips adopt a more deliberate decision-making strategy, carefully evaluating multiple alternatives and seeking more comprehensive information before committing to a decision. As a result, simplifying information alone may no longer provide sufficient support for high-involvement travel decisions.

These findings should be interpreted with appropriate caution, given that the respondents generally reported relatively low levels of task complexity (Mean = 2.13). Nevertheless, the significant negative moderating effect suggests that the relationship between task complexity and AI adoption is more complex than previously assumed. Rather than increasing the persuasive power of AI, higher task complexity appears to encourage more cautious decision-making behaviour. This finding highlights the need to reconsider how AI-generated recommendations should be designed to support travellers facing different levels of decision complexity.

The findings provide strong support for the mediating role of Perceived Value in linking AI-assisted search experiences with travel booking decisions. Perceived Value is an indirect-only full mediator between Perceived AI Intelligence and Travel Booking Decision as well as a complementary partial mediator between Perceived Ease of Use and booking decisions. These findings suggest that positive attitudes towards AI capabilities and system usability are not the only factors influencing travelers' buying decisions. Rather, users are more likely to book when they feel that AI travel information is providing them with value.

Cognitive Load Reduction, on the other hand, did not prove to be a significant mediator. While less cognitive effort could lead users to better interact with AI, it was not enough to move down to booking behavior. It is clear from this evidence, therefore, that Perceived Value is the main psychological process that links attributes of AI to consumer choice in the proposed S-O-R framework. This result contradicts the implicit assumption in the literature that decreasing mental strain results in an increase in behavioural intention. Rather, the findings indicate that an organism construct needs to actively convert external technological stimuli into perceived value before there is a strong chance of the occurrence of a behavioural reaction.

The integrated research framework accounted for about 48% of the variance in Travel Booking Decision, which is considered as satisfactory to explain the consumers' behaviour in AI-assisted tourism. While less influential than expected, the cognitive load component yielded valuable theoretical insights into the mechanisms of adoption of AI in the travel planning process. They also highlight the need to combine the Technology Acceptance Model with the S-O-R framework to understand travellers' behavioural reactions in an environment where AI is becoming more prevalent.

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