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Can I Trust GenAI to Plan My Next Trip?
A Multi-Method Approach to Optimizing Media Mix

Abstract

Although tourists can now book trips directly using generative artificial intelligence (GenAI), it remains unclear whether the real-time travel information it provides is comprehensive and sufficiently trustworthy enough to make booking decisions. The present research addresses this gap by integrating media richness, trust transfer, and the value-based adoption model (VAM) to investigate the impact of varying levels of travel information richness (text-only, text-image, and text-image-audio) on the booking behaviors of tourists using GenAI such as ChatGPT. With data from 578 participants, we tested the proposed structural and configurational models using a multi-analytical approach. Our findings revealed that the three media richness levels yield both analogous and distinctive effects on tourist perceptions regarding benefits, costs, trust formation, and intentions in ChatGPT online travel booking. Specifically, the text-image group demonstrated the strongest links from media richness to trust in ChatGPT, perceived benefit to value, and ultimately value to increased booking intention. Our findings from configurational modeling confirm a significant opportunity to harness the power of AI-empowered platforms for online travel booking.

Keywords: generative artificial intelligence, media richness, trust, value, privacy, online travel booking

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Introduction

ChatGPT, a generative artificial intelligence (hereafter, GenAI) model launched in 2022 by OpenAI, quickly gained over 100 million regular users globally (Sop & Kurçer, 2024). Recognized for its human-like interactions (Shin & Kang, 2023), this AI-driven language model offers a range of services, including educational content, translations, coding help, mathematical solutions, and travel planning (Ali et al., 2023; Ratten & Jones, 2023; Saif et al., 2024; Wong et al., 2023). In the tourism and hospitality industries, businesses such as Marriott's Renaissance Hotels and Wyndham Hotel use GenAI such as ChatGPT for personalized guest services that include dining suggestions and handling customer inquiries (Walters, 2023). Meta search engines such as Kayak and Expedia have also integrated GenAI into their businesses, allowing users to directly book flights, hotels, and rental cars from Online Travel Agencies (OTAs) via ChatGPT's interface. This makes the booking process more accessible and efficient for potential customers (Ali et al., 2023).

While ChatGPT-4—the premium version, ChatGPT-4o, has a subscription fee—offers a rich user experience with content such as text, images, and audio (Wong et al., 2023), it is limited in its multimedia support within the ChatGPT-4 travel booking service, particularly in industries such as airlines and car rentals where the integration of images and audio remains restricted. However, research has shown that rich media content can enhance user engagement (Liu et al., 2009; Wu et al., 2021), elevate the online shopping experience (Li & Meshkova, 2013), and indirectly improve the consumer's knowledge (Tong et al., 2022). Yet, the impact of AI-generated multi-media travel products on booking behaviors remains unknown. With increasing reliance on GenAI for travel planning and recommendations (Carvalho & Ivanov, 2023; Wong et al., 2023), online travel agencies and AI service

platforms need to offer reliable information and present travel content in an engaging, rich, and accessible format. Media richness theory postulates that using multiple items such as text, images, and videos simultaneously conveys information more clearly and coherently than using a single item (Alamäki et al., 2019). This multimodal approach can significantly influence user intentions to reuse apps and revisit websites (Wu et al., 2021). Therefore, for generative AI travel booking services to retain users, online travel agencies (OTA) need to incorporate rich and compatible content within the ChatGPT interface. Nevertheless, there is a noticeable gap in research on how media richness shapes the booking behaviors of GenAI users. The industry would therefore benefit from empirical research that identifies the optimal media richness that affects the mechanisms through which ChatGPT user trust is cultivated and value is perceived, thereby encouraging customers to book online using this AI platform. To address this research gap, the current study integrated media richness theory, trust transfer theory, and the VAM to develop conceptual models that predict how multimedia travel information can influence potential tourists' perceptions, trust, and booking decisions within ChatGPT. We employed a quasi-experimental method, dividing participants into three groups to evaluate the impact of media richness on the user experience. Group A was provided with travel information (including flights, hotels, and car rentals) in text format alone through the ChatGPT interface. Group B was given the same information in text format but with the addition of images. Group C, experiencing the highest level of media richness, received information presented through text, images, and audio.

The present study offers novel theoretical and practical contributions by using a powerful multi-analytical approach such as partial least squares structural equation modelling (PLS-SEM), multi-group analysis (MGA), fuzzy-set qualitative comparative analysis

(fsQCA), and deep learning to model tourist perceptions of and behaviors about online travel booking services using ChatGPT. Integrating concepts of media richness, trust transfer, and a VAM presents a new framework for enriching the tourism and hospitality literature, guiding scholars to a better understanding of tourists' behaviors towards GenAI -enabled travel booking services. Practically, the study yields notable insights for service providers on how to increase online booking by improving marketing strategies and facilitating data-driven decision-making empowered by GenAI helping to build trust and perceived value from the tourist's perspective.

Theoretical Background and Hypothesis Development

Media Richness Theory

Media richness theory, originally proposed by Daft and Lengel (1986), serves as a robust communication framework illustrating how the effective use of diverse communication channels can enhance the dissemination of complex information. The theory highlights that in uncertain situations with little information, delivering messages through richer communication channels can make messages clearer and easier to understand (Maity et al., 2018; Susskind, 2015). According to media richness theory, the richness of a medium is determined by its ability to incorporate various cues such as text, voice, and facial expressions during communication, thereby enabling a more insightful transfer of information to the recipient (Suh, 1999). Moreover, rich communication extends to the use of diverse languages (Chang & Lee, 2022) and high-quality video with enhanced visual clarity (Liu et al., 2009), facilitating easy interpretation of meaning for the receiver. Media richness theory has garnered significant attention in various fields, including business (Maity et al.,

2018), information systems (Suh, 1999), technological forecasting (Chang & Lee, 2022), and tourism hospitality (S.A. Lee et al., 2021). This widespread interest highlights the critical role of rich media content in shaping psychological behaviors.

Saeed et al. (2008) found that perceived media richness in 3D virtual spaces positively impacted the user's perceived ease of use and usefulness. Similarly, Norman et al. (2020) demonstrated that in-person interactions, which offer the highest media richness, were most effective for clear communication and building trust compared to electronic channels. Additionally, Tseng and Wei (2020) found that advertising products through interactive video advertisements, indicative of high media richness, significantly enhances customer attention and interest in the products compared to exposure to text message advertisements, indicative of low media richness. In a related context, Manglani (2023) argued that the theory of immersive media richness can explain how immersive green advertisements and social media can greatly enhance public awareness of green marketing practices, as well as the recognition of climate change and the necessity for adopting green products.

In the tourism context, Lee (2022) showed that the richness of tourism content presented via virtual reality substantially improved perceptions of both usefulness and enjoyment. Wu et al. (2021) applied media richness theory and discovered that presenting more vivid images of a travel destination through a mobile travel app equipped with advanced media technology could increase positive emotional response. Similarly, Lei et al. (2020) argued that implementing multiple cues, such as images, animations, icons, staff names, or facial photos during staff-customer interaction via hotel mobile app instant messages, can enhance the user's co-creation experience. This finding aligns with Alamäki et al. (2019), who revealed that participants who watched instructional videos on canoeing

showed a greater interest in participating in canoeing trips than those who viewed other types of promotional materials. With Airbnb, Chen and Chang (2018) noted that the variety of communication options available on the Airbnb website for interactions with hosts can bolster the guests' confidence while simultaneously reducing their uncertainty. In the hospitality context, Shaputra et al. (2023) revealed that hotel websites offering 3D visualizations with high media richness were more likely to positively influence users' trust and attitudes compared to those exposed to low media richness. Collectively, these findings highlight the significant influence of media richness on customers' perceptions, engagement, and trust, rendering it a crucial factor to consider in the context of GenAI online travel booking. Therefore, this study proposes the following hypotheses:

H1: The media richness of online travel booking through ChatGPT directly impacts perceived benefit.

H2: The media richness of online travel booking through ChatGPT directly impacts trust in ChatGPT.

H3: The media richness of online travel booking through ChatGPT directly impacts perceived sacrifice.

Trust Transfer Theory

Trust transfer theory posits that when an individual recognizes a link between a familiar trusted communication channel and an unfamiliar one, their trust might be transferred to the new channel (Gong et al., 2020). This transfer assumes that the connection between the two sources or channels implies credibility in the new channel (Zhao et al., 2019). According to Zhao et al. (2019), the successful activation of the trust transfer process involves the collaboration of three distinct yet interconnected entities: (a) principals, (b) trustees, and (c) trusted third parties. Zhao et al. (2019) claimed that the successful transfer of trust to the trustee occurs when the principal strongly endorses the trustworthiness of the third party, and

a close affiliation is established between the trustee and the third party. Based on this premise, previous research highlights that trust transfer theory can be categorized into two primary channels: intra- and inter-channel trust transfer (Kang & Kim, 2023; Xiao et al., 2019).

Intra-channel trust transfer commonly refers to the phenomenon where trust developed within a particular communication channel has the potential to transfer within the same channel (Xiao et al., 2019). For instance, in their study, N. Wang et al. (2013) found evidence of intra-channel trust transfer, observing that users who established trust in Dianping's online platform services (the Chinese equivalent of Yelp) were inclined to develop a high level of trust in Dianping's mobile platform services (N. Wang et al., 2013). For their part, Kang and Kim (2023) demonstrated inter-channel trust transfer, showing that individuals who trust a promotional video featuring a futuristic transportation system on YouTube were able to successfully transfer that trust to the travel mode company. This suggests that trust can be transferred between two different platforms—in this case, YouTube and the transport company—highlighting the occurrence of inter-channel trust transfer.

In the context of tourism, researchers have applied the trust transfer theory to examine the formation of trust among tourists. For instance, M. Kim and Kim (2020) found that travelers with a high level of trust in online travel reviews posted on major review sites (e.g., TripAdvisor) were more inclined to trust the travel destination featured on the same major review site. Additionally, Y.K. Lee et al. (2014) used the trust transfer concept and found that individuals with a positive attitude towards mega-events were likely to extend that positive attitude to the host country, illustrating a successful transfer of attitude. Therefore, based on the established link between trust transfer and trust in unfamiliar entities, we propose the

following hypothesis:

H4: Trust in ChatGPT has a positive influence on trust in OTA.

In addition to the potential influence of trust transfer, the literature consistently highlights a positive relationship between trust and perceived value (Choi et al., 2018; Lien et al., 2015). Specifically, within the tourism industry, Choi et al. (2018) discovered that trust in a shopping destination significantly improved the tourist's value perceptions of that destination. Similarly, Lien et al. (2015) found a positive link between trust in a hotel brand and the perceived value of the hotel in the hospitality industry. Based on these arguments, it is reasonable to suppose that tourists who trust an OTA are likely to perceive a higher value in their booking experiences, which is potentially enhanced by using advanced technologies such as ChatGPT. Consequently, this research posits the following hypothesis:

H5: Trust in OTA has a positive influence on perceived value.

Value-Based Adoption Model

The VAM developed by H.W. Kim et al. (2007) is a widely acknowledged theoretical framework that examines the factors influencing people's decisions to adopt new technologies. Unlike the technology acceptance model (TAM), which proposes that the adoption of new technology is driven by users' perceptions of 'usefulness' and 'ease of use' (Davis, 1989), The fundamental principle of the VAM is that users' adoption behavior is significantly influenced by their comprehensive evaluation of a new technology's quality, based on perceived benefits and sacrifices (Kang et al., 2023). Within this model, the constructs of benefits and sacrifices are identified as critical predictors of perceived value, which subsequently affects the intention to adopt new technology (Ling et al., 2020). In other

words, the value-based adoption framework is built on the principles of cost-benefit analysis, focusing on how individuals weigh the perceived benefits of new products/services against the potential costs or sacrifices before making an adoption decision (Lin et al., 2012).

Perceived Benefits. Previous studies define perceived benefit in several ways. In the context of AI-driven technology, Hong et al. (2023) defined perceived benefits as the anticipated positive outcomes that individuals expect from adopting an inhuman financial advisor. Similarly, in the mobile payment services, Gao et al. (2015) defined perceived benefits as the consumer's assessment of the extent to which they believe adopting a mobile payment service will improve their situation. Building upon this definition, the current study defines perceived benefit as the user's optimistic expectation of the benefits derived from engaging with online travel agent services via ChatGPT. Scholars typically approach perceived benefits from a multidimensional perspective, viewing them as either reflective or formative components (Gao et al., 2015; Gao & Waechter, 2017; Kang et al., 2023; Kang et al., 2024). For instance, Gao and Waechter (2017) identified (a) system quality, (b) information quality, and (c) service quality as reflective dimensions that collectively indicate positive user perception. Building on prior literature, this research conceptualizes system quality, information quality, and service quality as first-order reflective indicators of overall perceived benefit. These three dimensions represent distinct but interrelated aspects of the broader construct, where each dimension serves as an interchangeable indicator of the underlying latent variable. When applying this framework to GenAI services such as ChatGPT, perceived *system quality* refers to the user's evaluation of the technical attributes and overall effectiveness of ChatGPT's underlying system. It includes assessments of how easy it is to navigate the system, the visual attractiveness of the interface, the system's user-

friendliness, and the speed at which it loads all text. Moreover, users evaluate the information quality when considering ChatGPT services. Perceived *information quality* refers to the subjective evaluation of the utility of the information provided by the system. This includes the accuracy of responses from ChatGPT, the thoroughness of the information provided, and the applicability of the information to user needs. Finally, perceived *service quality* focuses on the user's assessment of how effectively ChatGPT meets their service expectations and fulfills their needs. It includes considerations of ChatGPT's professional tone, its ability to personalize responses, and the promptness of its replies. Overall, the present research categorizes the three elements—system benefit, information benefit, and service benefit—as first-order factors. Together, they constitute the 'perceived benefit,' which is identified as a second-order factor in this study.

Perceived Sacrifice. Perceived sacrifice is defined as the anticipated negative consequences and difficulties encountered in the decision-making process (Chung & Koo, 2015; Hong et al., 2023, Shukla, 2010). Specifically, when adopting new technology, people often expect potential sacrifices, including financial expenditures, the complexity of the technology, and time commitments of adopting innovations (Hong et al., 2023). Shukla (2010) further identified mental and physical efforts as potential sacrifices, especially in customer service environments. What is more, Xu et al. (2015) emphasize privacy concerns and technical challenges as critical components of perceived sacrifice.

Previous studies have regarded 'perceived sacrifice' as a multi-dimensional concept classified as a second-order factor (Chung & Koo, 2015; Kang et al., 2023; Xu et al., 2015). This study, therefore, maintains that users choosing ChatGPT services for real-time online travel bookings may have several initial concerns. With ChatGPT being a relatively new

entrant in generative AI applications, individuals may worry about the complexity of using the ChatGPT service for online travel booking, the risk of personal information exposure, and possible issues arising from cancellations. Building upon the work of Balapour et al. (2020) and Wang et al. (2019), we utilized perceived privacy and perceived conflict as the two primary components of perceived sacrifice when using GenAI services. These components are considered first-order factors, collectively forming the second-order factor of 'perceived sacrifice.'

Balapour et al. (2020) defined 'perceived privacy' in the mobile app context as the user's concern over the potential risk of losing personal information through unauthorized access or improper practices by app providers. The current study defines 'perceived privacy' as the user's concern about the safety and confidentiality of their personal and travel-related information shared during the booking process. It highlights concerns about potential misuse by unauthorized parties or the system. 'Perceived conflict' refers to the potential for disputes between a business and its customers over issues related to inadequate compensation from the consumer's point of view (Wang et al., 2019). In this study, 'perceived conflict' is characterized by the users' concerns over the possibility that an AI-driven online travel agent may not be able to provide a satisfactory resolution in case of disputes or errors.

Perceived Value. Kang et al. (2023) defines perceived value as a customer's evaluation of the total worth of a product or service. In a similar vein, Chung and Koo (2015) define perceived value as the consumer's subjective judgment concerning the quality and value of a product or service, which is influenced by comparing benefits with cost. Sweeney et al. (2001) further expanded upon this concept by noting that perceived value can develop even without direct purchase or usage, highlighting its importance in the early stages of the

consumer decision-making process and its impact on intentions to adopt or purchase.

Given the three essential elements outlined in the VAM framework, VAM has been methodically organized into a series of three consecutive phases. In the initial phase, users assess the expected benefits in relation to potential sacrifices, engaging in a preliminary cost-benefit analysis (Chung & Koo, 2015). Subsequently, the second phase involves a more detailed examination of the perceived value of the specific product or service, where users investigate deeper into the cost-benefit dynamics to determine its overall worth. In the final phase, the decision to adopt new technological services or products is made, based on an extensive assessment of the technology's overall value. This sequence highlights the significant role of perceived value that impacts consumers' behavior in the adoption process of new technology (Erdmann et al., 2023; Kang et al., 2023). The empirical evidence robustly supports the VAM framework, maintaining that individuals are more likely to positively evaluate and adopt a service or product when perceived benefits outweigh perceived sacrifices. This premise is underpinned by several hypotheses tested across various studies.

For instance, Kang et al. (2023) implemented the VAM to examine the adoption of service robots in hotels, restaurants, and cafés. Their research revealed that customers are more inclined to highly value service robots and prefer them over human staff when the perceived benefits surpass the associated costs. Similarly, Erdmann et al. (2023) validated the VAM within the retail industry, demonstrating a clear relationship between cost-benefit analysis and perceived value, which further influences purchase intentions. They observed that consumers who found augmented reality (AR) smart glasses to be beneficial and had more positive attributes compared to negative ones were more inclined to assess the product as high value, leading to a greater propensity to use AR smart glasses for future shopping. Yu

et al. (2019) extended the application of the value-based adoption framework to the realm of self-customization services and found that customers who perceive the benefits (e.g., perceived usefulness) of personalizing their—in this case—new vehicle to outweigh the sacrifices (e.g., technical complexity) were more inclined to assign a higher value to the self-customization service. This addition further corroborates the VAM's applicability across diverse industries, reinforcing the VAM framework that perceived value, driven by a balance between perceived benefits and sacrifices, plays a crucial role in influencing the adoption decisions of consumers. In light of the above empirical evidence, this research suggests the following hypotheses:

H6: The perceived benefits from using online travel booking via ChatGPT have a direct influence on perceived value.

H7: The perceived sacrifices from using online travel booking via ChatGPT have a direct influence on perceived value.

H8: The perceived value from using online travel booking via ChatGPT has a direct influence on booking intention.

ChatGPT Travel Booking Services with Varied Levels of Media Richness

The research consistently demonstrates that a platform's media richness has a direct impact on the user's engagement, comprehension, and decision-making processes (Jiang & Benbasat, 2007; Chen & Chang, 2018). Enhanced media presentations that incorporate vivid imagery, videos, and interactive elements not only command attention but also foster a deeper understanding of what is advertised. This enhanced understanding can lead to increased trust in the platform (Norman et al., 2020), broader overall satisfaction, and a greater likelihood of the user proceeding to book (Chen & Chang, 2018). Specifically, studies have found that interactions with more immersive product presentations can significantly elevate the user's experience, as demonstrated by Jiang and Benbasat (2007). Their research

indicated that participants exposed to vivid interactive product displays felt more engaged and had a better grasp of the product, compared to those who viewed static images or videos with or without narration. This heightened level of engagement was linked to a more favorable perception of the site's utility in aiding decision-making, positively influencing the user's attitudes toward the products and the likelihood of making a purchase. Moreover, a study by Norman et al. (2020) found that the lack of non-verbal cues in email communication led to communication challenges, highlighting the importance of richer media forms such as face-to-face interactions for building trust and effective communication.

In light of these findings, applying the concept of media richness to GenAI travel booking services suggests that offering choices with varying levels of media richness (text, image, audio) could significantly influence users' perceptions and behaviors. By providing a more immersive and engaging experience, we can expect different reactions from users exposed to services with low, medium, and high levels of media richness. Thus, the current study hypothesized that:

H9: Tourists exposed to ChatGPT travel booking services with varying levels of media richness (low, medium, high) will exhibit different perceptions and booking behaviors.

Figure 1 illustrates the integrated research framework for the nine aforementioned hypotheses.

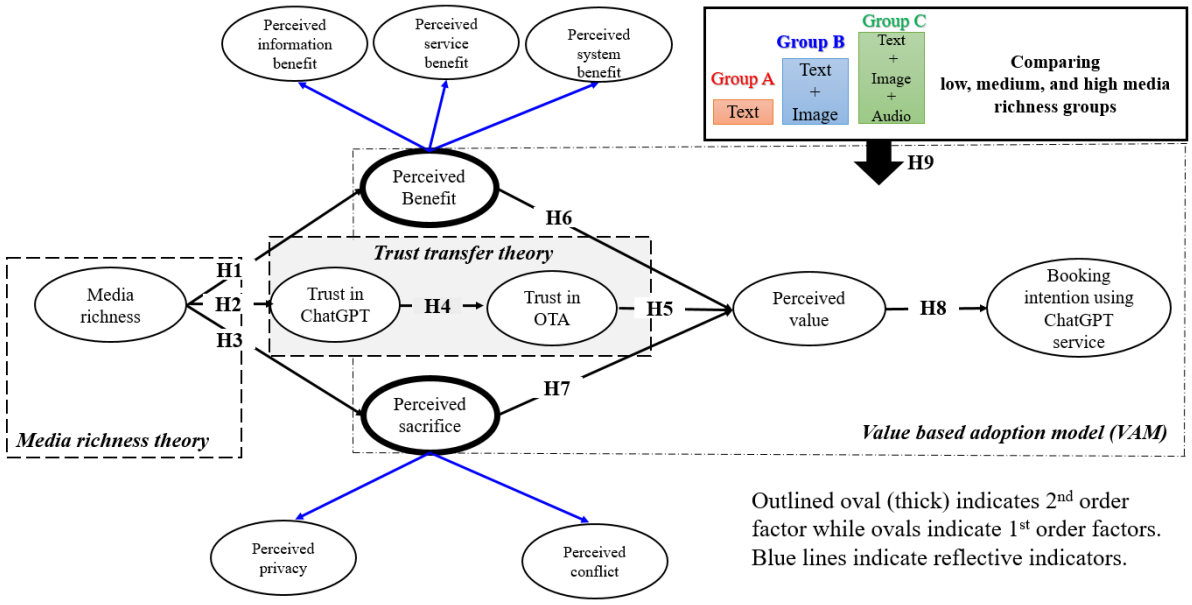


Figure 1. Conceptual model.

Methods

Data Collection and Participants

This study collected data via Embrain, an online panel company based in South Korea that specializes in recruiting participants for market research and academic studies. Embrain, with the largest pool of panel members in South Korea, ensures high survey response rates through comprehensive panel management, facilitating the efficient and accurate implementation of various surveys (Kang and Kim, 2023; Kim et al., 2024). A thorough screening process ensured that only individuals aged 18 or above were recruited. Participants were randomly assigned to one of the following conditions: Group A received text-only scenarios, Group B engaged with scenarios that included both text and images, and Group C experienced scenarios that combined text, images, and audio. The experiment was conducted over 7 days, from February 26th to March 3rd, 2024, beginning with 600 participants from Embrain's

panel. After a thorough review, 18 individuals were removed due to failing the manipulation check question, and an additional 4 were excluded for completing the survey too quickly. This led to a final sample size of 578 participants. Panel members who completed the survey were compensated with 6,000 KRW, equivalent approximately to $4.50 USD.

Scenario-Based Experiment

All participants in Groups A, B, and C were presented with a brief scenario in which they engaged in a simulated interaction with an AI travel agent via the ChatGPT chat interface (Supplementary A). This scenario, consistent across all three groups, depicted a potential tourist looking for family vacation deals to Jeju Island, South Korea, and needing help to book flights, hotels, and rental cars through the Kayak app integrated within the ChatGPT service. Kayak was chosen for this research due to its current status as the most widely used travel search engine integrated into GenAI platforms. Supplementary A details the specific content presented in each scenario based on media richness levels. Group A, representing the lowest level, encountered real-time flight, hotel, and rental car information, pricing, and booking methods exclusively in text format within the ChatGPT interface. Participants in Group B experienced a medium level of media richness, receiving the same information supplemented with images alongside the text. Finally, Group C, exposed to the highest level of media richness, had access not only to text and images but also to audio integrated into the online survey. While reading the scenario, Group C participants were required to listen to the provided audio services embedded within the online survey. To ensure that participants carefully engaged with the scenario, a manipulation check question was presented immediately afterward. This question tested their comprehension of key details from the scenario, and any participant failing the check was excluded from further analysis.

Measurement Development

This research incorporated a total of seven constructs, encompassing 40 measurement items, derived from the existing literature with slight modifications to better align with our specific research context. For instance, the construct of media richness was measured using five items originally developed by Brengman et al. (2024). The constructs of perceived information benefit, perceived service benefit, and perceived system benefit each comprised four items, which were adapted from the work of Gao and Waechter (2017). Trust in ChatGPT and trust in OTA were each assessed using four items, with the former adapted from Park et al. (2019) and the latter from Raza et al. (2023). Additionally, four items each for perceived privacy and perceived conflict were adapted from Balapour et al. (2020) and Wang et al. (2019), respectively. The assessment of perceived value was based on four items adapted from Shaw and Sergueeva (2019) while booking intention was measured using three items borrowed from Bhatiasevi and Yoopetch (2015). This study employed a 7-point Likert scale, ranging from (1) strongly disagree to (7) strongly agree, to assess the seven constructs previously mentioned. Additionally, it collected basic sociodemographic information and data on the participants' prior experiences with Generative AI services. A copy of the survey is provided as a supplementary file.

Content Validity and Pre-Test

To ensure the survey's translation was accurate for Korean respondents, we conducted a back-translation process. This process involved three bilingual professors fluent in both Korean and English along with a native English-speaking researcher, who followed the back-translation method proposed by Brislin (1980). The method included translating the survey from English to Korean and then back to English to ensure that the translated version

accurately reflected the original survey's meaning and details. Moreover, a pilot test was conducted by inviting four graduate students specializing in hospitality and tourism. The feedback from these students was essential for improving the survey tool. In particular, two respondents identified minor typographical errors and technical terms that required simplification. Additionally, several participants highlighted concerns regarding the low visibility and inadequate resolution of the simulated graphics. Some suggested enlarging the font size of the scenario text within the ChatGPT interface across all conditions. Following these adjustments, a pre-test was conducted with 60 participants from the Embrain panel who consented to participate in this preliminary evaluation. At this stage, participants were asked to assess whether the scenario design appeared realistic. Additional modifications were made to improve the survey's flow and to revise ambiguous phrases and awkward wording, thereby completing the face validity process.

Data Analysis

To gain a better understanding of how participants engage in travel booking using ChatGPT, this research adopted a multi-analytical approach that included both symmetrical (PLS-SEM and MGA) and asymmetrical (fsQCA) methodologies, along with deep learning techniques. Symmetrical methods are employed to evaluate the predictive capability of an input variable (X) in determining an outcome variable (Y), as they focus on establishing the presence and strength of linear relationships between variables (Kim et al., 2023). In contrast, asymmetrical methods such as fsQCA allow for the identification of patterns where improvements in a predictor variable (X) do not straightforwardly translate to enhancements in an outcome variable (Y), offering insights into the nuances and complexities of causal relationships (Ragin, 2017). While recent studies have combined fsQCA and artificial neural

networks (ANN; see Hew et al., 2023; Li et al., 2022), some researchers have simultaneously applied PLS-SEM, fsQCA, and ANN to gain deeper insights into the data, uncovering patterns that may not be evident through structured models alone (Kim et al., 2023; Sharma et al., 2024). This multi-analytical method approach ensures a comprehensive exploration of travel booking behaviors through ChatGPT by capturing both linear associations and intricate causal configurations. The combination of symmetrical and asymmetrical techniques within the context of consumer behavior has become more common in recent research, offering a more detailed perspective compared to relying solely on a single analytical method (Han et al., 2024; Kim et al., 2023).

Initially, the study used PLS-SEM and MGA to examine both the measurement model and the conceptual framework. This analysis was performed using the SmartPLS 4 software to adopt a symmetrical approach. Subsequently, to complement this with an asymmetrical perspective, fsQCA was employed as described by Kim et al. (2023), enabling a comparative validation of different configurations. This step aimed to explore rich outcomes through sufficient configuration solutions, causal combinations, and the analysis of necessary conditions (ANC). The study focused on the effects of media richness, trust transfer factors, and value-based adoption factors on booking intention across three types of media stimuli (i.e., low, medium, and high). Configurational modeling was conducted in three sequential steps using fsQCA 3.0 software, as per the methodology suggested by Olya (2023). Calibration of factors was achieved by assigning a value of 1 to indicate full membership, 0.5 for the threshold of being neither fully in nor out (i.e., cross-over point), and 0 for complete non-membership, following the guidelines established by Ragin (2017).

The study did not require pre-defined hypotheses about the relationships between input

and output variables due to the capability of artificial neural networks to explore a wide range of statistical relationships (Ripley, 1996). In contrast to conventional techniques like SEM or regression analysis, ANN has the unique advantage of identifying both linear and nonlinear relationships (Kim et al., 2023). Consequently, the analysis incorporated deep learning techniques using ANN and multi-layer perceptron (MLP) through the IBM SPSS Statistics 28 package, facilitating deep learning analysis across multiple hidden layers and MLP configurations. Moreover, the application of single-factor analysis methods, coupled with both straightforward and advanced model comparison techniques has effectively demonstrated that common method variance does not pose a significant issue in this research (Supplementary B).

Results

Sample Profiles

A total of 578 participants were included in the study (Supplementary C). Furthermore, these individuals were organized into three categories based on the stimuli they received. Information regarding the demographics and general characteristics of each group is elaborated in Supplementary D. Specifically, Group A (text stimuli, n=193) respondents tended to be males over 50 years of age, with high incomes, a university-level education, and married status. In contrast, Group B (text and image stimuli, n=191) respondents were predominantly female, younger, and single. Approximately half possessed an educational level lower than or equivalent to a high school diploma, coupled with lower income. Lastly, Group C (text/image/audio stimuli, n=194) respondents were mostly male, in their mid-40s, married, and with a medium income level.

Measurement Model

As shown in Supplementary E, a confirmatory factor analysis was conducted, revealing that all 34 variables had factor loadings greater than 0.75. This surpasses the acceptable threshold of 0.70 as established by J.F. Hair et al. (2017). To address multi-collinearity concerns, the variance inflation factor (VIF) was employed, and according to the criteria by J.F. Hair et al. (2017), multi-collinearity is considered manageable if VIF values are below 5. In this study, VIF scores ranged from 1.789 to 4.060, thus confirming the absence of multi-collinearity issues. Supplementary F reveals that Cronbach's alpha, composite reliability, and Rho_A for the variables all surpassed the 0.7 level, ensuring the scales' internal validity. The constructs' average variance extracted (AVE) was above 0.5, indicating strong convergent validity (J.F. Hair et al., 2017). In addition, discriminant validity was confirmed through the Heterotrait-Monotrait Ratio (HTMT) method, with the highest HTMT value recorded between trust in OTA and perceived benefit being 0.808. This value is below the threshold of 0.9, thereby acknowledging the discriminant validity. Moreover, the Q^2 values were found to be positive, ranging from 0.295 to 0.777 for the endogenous variables, which signifies acceptable predictive relevance.

Structural Model

Figure 2 illustrates the estimation of the conceptual model. The evaluation of the nine hypotheses was carried out using PLS-SEM with 5000 bootstrap re-samplings, following the methodology developed by J.F. Hair et al. (2017). As shown in Figure 2, R^2 estimates demonstrate the following levels of variance explained: perceived benefit at 58.0%, trust in ChatGPT at 36.1%, trust in OTA at 40.2%, perceived sacrifice at 0.6%, perceived value at 57.4%, and booking intention at 43.3% (J.F. Hair et al., 2020). The hypothesis testing

revealed significant findings: media richness notably impacted perceived benefit (H1: γ = 0.762, p <.001) and trust in ChatGPT (H2: γ = 0.601, p <.001), yet showed an insignificant effect on perceived sacrifice (H3: γ = -0.081, p >.05). Trust in ChatGPT significantly increased trust in OTA (H4: γ = 0.634, p <.001), and this trust in OTA was found to positively influence perceived value (H5: γ = 0.298, p <.001). Moreover, perceived benefit was identified as a significant predictor of perceived value (H6: γ = 0.514, p <.001), while perceived sacrifice had no meaningful impact on perceived value (H7: γ = 0.018, p >.05). Ultimately, perceived value was found to be a significant determinant of booking intention (H8: γ = 0.658, p <.001). In summary, H1, H2, H4, H5, H6, and H8 were supported, while H3 and H7 were not supported. The reasons for the lack of statistical significance for H3 and H7 require further exploration. However, it is worth noting that tourists may not necessarily perceive significant privacy risks or the potential for conflict when using the ChatGPT platform. This observation could account for why the perceived sacrifice did not significantly influence perceived value or why privacy concerns did not noticeably affect their perceptions.

In this study, the mediating roles of media richness, perceived benefit, perceived sacrifice, trust in ChatGPT, and trust in OTA on booking intention were explored using PLS-SEM bootstrap analysis with 5,000 resamples. The analysis revealed that media richness indirectly influenced booking intention (γ = 0.331, p <.001), perceived value (γ = 0.503, p <.001), and trust in OTA (γ = 0.381, p <.001). Additionally, trust in ChatGPT served as a mediator impacting both booking intention (γ = 0.124, p <.001) and perceived value (γ = 0.189, p <.001). Trust in OTA also showed an indirect effect on booking intention (γ = 0.338, p <.001). However, the mediating role of perceived sacrifice on booking intention was not statistically significant (γ = 0.012, p >.05). Therefore, the study confirms the indirect effects

of media richness, trust in ChatGPT, trust in OTA, and perceived benefit within this research context (Supplementary G). The f^2 values, ranging from 0.07 to 0.763, indicate the effect sizes within the model, where thresholds of 0.02, 0.15, and 0.35 represent small, medium, and large impacts, respectively. Given this range, the model outcomes demonstrate a spectrum of influences from minimal to substantial, indicating a suitable distribution of effect sizes across the studied variables. Additionally, age and gender were considered as potential moderating factors (see Supplementary H). However, results showed that neither age nor gender played significant moderating roles in this conceptual model and were therefore not included in the final version of the model.

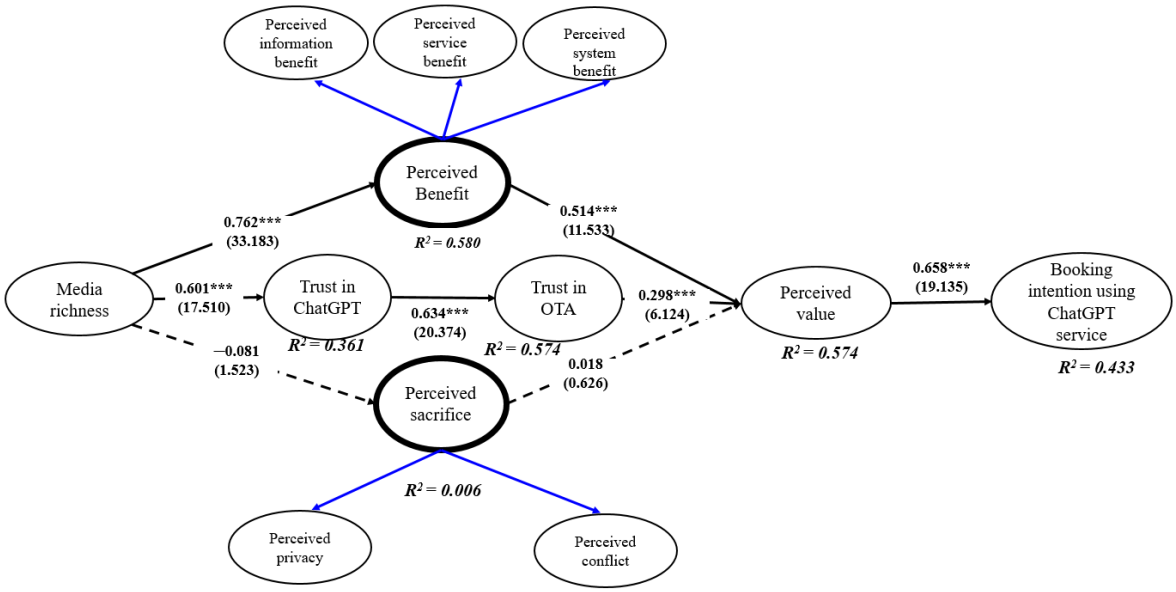


Figure 2. The result of path analysis (complete data group).

Assessment of Measurement Invariance

According to Henseler et al. (2016), a three-step MICOM (Measurement Invariance of Composite Models) analysis was conducted prior to performing the multigroup analysis (MGA). In the first step, we assessed configural invariance, which examines whether the

same model structure is valid across all three groups (Group A – text, Group B – text/image, and Group C – text/image/audio). The results confirmed that the proposed constructs and model parameters were identical across the three groups, thus establishing configural invariance.

Next, we evaluated compositional invariance using 1,000 permutation samples. The results indicated compositional invariance, as the composite scores for each group were statistically correlated, with permutation c values (=1) falling within the 95% confidence interval. None of the c values significantly deviated from one, further confirming compositional invariance (Kang et al., 2023).

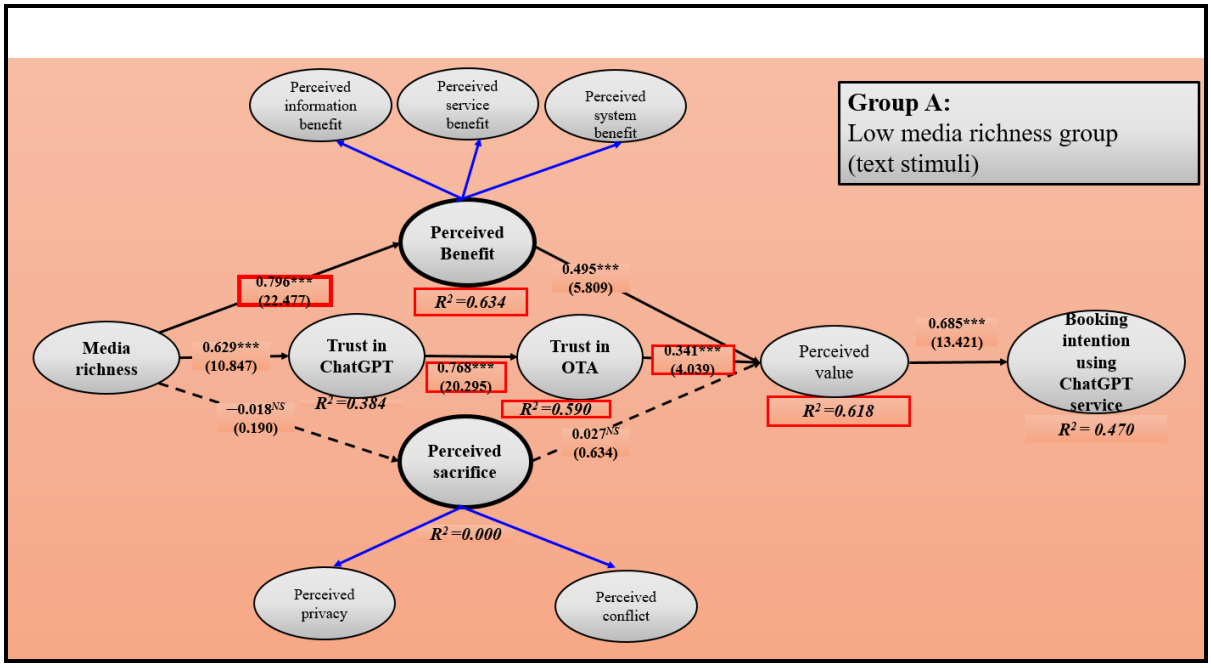
Finally, to achieve full measurement invariance, we tested for equal means and variances across the groups. The results showed that all seven constructs had non-significant permutation *p*-values ($p > 0.05$), indicating that the mean values and variances were equivalent between the groups. As a result, full measurement invariance was established, enabling meaningful comparisons between Group A and Group B, Group A and Group C, and Group B and Group C.

Comparing Three Types of Media Richness Groups

Using the MGA method, this study examined eight relationships across three experimental groups differentiated by varying degrees of media richness: low (Group A, text only), medium (Group B, text and image), and high (Group C, text, image, and audio). As shown in Figure 3, the findings revealed that Group A exhibited the most significant connections in terms of media richness to perceived benefit, trust in ChatGPT to OTA, and trust in OTA to perceived value. Meanwhile, Group B stood out with the most robust relationships, ranging from media richness to trust in ChatGPT, perceived benefit to perceived value, and perceived

value to booking intention. Contrary to expectations, Group C, despite its high media richness, demonstrated the weakest links in the hypothesized causal relationships among the three groups. For R^2 estimates, Group B emerged superior with an R^2 of 0.510 in booking intention, indicating that 51% of the variation in booking intention for respondents in this group could be explained by perceived value. These findings collectively indicate that the medium media richness condition (Group B), aligns most effectively with the theoretical model proposed in this study (Figure 3).

Among the 24 relationships analyzed, two exhibited significant differences (Supplementary I). Specifically, the relationship between trust in ChatGPT and trust in OTA differs significantly between the low media richness group and the medium media richness group (i.e., Group A vs. Group B), as well as between the low media richness group and the high media richness group (i.e., Group A vs. Group C), with both differences being positive and significant. Consequently, Hypothesis 9 receives partial support.



Kang, S. E., Kim, M. J., Kim, J. S., & Olya, H. (2024). Can I trust GenAI to plan my next trip? A multi-method approach to optimizing media mix. *Journal of Travel Research*.
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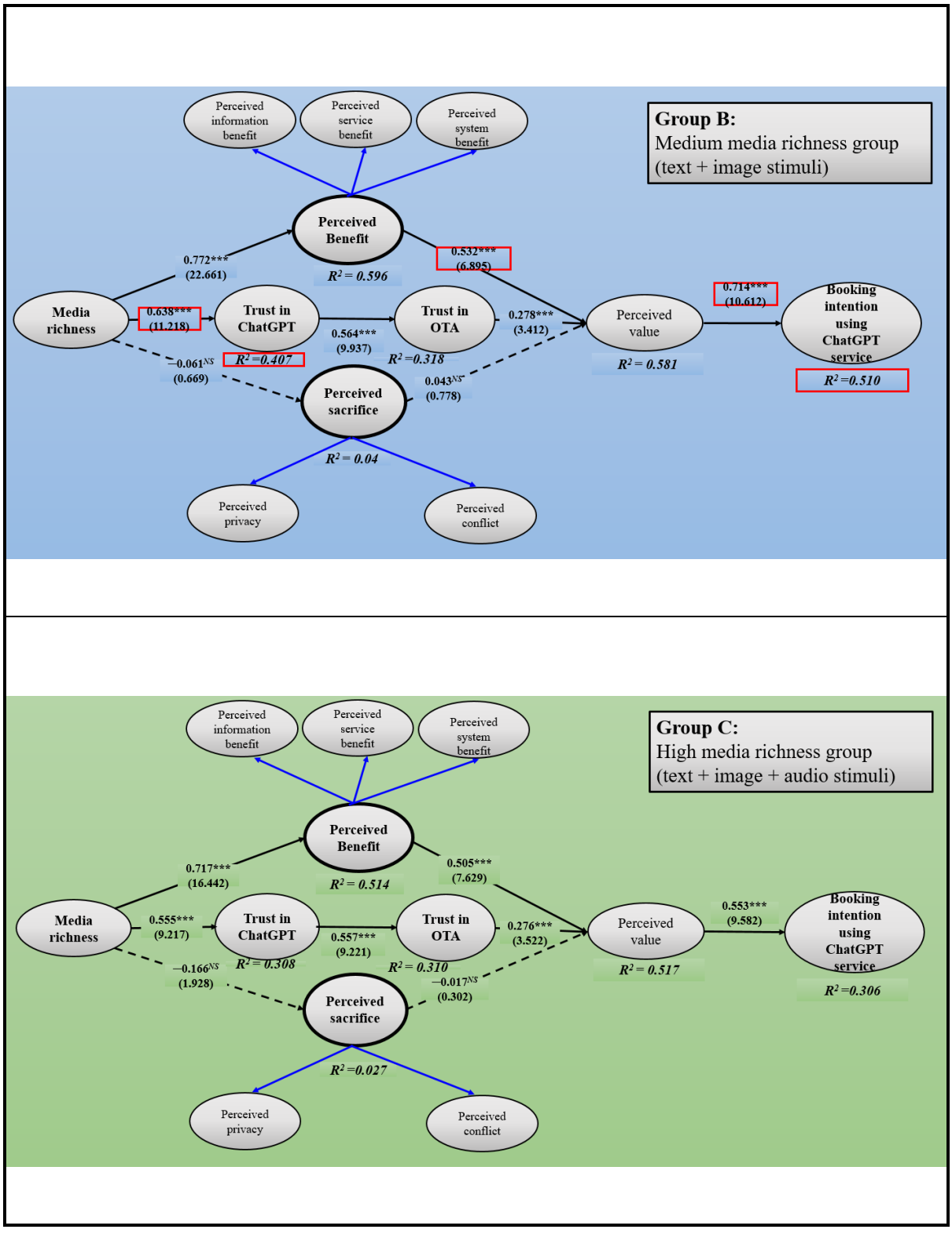


Figure 3. Comparing low (Group A), medium (Group B), and high (Group C) media richness groups. *Note:* ns= non-significant. The dotted line describes an insignificant hypothesis. ***p <.001.

Fuzzy-set Qualitative Comparative Analysis

Crucial elements for three different levels of media richness groups of the ChatGPT travel booking service were identified through an ANC, as detailed in Supplementary J. Following the established consistency threshold of > 0.90 (Olya, 2023), it was found that perceived benefits are considered a vital construct for booking behavior in Group A. For Group B, the perceived value was determined to be a fundamental component to drive booking behavior. Interestingly, for Group C, no critical factors were identified that influenced booking behavior. This discovery offers a notable divergence from the findings of symmetric analysis methods such as PLS-SEM and MGA, as discussed by Kim et al. (2023).

While ANC focuses on identifying how individual variables predict outcomes, fsQCA (Figure 4) investigates how combinations of variables work together, using terms such as configuration, recipe, algorithm, solution, and causal model to describe these complex relationships (Ragin, 2017). As Figure 4 illustrates, this study introduces a configurational model represented through a Venn diagram, grounded in the principles of complexity theory (Baggio, 2008). This model addresses scenarios that linear models fail to fully explain, due to the complex relationships among its indicators. Therefore, complexity theory provides a solid, dependable basis for this advanced model.

As shown in Supplementary K, five solutions are presented for Group A: Solution 1 proposes that tourists should opt for booking their trips through ChatGPT if they perceive benefits, even in the absence of media richness and trust in the platform. Solution 2 suggests that tourists are inclined to book their trips if they trust both ChatGPT and OTAs and also perceive value in doing so. According to Solution 3, some tourists may choose to make online bookings solely based on media richness and trust in ChatGPT, even if they do not

perceive benefits and make sacrifices. Solution 4 confirms the existence of a group of tourists who opt for online booking if they perceive benefits, make sacrifices, perceive value, and also find the communication media-rich. Lastly, Solution 5 for group A indicates that a combination of media richness, trust in ChatGPT and OTA, and perceived sacrifice creates a condition where tourists are inclined to use ChatGPT for online booking.

For Group B, five solutions are suggested: Solution 1 shows that media richness and trust in both ChatGPT and OTAs are sufficient for a group of tourists to use ChatGPT for online booking. According to Solution 2, media richness and perceived benefits and sacrifices stimulate tourists' intention to book online using ChatGPT. Alternatively (Solution 3), media richness, perceived benefits, and trust in OTAs are sufficient for a group of tourists to book their trips using ChatGPT. Solution 4 proposes that tourists who perceive benefits, value, and trust in ChatGPT, even in the absence of perceived sacrifices, intend to make online bookings. Solution 5 indicates that tourists who do not trust ChatGPT will use it for online travel booking if they trust in OTAs and perceive sacrifice.

In Group C, eight solutions were calculated, showcasing a more diverse range of configurations: Solution 1 indicates that despite a lack of trust in OTAs, media richness and perceived benefits are sufficient for some tourists to use ChatGPT for travel booking. Interestingly, Solution 2 confirms that some tourists who do not trust OTAs and perceive sacrifice use ChatGPT for travel booking if they are exposed to rich media. Alternatively, media richness and trust in ChatGPT are sufficient, even if they do not perceive value, for some tourists to make online bookings (Solution 3). According to Solution 4, tourists who trust ChatGPT, but are not OTAs, will book online if they are exposed to rich media. Solution 5 shows that media richness and perceived value, even if they do not trust OTAs, contribute

to the travel booking intention of tourists using ChatGPT. Solution 6 confirms that media richness and perceived value also stimulate tourists' travel booking intention, even in cases where they do not trust ChatGPT. Solution 7 suggests that a combination of media richness, perceived benefits, and trust in ChatGPT creates a condition in which tourists will use ChatGPT for travel booking. Lastly, Solution 8 confirms that media richness, perceived benefits, and value encourage tourists to use ChatGPT for online travel booking.

The analysis using fsQCA reveals both commonalities and distinctions across three levels of information richness in ChatGPT travel booking services. Across all groups, media richness, perceived benefit, trust in ChatGPT, and perceived value served as positive indicators of booking intention. This indicates that these four factors consistently contributed to online booking behaviors through ChatGPT across the groups. Notably, while the PLS-SEM analysis shows that perceived sacrifice is not a significant factor for any of the groups, fsQCA identifies perceived sacrifice as a core element for groups A and B. This indicates why a multi-analytical approach might offer insights into new complex phenomena such as using ChatGPT for online booking of trips.

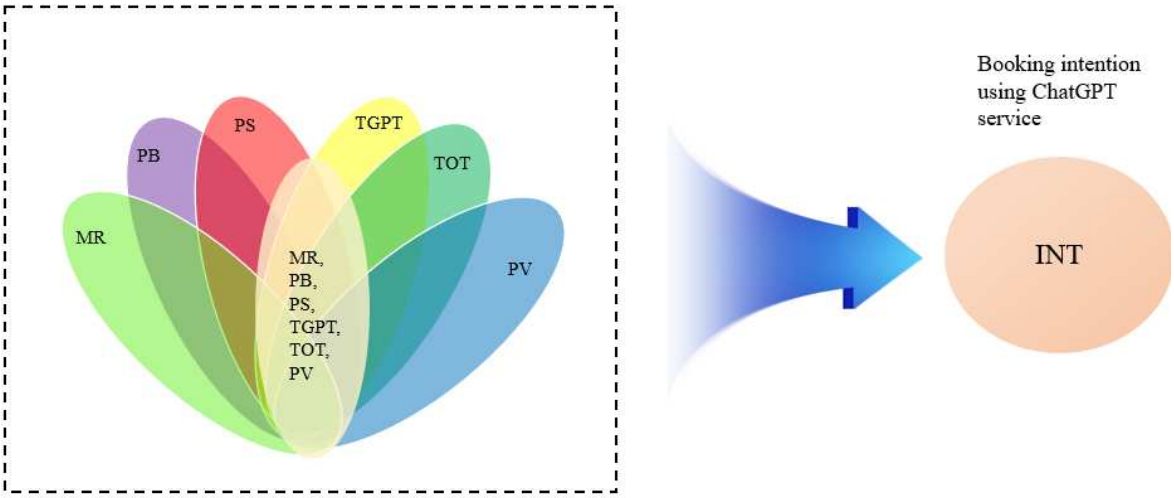


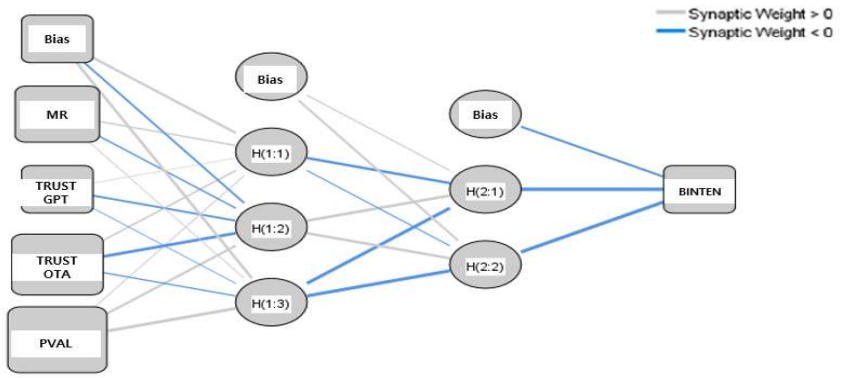
Figure 4. fsQCA model.
Note: MR stands for media richness; PB stands for perceived benefit; PS stands for perceived sacrifice; TGPT stands for trust in ChatGPT; TOT stands for trust in OTA; PV stands for perceived value.

Deep Learning

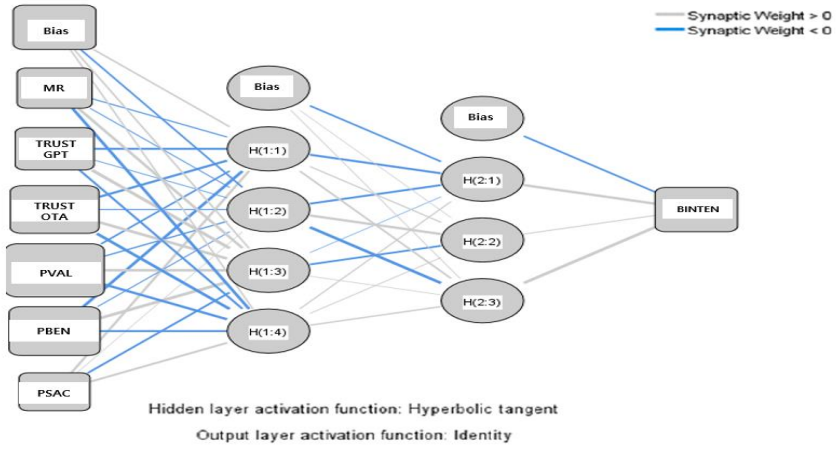
In this study, we developed a three-layer ANN framework to analyze the dependent variable, which efficiently generates hidden neuron nodes, as illustrated in Figure 5. We allocated 70% of the dataset for training and 30% for testing purposes (Kim et al., 2023; Kim et al., 2024). Among the three frameworks, Model B emerged as the most accurate, achieving a prediction accuracy of 64.3% (1 – relative error). Kim et al. (2024) suggested that endogenous variables are more accurately predicted using a deep learning-based AI method, indicating that Model B's prediction accuracy significantly surpasses that of PLS-SEM. This advantage is largely due to ANN's capability to recognize complex, nonlinear relationships through the application of the MLP approach and its layered architectural design. In predicting "booking intention," the analysis identified perceived value as the most influential independent variable at 100%, followed by perceived benefit (75.6%), trust in OTA (68.8%), trust in ChatGPT (39.1%), media richness (27.0%), and perceived sacrifice (14.4%). The investigation into deeper ANN structures and the MLP's ability to detect nonlinear patterns has produced

significant insights, particularly regarding Model B's performance and the pivotal role of independent variables, detailed in Supplementary L.

Model A (Trust Transfer model: Consists of media richness, trust in ChatGPT, trust in OTA, and perceived value)



Model B (Current research model including second order factor: Consists of media richness, perceived benefit, perceived sacrifice, trust in ChatGPT, trust in OTA, and perceived value)



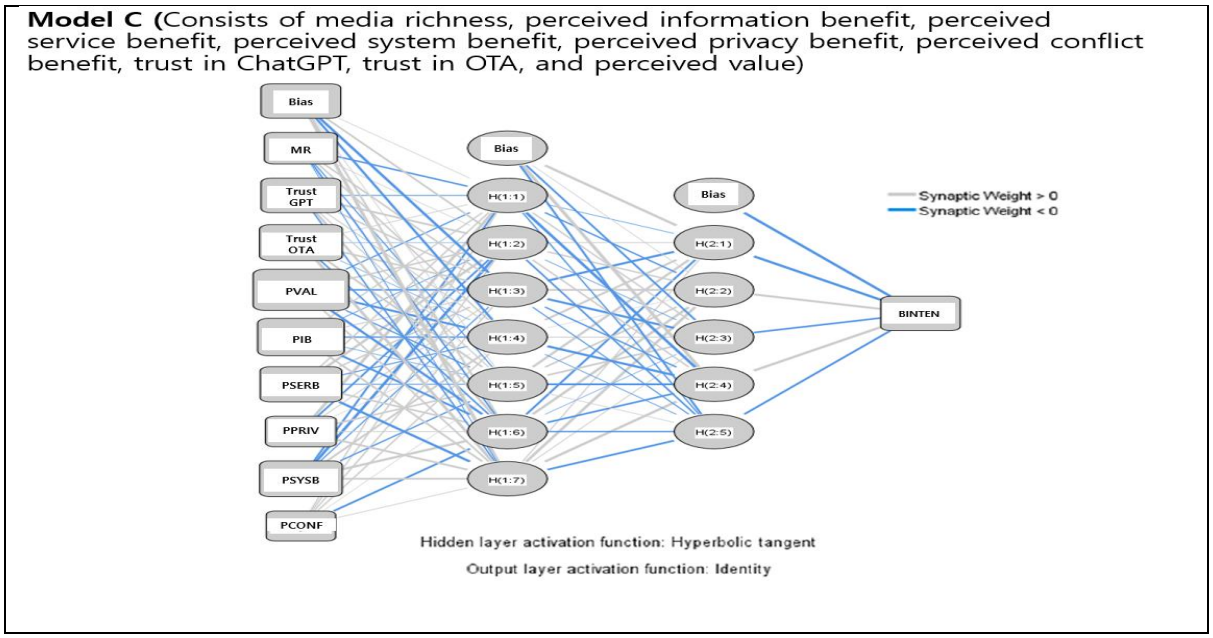


Figure 5. Comparing Models A, B, and C.

Conclusions and Implications

Discussions of Remark Findings

The analysis using PLS-SEM demonstrated that media richness has a positive effect on perceived benefit and trust in ChatGPT among all participant groups. This suggests that regardless of the different levels of media richness stimuli, the travel information provided through the ChatGPT interface significantly enhances positive perceptions and trust in ChatGPT's travel booking services. This finding partially aligns with the findings of previous media richness research (Lee, 2022; Norman et al., 2020; Tseng & Wei, 2020; Wu et al., 2021). On the other hand, this study found no significant evidence to support a link between media richness and perceived sacrifice, differing from expectations based on prior studies (Lai & Chang, 2011). Similarly, the influence of perceived sacrifice on perceived value was found to be negligible across all groups, contradicting previous research (Chung & Koo, 2015; Kang et al., 2023). This suggests that within the context of ChatGPT's travel booking

services, perceived sacrifice may not significantly impact users' perceptions. The reason for this heterogeneity appears in using PLS-SEM which assumes the relationships between the constructs are linear. However, findings from fsQCA showed that perceived sacrifice is a core element when its role is considered along with other predictors stimulating booking intention.

Furthermore, the study revealed that higher levels of trust in ChatGPT were associated with increased trust in OTA supporting the notion of trust transfer as discussed in prior literature (Kang & Kim, 2023; Kim & Kim, 2020). A positive relationship between trust in OTA and perceived value was also observed, indicating that greater trust in these platforms correlates with the higher perceived value of ChatGPT's travel booking services. This is consistent with findings from Choi et al. (2018) and Lien et al. (2015). Moreover, perceived benefits were positively linked to perceived value, echoing the results of Kang et al. (2023). This implies that individuals who notice the positive aspects of GenAI, such as its ability to deliver extensive travel itinerary details, provide quick responses to travel questions, and its ease of use, tend to view ChatGPT's services more positively and with greater approval. Additionally, the research demonstrated that perceived value positively influenced booking intentions across all scenarios, aligning with the findings of Erdmann et al. (2023). This suggests that tourists who hold a positive evaluation of GenAI's travel booking services are more likely to use them for booking their travel arrangements.

Through the comparison of three media richness levels using PLS-SEM and MGA, it was found that respondents exposed to text and images (Group B) demonstrated stronger relationships between media richness and trust in ChatGPT. This indicates that tourists are more inclined to trust GenAI services when the chat interface presents real-time travel

products (e.g., flights, hotel rooms, rental cars) through both text and visual imagery. This result supports the claims of media richness theory. Furthermore, Group B showed stronger relationships between perceived benefit and perceived value, which subsequently influenced their booking intentions. This suggests that individuals exposed to text and image stimuli, who formed a positive perception of GenAI's travel booking services, rated these services favorably and showed a higher likelihood of using ChatGPT for their future travel bookings compared to participants exposed to other types of media stimuli. This finding aligns with research by Jiang and Benbasat (2007), which showed that enhancing the visibility of online product information improves consumers' shopping experience.

In the analysis of necessary conditions through fsQCA, it was found that the factor of perceived benefit is critical for predicting booking intentions in Group A. Conversely, perceived value is identified as a pivotal element in driving booking behavior for Group B. No necessary conditions were discovered for forecasting booking intentions in Group C. These outcomes show a partial congruence with the findings of Olya (2023), highlighting diverse factors influencing booking intentions and behaviors across different groups. Additionally, from analyzing causal configurations across three media stimulus types, Group A respondents displayed a higher level of perceived sacrifice for booking behaviors. In Group B, trust in OTA was key in predicting booking intentions. For Group C, media richness and trust in ChatGPT were identified as a significant driver for strong booking intentions. A comparison of three models using a deep learning analysis technique revealed that the current research model outperforms others in predicting booking intentions. This marks a significant advancement in understanding the mechanisms through which ChatGPT users employ AI to book their trips.

Theoretical Implications

This research contributes theoretically to the tourism and hospitality literature by integrating three theories of media richness, trust transfer, and the VAM to predict the booking intention of tourists using GenAI, such as ChatGPT. The proposed model is novel and demonstrates strong predictive power, as evidenced by the R-squared values explaining over 50% of the variance in perceived value across all three groups (Group A: text-only, Group B: text-image, and Group C: text-image-audio). The results from the MGA revealed that among the three groups compared, participants in Group B, who were exposed to both text and images, exhibited the highest path coefficient scores for the impact of perceived value on booking intention ($\gamma = 0.714$).

The study also showed that an enhanced level of media richness in Group B significantly boosts trust in ChatGPT. This means tourists who were exposed to both text and images providing real-time information on flights, hotel accommodations, and car rentals demonstrated a greater level of trust in ChatGPT than those in the other two groups. This research establishes a positive relationship between media richness and trust within the domain of ChatGPT's online travel booking services. Thus, our findings contribute to the existing knowledge of the tourism industry by applying media richness theory to comprehend the extent to which varying levels of media richness influence tourist behavior regarding the adoption of generative AI for travel booking.

Furthermore, results from PLS-SEM did not reveal the indirect impact of perceived sacrifice on booking behavior, whereas fsQCA findings suggested that perceived sacrifice can be a part of the solution in predicting booking behavior when the construct is combined with other factors. This finding highlights the relevance of complexity theory, which

emphasizes the interactions and interdependencies among variables that can lead to outcomes not identified through traditional symmetrical methods. Consequently, fsQCA offers a deeper insight into the role of the perceived sacrifice factor in shaping tourist's booking behavior. fsQCA calculated various unique solutions for three study groups, indicating that given different levels of media richness and their perceptions, it is highly likely that more tourists use GenAI for travel booking.

Finally, deep learning is a data-driven approach used to validate or challenge existing theoretical discourses by uncovering subtle patterns within a specific phenomenon. In this research, the deep learning analysis serves as a powerful technique to identify the most effective models and to determine the essential factors that significantly influence booking behavior. Notably, our research model (Model B, depicted in Figure 5) demonstrated the highest prediction accuracy among the three models examined. The current conceptual model particularly highlighted the significance of perceived value as the most critical factor affecting booking decisions. As the first study to employ deep learning in establishing a connection between perceived value and booking intention within the generative AI context, the study contributes to the existing literature by enriching our understanding of the dynamics between these two constructs. Similarly, the results from SEM also showed that perceived value accounts for over 30% of the variance in booking intentions for the entire sample. The substantial variance explained by our framework not only affirms the model's robustness but also offers a significant contribution to explaining individuals' booking behaviors within the Generative AI platform. The explanatory power of this model guides future research, facilitating its application across various domains.

Practical Implications

The findings of this study have several practical implications. First, the results from the PLS-SEM highlight the importance for OTA to understand that enhancing the GenAI online travel booking system with increased media richness is imperative in shaping tourists' online booking experiences. This suggests that developers of the ChatGPT platform and travel agencies should prioritize making ChatGPT more visually engaging to secure a competitive advantage in the online booking industry. Currently, ChatGPT primarily offers textual details about flights, hotels, and car rentals, but it lacks visual cues such as logos, interior images of hotels, and photos of rental vehicles. Integrating textual travel information with such high-quality visuals and audio/video content will allow users to acquire a more complete overview of their travel and pricing options. This will significantly enhance their trust and improve their perceptions of the ChatGPT online travel booking service.

Second, consistent with trust transfer theory, the MGA results have shown that trust in ChatGPT significantly and positively influences trust in OTA across all examined groups. Therefore, for tourists to effectively shift their trust from ChatGPT to the OTA platform, ChatGPT must establish itself as a reliable, secure, and trustworthy entity. The introduction of new AI technology often brings about a degree of skepticism and uncertainty, especially regarding the travel booking services provided by ChatGPT. Addressing this, the ChatGPT interface needs to include educational video content that explains the workings of both the AI and the travel booking system within ChatGPT. For instance, tutorial videos that transparently explain the process of how the AI selects and organizes travel deals should be made available. Additionally, showcasing testimonials from users who have successfully utilized ChatGPT for travel bookings can be a significant trust-building tool for new users.

Third, the fsQCA analysis (Supplementary K) reveals that even without media richness in Groups A (solution 1, 2) and B (solution 4,5), some factors still led to high booking intentions. These findings indicate that OTA should focus on building trust and highlighting the perceived benefits, costs, and value of their offerings to enhance booking intentions in ChatGPT environments, regardless of the media richness involved. Additionally, it is recommended that representatives from OTA receive training to improve their skills in deep learning techniques to gain a deeper understanding of potential tourists' booking behaviors on the GenAI platform.

Limitations and Future Research

Although the present study offers meaningful perspectives on the tourism and hospitality industry, it has several limitations. First, the research was limited to a single country, resulting in a largely mono-cultural group of respondents. To broaden the applicability of these findings, future research should aim to include samples from countries with diverse cultures. Additionally, the framework developed in this study was tested solely within the context of a ChatGPT online travel booking service. Future work is needed to explore the applicability of this model across other emerging generative AI travel booking platforms, such as Gemini, Microsoft Copilot, and Claude. Furthermore, future research should consider incorporating potential moderating variables (e.g., travel season, purpose of travel) in the GenAI scenario, which could diminish or even reverse the positive effects of media richness. Investigating these moderators could offer deeper insights on boundary conditions affecting tourists' booking behaviors on GenAI platforms and generate further implications for the tourism industry. Lastly, although this study employed a multi-analytical approach using PLS-SEM, fsQCA, MGA, and deep learning techniques, mixed methods such as interviews

and action research could further enhance our understanding of tourist booking behaviors as well as collaborative mechanisms between AI services and OTAs.

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Supplementary A. Questionnaire.

Survey on ChatGPT

Hello,

We are conducting this survey to better understand tourist behavior with respect to ChatGPT. This study is supported by OOO University (Grant No.: OOO_xxxxxxxx). Your sincere response will contribute to our understanding of how ChatGPT may contribute to tourism. Your response is completely anonymous and will be used only for academic purposes.

We greatly appreciate your time and cooperation in completing this questionnaire.
Thank you very much!

Researchers

Names of the researchers and university are eliminated for anonymity.
The layout of this questionnaire is only for MS word file which is quite different from the online survey screen.

February 1 – 10, 2024

Note 1*:** In this survey, the term ***ChatGPT is defined as a large language model developed by Open AI, specifically designed for generating human-like text responses in natural language conversations

***Note 2*:** In this study, the term **online travel agency (OTA)** is a platform (e.g., Kayak, Booking.com, Expedia, Travelocity) that allows users to book and arrange travel-related services and products online.

Screen question (SQ)

We care about the quality of our survey data and hope to receive the most accurate measures of your opinions, so it is important to us that you thoughtfully provide your best answer to each question in the survey.

SQ1. Do you commit to providing your thoughtful and honest answers to the questions in this survey?

1. I will provide my best answers: Go to the next question.

2. I will not provide my best answers: End the survey.

3. I can't promise either way: End the survey.

Demographic characteristics[Quota]

DQ1. What is your gender?

① Male ② Female ③ Other

DQ2. What is your year of birth? _____year.

DQ3. Where are you living now?

① Seoul ②Busan ③Daegu ④Incheon ⑤Daejeon ⑥Ulsan ⑦Gwangju ⑧Sejong ⑨Gyeonggi ⑩Gangwon ⑪Chungbuk ⑫Chungnam ⑬Jeonbuk ⑭Jeonnam ⑮Kyungbuk ⑯ Gyeongnam ⑰ Jeju

General information

Familiarity

GQ1. How familiar are you with ChatGPT services?

① Not at all familiar ---------- ⑦ Extremely familiar

Knowledge

GQ2. How knowledgeable are you about ChatGPT services?

① Not at all knowledgeable ---------- ⑦ Extremely knowledgeable

Previous experience ChatGPT

GQ3. Have you ever used ChatGPT services before?

① No

② Yes ☞ If you checked "yes," please answer the following GQ3_1 questions.

GQ3_1. If yes, what purposes have you used ChatGPT for? (feel free to select one or more if you have multiple experience)

① Casual conversations and entertainment ② Professional writing ③ Educational learning ④ Language translation ⑤ Coding assistance ⑥ Information search ⑦ Other _____

Previous experience_OTA

GQ4. Have you ever used OTA (e.g., Kayak, booking.com, expedia) services before?

① No

② Yes ☞ If you checked "yes," please answer the following GQ4_1questions.

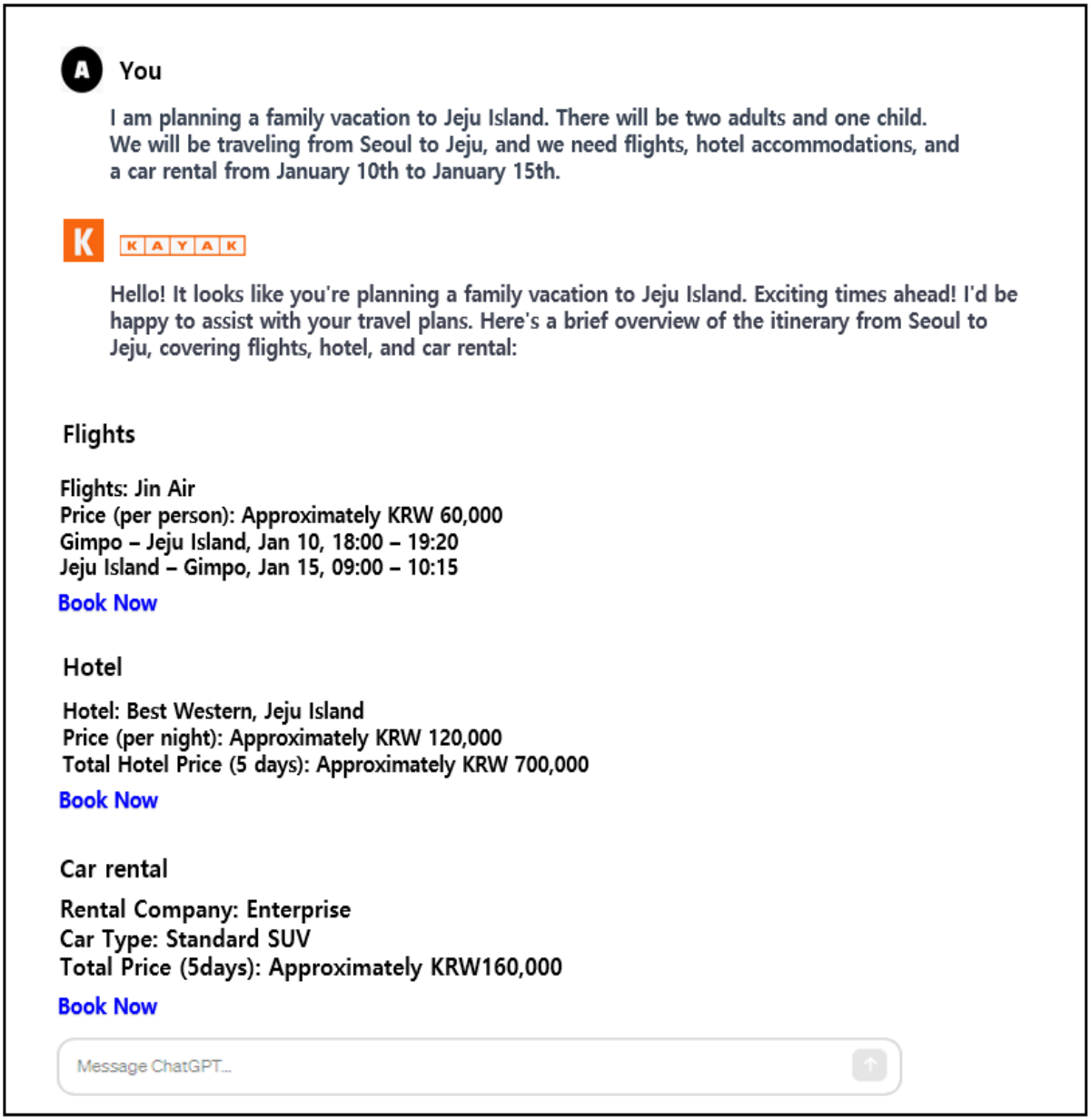
GQ4_1. If yes, what purposes have you used OTA for? (feel free to select one or more if you have multiple experience)

① Flight bookings ② Hotel reservations ③ Car rentals ④ Cruise Reservations ⑤ Vacation package bookings ⑥ Other _____

Instructions
On the next page, you will read about how you can use ChatGPT to plan a trip and book flights, hotels, and rental cars. Take your time to read the information. Afterward, you will be asked several questions. When you are ready, go to the next page.

Group A (n= 200) (Text stimuli)

Kang, S. E., Kim, M. J., Kim, J. S., & Olya, H. (2024). Can I trust GenAI to plan my next trip? A multi-method approach to optimizing media mix. *Journal of Travel Research*.
https://doi.org/10.1177/00472875241305630



Kang, S. E., Kim, M. J., Kim, J. S., & Olya, H. (2024). Can I trust GenAI to plan my next trip? A multi-method approach to optimizing media mix. *Journal of Travel Research*.
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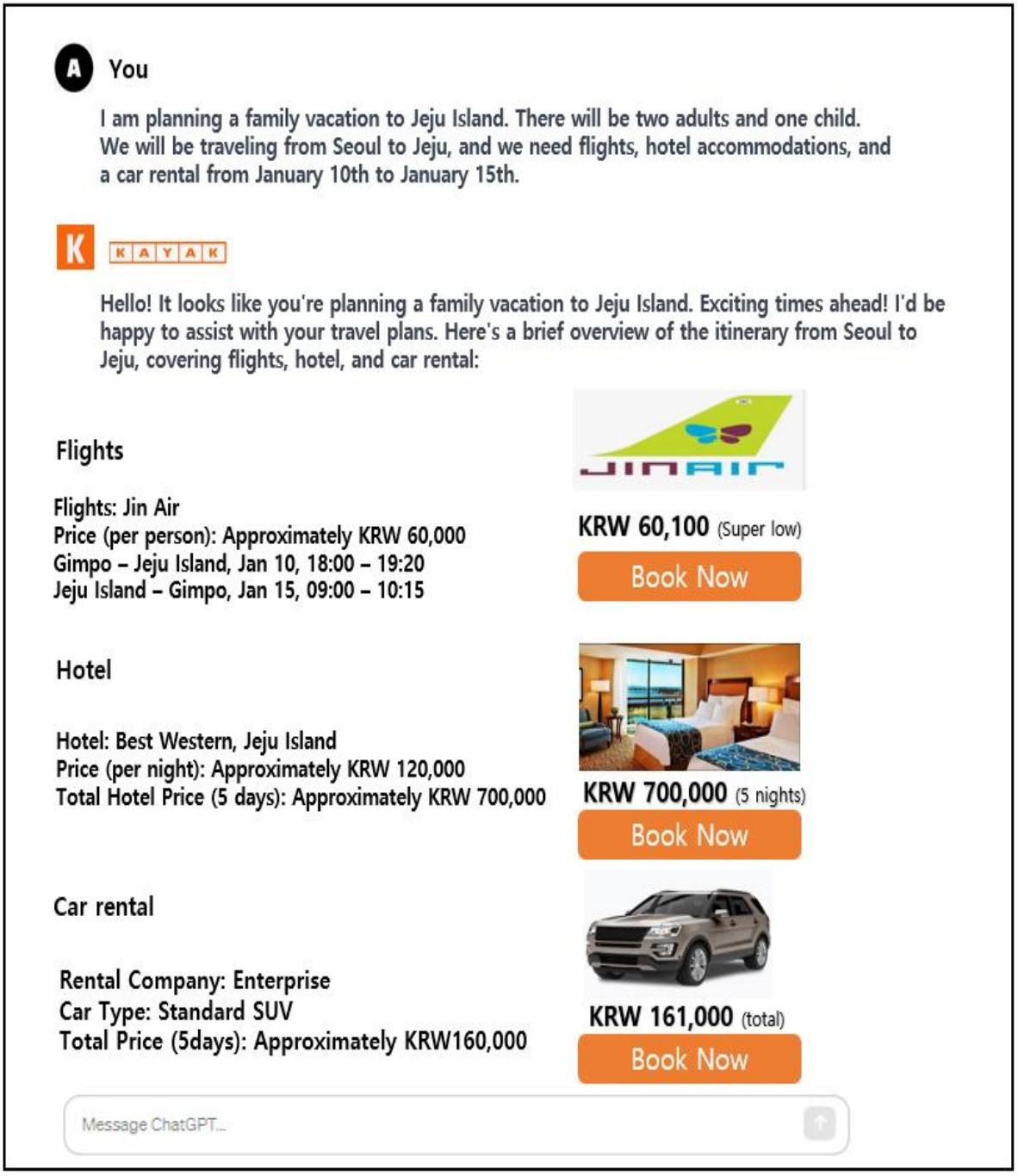
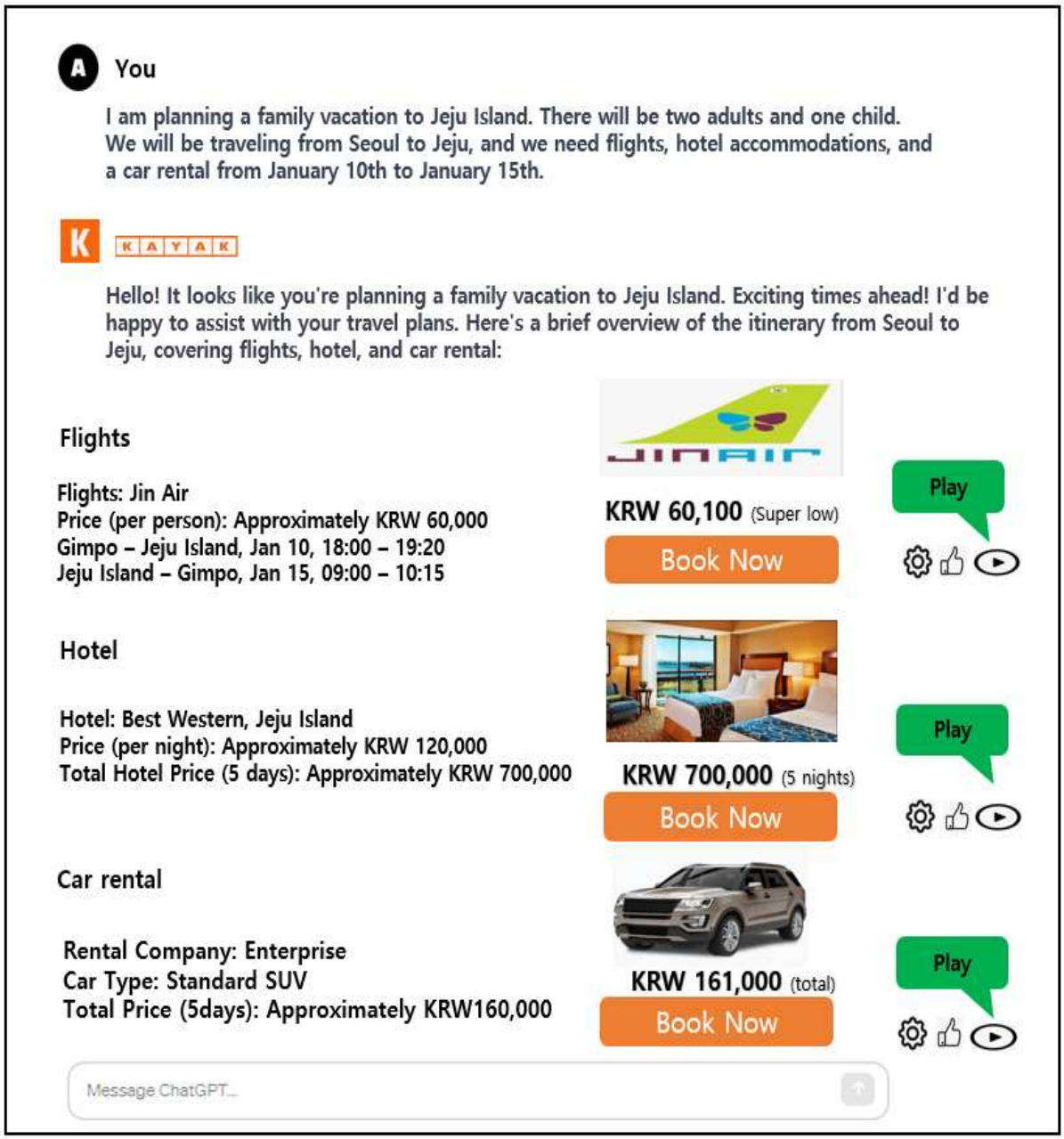
Group B (n= 200) (Text + Image stimuli)



Group C (n= 200) (Text + Image + Video Stimuli)



Attention check question (n= 600, all group)

Kang, S. E., Kim, M. J., Kim, J. S., & Olya, H. (2024). Can I trust GenAI to plan my next trip? A multi-method approach to optimizing media mix. *Journal of Travel Research*.
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ACQ1: Please fill in the blank with the correct option
Considering the scenario presented, _____.

[1] A ChatGPT service offered recommendations for family vacation including flight, hotel, and car rentals.
[2] A human travel operator provided recommendations for local restaurant cuisine.

Construct

Please choose the closest one to your ChatGPT experience in a tourism context [Select one for each] (1: strongly disagree; 2: disagree; 3: somewhat disagree; 4: neither agree nor disagree; 5: somewhat agree; 6: agree; 7: strongly agree).

CQ1. Media richness	Strongly disagree	Dis-agree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1. ChatGPT transmitted a variety of cues beyond the textual information.	1	2	3	4	5	6	7
2. ChatGPT uses rich and varied information.	1	2	3	4	5	6	7
3. ChatGPT is tailored to the user.	1	2	3	4	5	6	7
4. ChatGPT′s communication was vivid.	1	2	3	4	5	6	7
5. ChatGPT′s communication was clear.	1	2	3	4	5	6	7

CQ2. Perceived information benefit	Strongly disagree	Dis-agree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1. ChatGPT provides travel itinerary information relevant to my needs	1	2	3	4	5	6	7
2. ChatGPT provides sufficient travel itinerary information	1	2	3	4	5	6	7
3. ChatGPT provides accurate travel itinerary information	1	2	3	4	5	6	7
4. ChatGPT provides up-to-date travel itinerary information	1	2	3	4	5	6	7

CQ3. Perceived service benefit	Strongly disagree	Dis-agree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1. ChatGPT provides on-time services for travel needs	1	2	3	4	5	6	7
2. ChatGPT provides prompt responses to travel-related queries							
3. ChatGPT provides professional services tailored to travel requirements	1	2	3	4	5	6	7

4. ChatGPT provides personalized services catering to individual preferences in travel	1	2	3	4	5	6	7

CQ4. Perceived system benefit	Strongly disagree	Dis-agree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1: ChatGPT for travel itineraries quickly loads all the text	1	2	3	4	5	6	7
2: ChatGPT for travel itineraries is easy to use	1	2	3	4	5	6	7
3: ChatGPT for travel itineraries is easy to navigate	1	2	3	4	5	6	7
4: ChatGPT for travel itineraries is visually attractive	1	2	3	4	5	6	7

CQ5. Perceived privacy	Strongly disagree	Dis-agree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1. In general, it would be risky to give my personal information to ChatGPT service for travel itineraries	1	2	3	4	5	6	7
2. There would be a high potential for loss associated with giving my personal information to ChatGPT service for travel itineraries	1	2	3	4	5	6	7
3. Providing ChatGPT service with my personal information would involve many unexpected problems	1	2	3	4	5	6	7
4: There would be too much uncertainty associated with giving my personal information to ChatGPT service for travel itineraries	1	2	3	4	5	6	7

CQ6. Perceived Conflict	Strongly disagree	Dis-agree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1. Using an online travel agency platform via ChatGPT service may not be properly compensated	1	2	3	4	5	6	7
2. There would be some potential imperfections with the compensation systems when using an online travel agency platform (e.g., kayak) via ChatGPT service	1	2	3	4	5	6	7
3. An online travel agency platform (e.g., kayak) via ChatGPT service may not be able to provide me with a proper conflict resolution process when an error occurs	1	2	3	4	5	6	7
4. I might be concerned about the potential miscommunication arising from the use of ChatGPT in the travel recommendations	1	2	3	4	5	6	7

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CQ7. Trust in Chat GPT	Strongly disagree	Dis-agree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1. I trust the ChatGPT service to be reliable	1	2	3	4	5	6	7
2. I trust the ChatGPT service to be secure	1	2	3	4	5	6	7
3. I believe the ChatGPT service are trustworthy	1	2	3	4	5	6	7
4. Overall, I trust the ChatGPT service	1	2	3	4	5	6	7

CQ8. Trust in OTA	Strongly disagree	Dis-agree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1. Online travel agencies (e.g., kayak) on ChatGPT service are trustworthy	1	2	3	4	5	6	7
2. Online travel agencies (e.g., kayak) on ChatGPT service consider my best interests	1	2	3	4	5	6	7
3. I believe in the information provided by online travel agencies (e.g., kayak) on the ChatGPT service	1	2	3	4	5	6	7
4. Online travel agencies (e.g., kayak) on ChatGPT leave people with the impression that they keep their promises	1	2	3	4	5	6	7

CQ9. Perceived value	Strongly disagree	Dis-agree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Despite the risks involved in sharing my personal information, I believe that using ChatGPT service for travel itineraries ...							
1 ...is valuable	1	2	3	4	5	6	7
2 ...is worthwhile	1	2	3	4	5	6	7
3 ...overall delivers good value	1	2	3	4	5	6	7
4 ...is beneficial to me	1	2	3	4	5	6	7

CQ10. Booking intention	Strongly disagree	Dis-agree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1.Assuming I had access to ChatGPT online travel booking (e.g., airlines, car rentals, hotels), I intend to use it	1	2	3	4	5	6	7

2. Given that I had access to ChatGPT online travel booking (e.g., airlines, car rentals, hotels), I predict that I would use it	1	2	3	4	5	6	7
3. I intend to use ChatGPT online travel booking (e.g., airlines, car rentals, hotels), as often as needed	1	2	3	4	5	6	7
4. I intend to continue using ChatGPT online travel booking (e.g., airlines, car rentals, hotels), in the future	1	2	3	4	5	6	7

Demographic characteristics

DQ3. What is the highest level of education you have completed?

① Less than high school or high school diploma ② 2-year degree ③ 4-year degree ④ Graduate School or Graduate Degree

DQ4. What is your marital status?

① Single ② Married ③Divorced/Separated ④ Widow(er) ⑤ Other (specify) _____

DQ5. What is your monthly household income?

①Less than 2.00 million won ②2.00-3.99 million won ③4.00-5.99 million won ④ 6.00-7.99 million won ⑤8.00 million won or more

DQ6. What is your main occupation?

①Professional (e.g., attorney, engineer, architect) ②Entrepreneur/Self-employed ③Service employee ④Office/Administrative/Clerical ⑤Civil Servant (Government) ⑥Home maker ⑦Retiree ⑧Student ⑨Unemployed ⑩ Other (specify)_____

Thank you very much for your time and participation!

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Supplementary B. Common Method Bias Tests.

Test method	Test	Result
Harmon single-factor test	Eight factors appeared (the total 79.6% variance explained) First factor: 41.9% Second factor: 14.3% Third factor: 6.5% Fourth factor: 6.3% Fifth factor: 4.9% Sixth factor: 4.4% Seventh factor: 1.3%	Given that multiple factors emerged from the analysis and the variance explained by the first factor is below 50%, it can be inferred that common method bias does not significantly affect the study's results (Podsakoff et al., 2003).
Comparing single factor model (simple model; all 8 independent factors considered one variable) and hypotheses model (complex)	*Simple model:* SRMR: 0.110 (the smaller the better) AVE: 0.641 (the larger the better) R^2: 56.8% (the bigger the better) *Research model:* SRMR: 0.077 AVE: 0.721 R^2: 39.5%	The outperformance of the complex model compared to the simple model indicates that common method bias does not present a substantial issue in this research (Korsgaard & Roberson, 1995).

Note: All tests show that common method bias is not problem in this study.

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Supplementary C. Demographic Characteristic and General Information of the Entire Group.

Characteristics	578 (n)	100 (%)
Gender		
Male	293	50.7
Female	285	49.3
Other	0	0.0
Age		
Between 18 and 29 years old	133	23.0
Between 30 and 39 years old	125	21.6
Between 40 and 49 years old	152	26.3
50 years old and over	168	29.1
Educational level		
Less than or high school diploma	87	15.1
2-year college	102	17.6
University	314	54.3
Graduate school or higher	75	13.0
Marital status		
Single	267	46.2
Married	288	49.8
Divorced	18	3.1
Widowed	4	.7
Other	1	.2
Monthly household income		
Less than KRW 2.000-3.999 million	45	7.8
From KRW 2.000 to 4.000 million	160	27.7
From KRW 4.000 to 6.000 million	162	28.0
From KRW 6.000 to 8.000 million	118	20.4
KRW 8,000 million or more	93	16.1
Occupation		
Professional (e.g., attorney, engineer)	53	9.2
Business owner/self-employed	41	7.1

Service worker	53	9.2
Office/administrative/clerical worker	229	39.6
Civil servant (government)	22	3.8
Home maker	49	8.5
Student	8	1.4
Retiree	55	9.5
Unemployed	41	7.1
Other	27	4.7
Providing honest answers		
Yes	578	100.0
No	0	0.0
Familiarity with using ChatGPT services		
1. Not at all familiar	50	8.7
2. slightly familiar	112	19.4
3. Somewhat familiar	74	12.8
4. Moderately familiar	119	20.6
5. Fairly familiar	128	22.1
6. Very familiar	70	12.1
7. Extremely familiar	25	4.3
Knowledge of ChatGPT services		
1. Not at all knowledgeable	27	4.7
2. slightly knowledgeable	68	11.8
3. Somewhat knowledgeable	64	11.1
4. Moderately knowledgeable	92	15.9
5. Fairly knowledgeable	195	33.7
6. Very knowledgeable	106	18.3
7. Extremely knowledgeable	26	4.5
Previous experience using ChatGPT		
Yes	311	53.8
No	267	46.2

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Supplementary D.

Demographic Characteristic and General Information of the Three Types of ChatGPT.

Characteristics	Group A (%)	Group B (%)	Group C (%)
Gender			
Male	50.8	49.2	50.5
Female	49.2	50.8	49.5
Other	0.0	0.0	0.0
Age			
Between 18 and 29 years old	22.8	28.8	23.7
Between 30 and 39 years old	21.8	22.0	21.6
Between 40 and 49 years old	25.9	27.2	28.9
50 years old and over	29.5	21.5	25.8
Educational level			
Less than or high school diploma	14.5	50.8	17.5
2-year college	16.1	22.5	14.4
University	57.0	13.1	55.2
Graduate school or higher	12.4	13.6	12.9
Marital status			
Single	44.6	52.4	44.3
Married	50.3	44.0	52.6
Divorced	4.1	3.1	2.1
Widowed	1.0	.5	.5
Other	0.0	0.0	.5
Monthly household income			
Less than KRW 2.000	7.8	26.2	6.7
From KRW 2.000-3.999 million	16.6	29.3	26.3
From KRW 4.000 to 5.999 million	25.9	18.3	28.9
From KRW 6.000 to 7.999 million	19.2	8.9	23.7
KRW 8,000 million or more	30.6	17.3	14.4
Occupation			
Professional (e.g., attorney, engineer)	10.4	6.8	10.3
Business owner/self-employed	8.3	6.3	6.7
Service worker	13.0	8.9	5.7

Office/administrative/clerical worker	37.3	42.3	39.2
Civil servant (government)	3.1	4.7	3.6
Home maker	8.3	8.4	8.8
Student	1.6	1.0	1.5
Retiree	8.3	11.0	9.3
Unemployed	6.7	6.8	7.7
Other	3.1	3.7	7.2
Providing honest answers			
Yes	100.0	100.0	100.0
No	0.0	0.0	0.0
Familiarity with using ChatGPT services			
1. Not at all familiar	10.4	7.3	8.2
2. slightly familiar	17.6	20.9	19.6
3. Somewhat familiar	13.5	16.2	8.8
4. Moderately familiar	18.7	20.4	22.7
5. Fairly familiar	24.9	17.3	24.2
6. Very familiar	9.8	14.1	12.4
7. Extremely familiar	5.2	3.7	4.1
Knowledge of ChatGPT services			
1. Not at all knowledgeable	4.7	3.7	5.7
2. slightly knowledgeable	10.9	15.2	9.3
3. Somewhat knowledgeable	15.5	7.3	10.3
4. Moderately knowledgeable	14.0	16.8	17.0
5. Fairly knowledgeable	34.2	35.1	32.0
6. Very knowledgeable	15.5	17.8	21.6
7. Extremely knowledgeable	5.2	4.2	4.1
Previous experience using ChatGPT			
Yes	51.3	52.4	57.7
No	48.7	47.6	42.3

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Supplementary E. Confirmatory Factor Analysis of Measurement Model.

Constructs	FL*	t-value	CI*** 2.5%	CI*** 97.5%	VIF**
Media richness					
1. ChatGPT transmitted a variety of cues beyond the textual information.	0.833	46.525	0.794	0.865	2.305
2. ChatGPT uses rich and varied information	0.837	53.592	0.804	0.865	2.338
3. ChatGPT is tailored to the user	0.840	55.405	0.808	0.868	2.248
4. ChatGPT′s communication was vivid.	0.865	64.709	0.835	0.888	2.575
5. ChatGPT′s communication was clear.	0.806	44.448	0.767	0.839	2.043
Perceived information benefit					
1. ChatGPT provides travel itinerary information relevant to my needs	0.850	65.331	0.824	0.874	2.153
2. ChatGPT provides sufficient travel itinerary information	0.875	73.782	0.85	0.897	2.454
3. ChatGPT provides accurate travel itinerary information	0.862	65.842	0.835	0.886	2.453
4. ChatGPT provides up-to-date travel itinerary information	0.845	60.21	0.816	0.870	2.094
Perceived service benefit					
1. ChatGPT provides on-time services for travel needs	0.840	48.486	0.802	0.870	2.250
2. ChatGPT provides prompt responses for travel-related queries	0.807	39.83	0.764	0.843	1.806
3. ChatGPT provides professional services tailored to travel requirements	0.871	69.986	0.845	0.894	2.273
4. ChatGPT provides personalized services catering to individual preferences in travel	0.827	47.677	0.790	0.858	2.656
Perceived system benefit					
1. ChatGPT for travel itineraries quickly loads all the text	0.842	54.707	0.810	0.869	2.352
2. ChatGPT for travel itineraries is easy to use	0.857	59.751	0.826	0.884	2.372
3. ChatGPT for travel itineraries is easy to navigate	0.850	59.884	0.819	0.875	2.333
4. ChatGPT for travel itineraries is visually attractive	0.755	32.952	0.706	0.795	1.789
Perceived privacy					
1. In general, it would be risky to give my personal information to ChatGPT service for travel itineraries	0.886	67.284	0.857	0.909	2.692
2. There would be a high potential for loss associated with giving my personal information to ChatGPT service for travel itineraries	0.852	57.566	0.820	0.879	2.313
3. Providing ChatGPT service with my personal information would involve many unexpected problems	0.874	69.709	0.847	0.896	2.563
4: There would be too much uncertainty associated with giving my personal information to ChatGPT service for travel itineraries	0.879	67.813	0.851	0.903	2.637
Perceived conflict					
1. Using an online travel agency platform via ChatGPT service may not be properly					

compensated	0.818	44.554	0.779	0.850	1.986
2. There would be some potential imperfections with the compensation systems when using an online travel agency platform (e.g., kayak) via ChatGPT service	0.866	60.013	0.836	0.892	2.408
3. An online travel agency platform (e.g., kayak) via ChatGPT service may not be able to provide me with a proper conflict resolution process when an error occurs	0.889	85.669	0.867	0.908	2.726
4. I might be concerned about the potential miscommunication arising from the use of ChatGPT in the travel recommendations	0.858	62.664	0.829	0.883	2.296
Trust in ChatGPT					
1. I trust the ChatGPT service to be reliable	0.926	146.17	0.913	0.938	4.018
2. I trust the ChatGPT service to be secure	0.869	67.521	0.841	0.892	2.533
3. I believe the ChatGPT service are trustworthy	0.926	129.49	0.91	0.938	4.060
4. Overall, I trust the ChatGPT service	0.915	115.09	0.898	0.929	3.516
Trust in OTA					
1. Online travel agencies (e.g., kayak) on ChatGPT service are trustworthy	0.895	102.75	0.876	0.911	3.004
2. Online travel agencies (e.g., kayak) on ChatGPT service consider my best interests	0.806	40.706	0.765	0.842	1.789
3. I believe in the information provided by online travel agencies (e.g., kayak) on the ChatGPT service	0.897	98.941	0.878	0.913	2.997
4. Online travel agencies (e.g., kayak) on ChatGPT leave people with the impression that they keep their promises	0.845	58.422	0.814	0.871	2.17
Perceived value					
1 ...is valuable	0.905	96.628	0.885	0.921	3.234
2 ...is worthwhile	0.893	88.743	0.872	0.911	3.019
3 ...overall delivers good value	0.890	95.95	0.87	0.907	2.712
4 ...is beneficial to me	0.880	84.178	0.858	0.899	2.575
Booking intention					
1. Assuming I had access to Chat GPT online travel booking (e.g., airlines, car rentals, hotels), I intend to use it	0.941	166.16	0.929	0.951	3.962
3. I intend to use ChatGPT online travel booking (e.g., airlines, car rentals, hotels), as often as needed	0.937	137.78	0.923	0.949	3.911
4. I intend to continue using ChatGPT online travel booking (e.g., airlines, car rentals, hotels), in the future	0.940	160.43	0.928	0.951	3.844

Note: *Factor loading; **Variance inflation factor of multi-collinearity, ***Confidence intervals.

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Supplementary F. Reliability and Discriminant Validity.

	Heterotrait_Monotrait Ratio (< 0.9)						
Construct	1	2	3	4	5	6	7
1. Booking intention							
2. Media richness	0.672						
3. Perceived benefit	0.752	0.837					
4. Perceived sacrifice	0.156	0.094	0.115				
5. Perceived value	0.711	0.693	0.792	0.092			
6. Trust in ChatGPT	0.629	0.659	0.643	0.234	0.622		
7. Trust in OTA	0.701	0.731	0.808	0.161	0.745	0.699	
Mean	4.932	4.698	4.832	4.519	4.970	4.464	4.603
Standard deviation	0.351	0.544	0.155	0.231	0.419	0.427	0.462
Cronbach's alpha $\geq$ 0.7	0.933	0.893	0.927	0.878	0.914	0.930	0.884
Rho_A (reliability coefficient) > 0.7	0.935	0.893	0.928	0.880	0.915	0.932	0.887
Composite reliability > 0.7	0.957	0.921	0.937	0.904	0.940	0.950	0.920
AVE > 0.5	0.882	0.700	0.555	0.541	0.795	0.827	0.742
$Q^2 > 0$	0.295	–	0.578	0.777	0.375	0.356	0.578

Note: –: Exogenous variables give effects to endogenous variables so only endogenous variables have an effect size in causal modeling.

Kang, S. E., Kim, M. J., Kim, J. S., & Olya, H. (2024). Can I trust GenAI to plan my next trip? A multi-method approach to optimizing media mix. *Journal of Travel Research*. https://doi.org/10.1177/00472875241305630

Supplementary G. Mediating (indirect) Effects.

Path	Direct effect	Indirect effect	Total effect	f^2
Media richness → Perceived benefit	0.762***		0.762***	1.382
Media richness →Trust in ChatGPT	0.601***		0.601***	
Media richness →Perceived sacrifice	-0.081^{ns}		-0.081^{ns}	0.07
Media richness →Booking intention		0.331***	0.331***	
Media richness →Perceived value		0.503***	0.503***	
Media richness →Trust in OTA		0.381***	0.381***	
Trust in ChatGPT →Trust in OTA	0.634***		0.634***	
Trust in ChatGPT →Booking intention		0.124***	0.124***	
Trust in ChatGPT →Perceived value		0.189***	0.189***	
Trust in OTA → Perceived value	0.298***		0.298***	
Trust in OTA → Booking intention		0.196***	0.196***	
Perceived benefit → Perceived value	0.514***		0.514***	0.287
Perceived benefit → Booking intention		0.338***	0.338***	
Perceived sacrifice → Perceived value	0.018^{ns}		0.018^{ns}	0.001
Perceived sacrifice → Booking intention		0.012^{ns}	0.012^{ns}	
Perceived value →Booking intention	0.658***		0.658***	0.763

Note: ***p<.001; ns = not significant.

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Supplementary H. Moderating Effects.

Path	Estimate	t-Value	p- Value	Supported
Age x Trust in ChatGPT_→Trust in OTA_	0.07	1.852	0.064	Not supported
Age x Perceived risk →Perceived Value	-0.041	1.413	0.158	Not supported
Age x Media Richness → Perceived benefit	-0.015	0.480	0.631	Not supported
Age x Media Richness →Perceived risk	-0.105	1.996	0.046	Not supported
Age x Media Richness →Trust in ChatGPT	-0.048	1.322	0.186	Not supported
Age x Perceived Benefit →Perceived Value	-0.029	0.620	0.536	Not supported
Age x Trust in OTA →Perceived Value	0.036	0.738	0.460	Not supported
Gender x Media Richness →Perceived Benefit	-0.015	0.226	0.822	Not supported
Gender x Media Richness →Perceived Risk	-0.001	0.006	0.996	Not supported
Gender x Media Richness→ Trust in ChatGPT	-0.084	1.027	0.305	Not supported
Gender x Trust in ChatGPT →Trust in OTA	-0.047	0.627	0.530	Not supported
Gender x Perceived Risk → Perceived Value	-0.003	0.050	0.960	Not supported
Gender x Trust in OTA → Perceived Value	0.187	2.068	0.059	Not supported
Gender x Perceived Benefit → Perceived Value	-0.196	2.232	0.056	Not supported

Kang, S. E., Kim, M. J., Kim, J. S., & Olya, H. (2024). Can I trust GenAI to plan my next trip? A multi-method approach to optimizing media mix. *Journal of Travel Research*.
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Supplementary I. Differences of the Path Coefficients among Three Groups.

H	Path	Group A, B, and C	Path difference	p-value (A-B/A-C/B-C)	Hypothesis test
H1	Media richness → Perceived benefit	Text only and Text/image	-0.024	0.611	Not supported
		Text only and Text/image/audio	0.079	0.158	
		Text/image and Text/image/audio	0.055	0.32	
H2	Media richness → Trust in ChatGPT	Text only and Text/image	0.018	0.814	Not supported
		Text only and Text/image/audio	0.083	0.317	
		Text/image and Text/image/audio	0.065	0.435	
H3	Media richness → Perceived sacrifice	Text only and Text/image	-0.043	0.745	Not supported
		Text only and Text/image/audio	0.104	0.406	
		Text/image and Text/image/audio	0.147	0.257	
H4	Trust in ChatGPT → Trust in OTA	Text only and Text/image	-0.204	0.002	Partially supported
		Text only and Text/image/audio	0.007	0.934	
		Text/image and Text/image/audio	0.211	0.002	
H5	Trust in OTA_→ Perceived value	Text only and Text/image	-0.063	0.593	Not supported
		Text only and Text/image/audio	0.002	0.995	
		Text/image and Text/image/audio	0.065	0.579	
H6	Perceived benefit → Perceived value	Text only and Text/image	0.036	0.757	Not supported
		Text only and Text/image/audio	0.026	0.793	
		Text/image and Text/image/audio	-0.01	0.936	
H7	Perceived sacrifice → Perceived value	Text only and Text/image	0.016	0.814	Not supported
		Text only and Text/image/audio	0.06	0.445	
		Text/image and Text/image/audio	0.044	0.529	
H8	Perceived value → Booking intention	Text only and Text/image	0.029	0.703	Not supported
		Text only and Text/image/audio	0.161	0.082	
		Text/image and Text/image/audio	0.132	0.086	

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Supplementary J. The Analysis of Necessary Conditions to Predict Booking Intention Using ChatGPT Service

Antecedent condition	**Outcome: Group A (text only / low media richness)**		**Results**
	Consistency	Coverage	
Media richness	0.844	0.879	Unnecessary
Perceived benefit	0.883	0.910	Necessary
Perceived sacrifice	0.754	0.779	Unnecessary
Trust in ChatGPT	0.840	0.895	Unnecessary
Trust in OTA	0.849	0.903	Unnecessary
Perceived Value	0.878	0.895	Unnecessary
Antecedent condition	**Outcome: Group B (text & image / medium media richness)**		
	Consistency	Coverage	
Media richness	0.828	0.895	Unnecessary
Perceived benefit	0.845	0.916	Unnecessary
Perceived sacrifice	0.731	0.782	Unnecessary
Trust in ChatGPT	0.847	0.876	Unnecessary
Trust in OTA	0.847	0.908	Unnecessary
Perceived Value	0.866	0.900	Necessary
Antecedent condition	**Outcome: Group C (text,image & audio/high media richness)**		
	Consistency	Coverage	
Media richness	0.849	0.882	Unnecessary
Perceived benefit	0.821	0.886	Unnecessary
Perceived sacrifice	0.729	0.771	Unnecessary
Trust in ChatGPT	0.826	0.868	Unnecessary
Trust in OTA	0.779	0.899	Unnecessary
Perceived Value	0.839	0.877	Unnecessary

Kang, S. E., Kim, M. J., Kim, J. S., & Olya, H. (2024). Can I trust GenAI to plan my next trip? A multi-method approach to optimizing media mix. *Journal of Travel Research*. https://doi.org/10.1177/00472875241305630

Supplementary K. Sufficient Causal Configurations for Three Types of Media Stimuli.

Group A: text only (low media richness) (Coverage: 0.885; Consistency: 0.869)	Raw coverage	Unique coverage	Consistency
~MR*PBEN*~TRUSTGPT	0.521	0.005	0.908
TRUSTGPT*TRUSTOTA*PVAL	0.754	0.018	0.956
MR*PBEN*~PSAC*TRUSTGPT	0.599	0.003	0.964
MR*PBEN*PSAC*PVAL	0.655	0.011	0.952
MR*PSAC*TRUSTGPT*TRUSTOTA	0.618	0.001	0.948
Group B: text and image (medium media richness) (Coverage: 0.884; Consistency: 0.879)	Raw coverage	Unique coverage	Consistency
MR*TRUSTGPT*TRUSTOTA	0.512	0.006	0.944
MR*PBEN*PSAC	0.607	0.010	0.949
MR*PBEN*TRUSTOTA	0.729	0.032	0.959
PBEN*~PSAC*TRUSTGPT*PVAL	0.571	0.010	0.980
PSAC*~TRUSTGPT*TRUSTOTA	0.501	0.000	0.938
Group C: text, image, and audio (high media richness) (Coverage: 0.884; Consistency: 0.859)	Raw coverage	Unique coverage	Consistency
MR*PBEN*~TRUSTOTA	0.566	0.006	0.915
MR*~PSAC*~TRUSTOTA	0.621	0.009	0.950
MR*TRUSTGPT*~PVAL	0.544	0.002	0.910
MR*TRUSTGPT*~TRUSTOTA	0.566	0.001	0.906
MR*~TRUSTOTA*PVAL	0.566	0.000	0.911
MR*~TRUSTGPT*PVAL	0.553	0.001	0.917
MR*PBEN*TRUSTGPT	0.740	0.004	0.943
MR*PBEN*PVAL	0.751	0.009	0.933

Note: ~: Negation; MR: Media richness; PBEN: Perceived benefit; PSAC: Perceived sacrifice; TRUSTGPT: Trust in ChatGPT; TRUSTOTA: Trust in OTA; PVAL: Perceived value.

Kang, S. E., Kim, M. J., Kim, J. S., & Olya, H. (2024). Can I trust GenAI to plan my next trip? A multi-method approach to optimizing media mix. *Journal of Travel Research*. https://doi.org/10.1177/00472875241305630

Supplementary L. Comparing Three Models by Deep Learning.

Models	Model A: trust transfer model (output neuron: BINTEN)	Model B: Current research model* (output neuron: BINTEN)	Model C (output neuron: BINTEN)
Sum of squares error	Training: 83.716	Training: 82.185	Training: 86.266
	Testing: 0.430	Testing: 0.417	Testing: 0.417
Relative error	Training: 53.940	Training: 29.236	Training: 32.626
	Testing: 0.476	**Testing: 0.357**	Testing: 0.415
Independent variable importance	MR: 73.2%	MR: 27.0%	MR: 28.8%
	TRUSTGPT: 49.8%	TRUSTGPT: 39.1%	TRUSTGPT: 50.6%
	TRUSTOTA: 86.1%	TRUSTOTA: 68.8%	TRUSTOTA: 59.8%
	PVAL: 100.0%	PVAL: 100.0%	PVAL: 100.0%
		PBEN: 75.6%	PIB 71.6%
		PSAC: 14.4%	PSERB: 56.5%
			PSYSB: 59.4%
			PPRIV: 21.9%
			PCONF: 17.5%

Note: MR: Media richness; TRUSTGPT: Trust in ChatGPT; TRUSTOTA: Trust in OTA; PVAL: Perceived value; PBEN: Perceived benefit; PSAC: Perceived sacrifice; PIB: Perceived information benefit; PSERB: Perceived service benefit; PSYSB: Perceived system benefit; PPRIV: Perceived privacy; PCONF: perceived conflict. *Model B is the current research model including second order factor of VAM.