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Examining Consumer's Intention to Adopt AI-Chatbots in Tourism Using Partial Least Squares Structural Equation Modeling Method

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Abstract: Artificial intelligence (AI) is an important link between online consumers and the tourism industry. AI-chatbots are the latest technological advancement that have shaped the tourism industry. AI-chatbots are a relatively new technology in the hospitality and tourism industries, but little is known about their use. The study aims to identify factors influencing AI-chatbot adoption and their use in improving customer engagement and experiences. Using an offline survey, researchers collected data from 530 respondents. Using the structural equation modeling technique, the conceptual model was empirically tested. According to the results, the S-O-R theoretical framework is suitable for evaluating chatbot adoption intentions. Additionally, the structural model supported the ten hypotheses, validating the suggested directions of substantial impacts. In addition to practitioners and tourism managers, this study also has broad implications for scholars.

Keywords: S-O-R model; AI-chatbots; cognitive attitude; affective attitude; anthropomorphism; travelers' intention; technology adoption; PLS-SEM; multivariate analysis

MSC: 62H15

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1. Introduction

Artificial intelligence (AI) increasingly drives interactions between online consumers and the tourism industry [1,2]. Indeed, technological advancements (such as AI-chatbots and automation) are transforming the tourism industry's functions today [3,4]. For instance, AI-chatbots are now so integrated into the online experience that consumers cannot tell if they are communicating with a chatbot or a human [5]. Adam et al. [6] posited, "AI-based chatbot is a particular type of chatbot designed for turn-by-turn conversations with human users based on the textual input". Chatbots can be interacted with through text or voice and assisted by intelligent back-end technologies to facilitate communication [7]. Consumers and service providers benefit from travel chatbots since they can use them for travel planning, booking, and support, while companies gain from increased engagement, revenue prospects, and competitive advantages [3]. Tussyadiah and Miller [8] discussed the application of AI-chatbots in hotels, emphasizing both the social and economic benefits of interacting with consumers since they can use personal data, deliver consistent services, and be aware of customers' needs. It is anticipated that chatbot applications and other technology-enabled alternatives will improve business sustainability in the long run [9].

Since technology impacts all generations, a better understanding of consumer adoption of AI-chatbots is essential for the growth of the tourism industry [10,11]. To conduct sustainable business, the tourism sector must utilize new technologies to change how it communicates with consumers. Many research studies on AI-chatbots have focused on their technological features [7], consumers' inferences of human characteristics to AI-chatbots, and their consequences on interaction [12]. While AI-chatbots are an emergent technology in the hospitality and tourism industry, little research has investigated their adoption [13–15]. To ensure the long-term deployment of AI-chatbots, more empirical research must be conducted on customers' perceptions of and attitudes towards AI-chatbots in this context [16]. Given the current context, tourism literature does not reveal the extent to which interacting with a stand-alone chatbot might affect customers' positive attitude, as opposed to an interactive website. While technology imperative models, such as the "Technology Acceptance Model" (TAM), offer knowledge about AI-chatbot adoption in developing contexts, they tend to focus primarily on early adoption and lack insight into how attitudes are formed through functional websites and resulting purchases [17]. It is argued that the adoption process occurs sequentially and could be better comprehended using the "Stimulus-Organism-Response" (S-O-R) approach. As a result, to determine the attributes that lead consumers to adopt AI-chatbots, we have proposed the following research questions.

RQ1. What are the key attributes that determine the attitude towards adopting AI-based chatbots in tourism?

RQ2. To what extent does consumer attitude influence their responses to tourism chatbots?

The S-O-R approach is a comprehensive theoretical approach for analyzing the relationship between stimulus, organism, and response [18]. The following reasons make it appropriate for us to answer our research questions. First, the S-O-R approach is based on a coherent approach, incorporating principles from several disciplines such as information systems, psychology, and consumer behavior. Second, this approach provides a more holistic understanding of consumers' cognitive and affective feelings, as well as their subsequent actions as a result of their engagement with the shopping experience [19]. Third, no research has utilized the S-O-R theoretical framework to analyze the influence of AI-chatbot characteristics on future adoption intentions in developing markets. Therefore, this study aims to examine AI-chatbot adoption uniquely to support the travel and hospitality industries by understanding the key attributes that drive the adoption of AI-chatbots.

Although the literature around AI-chatbots is gradually increasing, it is vivid. Over the recent past, a few papers have been published on AI chatbots, however, their focus had largely been on the health industry [20,21], financial services [22,23] or retailing/brand [24]. Hence, a lack of studies on AI-chatbots in tourism warrants a need for the current research. Consequently, this study pioneers to provide deeper insights into AI-chatbots and technological automation from varied perspectives; first, this study sought to analyze factors influencing chatbot adoption in tourism, resulting in better theoretical and managerial understanding. For instance, the findings of this study will aid tourism companies in enhancing customer experiences and interactions through AI-chatbots. Second, this study examines how social behavior triggered by anthropomorphism can impact consumers' cognitive and affective attitudes. Third, the current study examines whether AI-chatbots have the notion to control interactivity without textual information. Therefore, the current study seeks to fill the void in the literature by examining consumers' intention to adopt AI-chatbots in tourism.

2. Literature Review

2.1. S-O-R Theory

As Mehrabian and Russell [25] proposed, the S-O-R approach is based on the classic stimulus-response notion, which was first proposed by Woodworth [26]. The S-O-R approach has been extensively applied to the study of the human decision-making process [27]. Environmental signals are viewed as a 'stimulus' [28] that induces and modulates consumers' cognitive and affective behavior [29,30]. Furthermore, the S-O-R model is based on both internal and external elements, with 'stimuli' such as brand image, product function, and visual aesthetics leading to intuitive and cognitive 'response' in consumer behavior [31] and 'organism' acting as both a mediator and an internal factor [32]. This model's overarching assumption is that it will "stimulate emotions" to elicit the required responses from consumers. More precisely, "stimuli" is recognized as the environmental factors experienced by individuals [33] that will stimulate them [34]. "Stimuli" is described in this study as the distinctive characteristics of the chatbot that would arouse its users. The second block, "organism", can be characterized as an individual's emotional and cognitive state and their subconscious act of intervening between stimuli and responses [35]. For example, in this study, the "organism" comprises the consumers' affective and cognitive attitudes toward chatbot adoption. Finally, consumers' behavioral repercussions or outcomes to the environment have been described as the third factor, "response". Therefore, adoption intention can be argued to reflect approach behavior and, consequently, regarded as a response element in this study.

The S-O-R approach has been used in a variety of areas, including online purchasing [35], online retail websites [35], and the tourism industry [18]. Consequently, we utilized the underpinnings of the S-O-R approach to explore consumers' organism processes and responses to the AI-chatbots in the context of the travel industry.

2.2. Perceived Usability

Following the definition established by Hoehle and Venkatesh [36], we define "chatbot usability" as the extent to which AI-chatbots are utilized to accomplish a specific objective with quality and efficiency. As such, it integrates "*components of design*", "*ease of use*", and "*perceived usefulness*" [36]. Furthermore, according to a survey, consumers often view organizations employing AI-chatbots as innovative as they can initiate communication or demonstrate the usability of their products on platforms [37]. In the context of customer encounters, we may presume that if a chatbot is effective (e.g., well-designed, informative, and convenient to use), the consumer would have a more positive feeling toward AI-chatbots and experience more authority [38]. When an AI-chatbot is easy to use, the interaction works better and feels more natural. With such an engagement, consumers are less likely to question the chatbot, less inclined to consider it creepy, and more receptive to using them. Prior scholars have noted a significant relationship between perceived usability and attitude in different contexts, for instance, blockchain technology [39], social media transactions [40], and AI-powered online travel services [41]. In the context of chatbots, Kasilingam [42] highlighted the significant positive relationship between perceived usability and attitude components. Furthermore, scholars have mentioned that perceived usability and its components have positively influenced the various dimensions of attitude. Hence, we formulate the following hypotheses:

Hypothesis 1 (H1). *There is a positive relationship between perceived usability and cognitive attitude toward AI-chatbots.*

Hypothesis 2 (H2). *There is a positive relationship between perceived usability and affective attitude toward AI-chatbots.*

2.3. Interactivity

Perceived interactivity is a vital characteristic of efficient online or in-person communication [43]. The literature has identified three aspects of perceived interaction: perceived interactivity as a technical feature, information sharing mechanism, and user perception [44]. According to the theoretical explanation of interactivity [45], both a chatbot and an interactive website have interactive media qualities that determine the various aspects of perceived interaction. Furthermore, a recent meta-analysis found that perceived interactivity helped create favorable user attitudes [46]. Interactivity is a key feature of digital technologies [47] that directly impacts the consumer experience [48]. Previous researchers have found that AI technologies stimulate a high degree of interactivity [49–51]. Park and Yoo [52] recently demonstrated that perceived interactivity with augmented reality influences mental imagery, which leads to a positive consumer attitude. Many cognitive, emotional, and behavioral reactions associated with consumer experiences are influenced by interactivity [53]. Therefore, we propose the following hypotheses:

Hypothesis 3 (H3). *There is a positive relationship between interactivity and cognitive attitude toward AI-chatbots.*

Hypothesis 4 (H4). *There is a positive relationship between interactivity and affective attitude toward AI-chatbots.*

2.4. Perceived Intelligence

The term perceived intelligence was created by AI [54,55], including competency, knowledge transmission, responsiveness, intelligence, and reasonable reply of chatbot [56–58]. Concerning AI-chatbots, perceived intelligence is concerned with the capability to comprehend and provide a response by interpreting natural speech and producing favorable results [59,60]. Previous research [61] has suggested that perceived intelligence is one of the key determinants of robot adoption in the context of hotel service robots. Furthermore, Yu [62] discovered that perceived intelligence is related to robots' competence to speak multiple languages, articulation, and ability to offer the service. Prior research has found a strong link between perceived intelligence and chatbot adoption. According to researchers, since cognitive and reasoning capacity in data processing has become an essential component of many AI algorithms [63], intelligence seems to be a crucial identity for any AI-powered system [64].

Similarly, Dellermann et al. [65] stated that digital tools have begun to play a vital role in consumers' lives, and their intelligence is perpetuating as a result of learning. In their study, Yang et al. [66] stated that automation intelligence could improve retail operations and provide personalized service to consumers. Since the literature suggests that perceived intelligence comprises both functional and hedonic attributes, this study considers perceived intelligence a key attribute of AI-chatbots since it requires interaction and cooperation to offer a proficient service to consumers for travel planning, and postulates the following hypotheses.

Hypothesis 5 (H5). *There is a positive relationship between perceived intelligence and cognitive attitude toward AI-chatbots.*

Hypothesis 6 (H6). *There is a positive relationship between perceived intelligence and affective attitude toward AI-chatbots.*

2.5. Anthropomorphism

Anthropomorphism is closely related to human traits and behavior concerning non-human entities such as AI-chatbots and robots [67]. It strengthens consumers' confidence and sense of stability, resulting in a more positive attitude [55,68]. The literature on anthropomorphism of AI-chatbots discusses how using AI-chatbots for small conversations and dialogues has increased users' perceptions of chatbot trustworthiness, competence, and involvement [69]. Similarly, Araujo [70] reported that consumers' impressions of engaging with other social entities favorably impacts their emotional attachment to a chatbot company. Research suggested that the anthropomorphic attributes of AI-chatbots are an important predictor of consumers' attitudes [7,62,71]. Although no previous studies have looked into how anthropomorphic characteristics of AI-chatbots influence attitude dimensions, it is likely that human-like characteristics of chatbots are linked to both consumers' cognitive and affective attitudes. Thus, we postulate the following hypotheses:

Hypothesis 7 (H7). *There is a positive relationship between anthropomorphism and cognitive attitude toward AI-chatbots.*

Hypothesis 8 (H8). *There is a positive relationship between anthropomorphism and affective attitude toward AI-chatbots.*

2.6. Affective and Cognitive Attitude

Attitude is a broad, long-term assessment of an individual, location, or thing [71]. Attitude is a multidimensional construct with various dimensions such as cognition, affect, value, and consciousness [72]. Following Eroglu's [29] categorization of attitude, we employed two dimensions of attitude: affective attitude and cognitive attitude. Individuals' cognitive attitude describes how much they like or dislike an object based on its value and functions [73]. However, affective attitude concerns an individual's emotions and feelings from experiencing an object [72]. Attitude has been employed in many studies and contexts [71]. Consumer attitudes and purchasing intention or behavior have a significant and favorable relationship [74,75]. We assumed a significant positive association between cognitive and affective attitude and purchase intention, and hence proposed the following hypotheses:

Hypothesis 9 (H9). *There is a positive relationship between cognitive attitude and adoption intention toward AI-chatbots.*

Hypothesis 10 (H10). *There is a significant relationship between the affective attitude and adoption intention toward AI-chatbots.*

3. Method

3.1. Research Instrument

The items used to measure the constructs in the current study were adapted from the prior literature related to AI-chatbots (Table A1). Perceived usability, with nine items, was taken from Chen et al. [76]. Interactivity was adapted from Arghashi and Yuksel [77] with four items. Perceived intelligence was assessed with five items adapted from Pillai and Sivathanu [3]. The scale of anthropomorphism was adopted from Melián-González et al. [78], with four items. Consumers' affective and cognitive attitudes were assessed using the five items and four items borrowed from Suprarno [79]. Finally, consumers' intention to adopt AI-chatbots was assessed with four items adapted from Melián-González et al. [78]. All the items were scored on a seven-point Likert scale, with one representing "strongly disagree" and seven representing "strongly agree". In order to test the validity of the measuring items, a pilot study was carried out with 30 travelers who had prior experience utilizing the AI-chatbot-based travel services. The travelers were drawn from a Government Engineering Institute.

3.2. Data Collection and Respondents

There were two parts to the survey questionnaire. The first half of the survey contains demographic data from respondents, while the second contains structured questionnaires covering relevant variables. The data was collected in the National Capital Territory of Delhi (NCT), which had been chosen because of the higher churning rate of the working population, practically capturing representation throughout the country. NCT is also a certain territory and the provincial capital of India, with a cosmopolitan society and a reputation as a learning center in the country's north. Purposive sampling, a non-probability sampling approach, was utilized in the current study. This method is preferred for data collection when the population is unknown and getting responses from the complete sampling frame is challenging [80]. The respondents were approached at the Delhi airport using an intercept survey method.

Furthermore, for the current study, an airport intercept survey is a better sampling strategy as it entails receiving responses from consumers traveling and using AI-chatbots and other self-service technology during travel. The survey was conducted between 1 April and 15 April 2022. Accordingly, 700 questionnaires were handed to airport visitors, and

563 responses were received. Following the initial screening, 530 valid questionnaires were selected for data analysis, yielding an 80.42% response rate. The demographic descriptions of the respondents are depicted in Table 1.

Table 1. Demographic details.

Variables	Categories	Frequency	Percentage
Gender	Male	361	68.11
	Female	169	31.89
Age	18–30	273	51.5
	31–45	148	27.9
	46–60	97	18.3
	Above 60	12	2.3
Education	Bachelor	316	59.6
	Master	198	37.3
	Ph.D.	16	3.1
Household Income/Month (INR)	30,000–50,000	29	5.5
	50,001–70,000	134	25.3
	70,001–90,000	219	41.3
	Above 90,000	148	27.9

3.3. Analytical Method

To empirically validate the conceptual model (see Figure 1) and the hypothesized relations amongst the research constructs, we employed Anderson and Gerbing's [81] 'two-step technique' of 'structural equation modeling' (SEM) using Adanco software. Next, following Hair et al. [82] and Sadiq et al. [83], we conducted a preliminary analysis to look for outliers and missing data before processing with statistical analysis of the data; following which, we conducted a data normality test, along with a common method bias test.

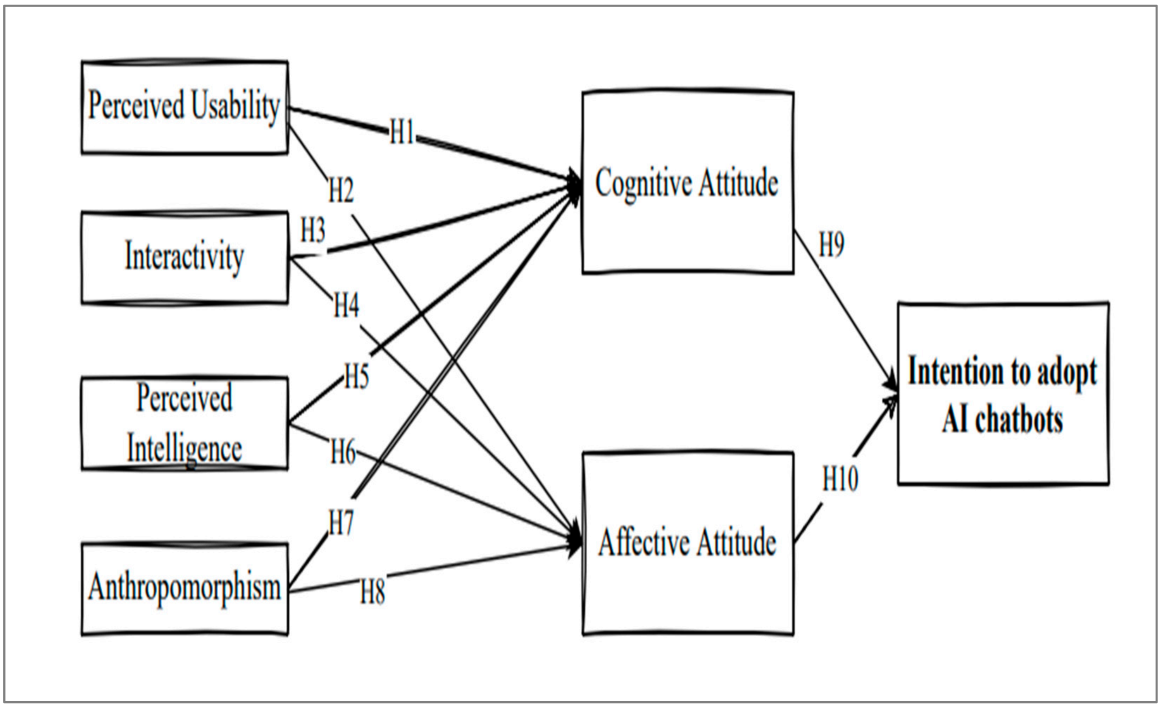

Figure 1. Conceptual model.

4. Results

4.1. Construct Reliability and Validity

Outer loadings, Joreskog's rho (ρ), average variance extracted [84,85], and Mcdonald's omega (ω) [86,87] for each construct were examined to measure both construct reliability and validity. The extracted Omega and Joreskog's values exceeded the cut-off value of 0.70 [84,88,89] for all the constructs (see Table 2).

Table 2. Reliability and validity of research model.

Variable	Items Code	FL [1]	AVE [2]	ω [3]	ρ [4]
Perceived usability	PU1	0.82	0.63	0.82	0.87
	PU2	0.80			
	PU4	0.76			
	PU5	0.79			
Interactivity	INT1	0.87	0.67	0.87	0.88
	INT2	0.81			
	INT3	0.82			
	INT4	0.77			
Perceived intelligence	PIE1	0.78	0.64	0.86	0.88
	PIE2	0.83			
	PIE3	0.82			
	PIE4	0.76			
Anthropomorphism	ANH1	0.73	0.57	0.82	0.84
	ANH2	0.72			
	ANH3	0.76			
	ANH4	0.80			
Affective attitude	AA1	0.89	0.75	0.90	0.93
	AA2	0.87			
	AA3	0.91			
	AA4	0.83			
	AA5	0.84			
Cognitive attitude	CA1	0.81	0.58	0.84	0.85
	CA2	0.77			
	CA3	0.70			
	CA4	0.76			
Intention to adopt chatbots	INA1	0.86	0.72	0.89	0.91
	INA2	0.89			
	INA3	0.81			
	INA4	0.84			

Notes: [1] = factor loading; [2] = average variance extracted; [3] = Mcdonald's omega; [4] = Joreskog's rho.

The AVE for all the constructs was calculated to test construct validity, and the results exceeded the recommended level of 0.50 [90]. Affective attitude had a maximum AVE value of 0.75 with a minimum AVE value of 0.57 for anthropomorphism. Furthermore, the discriminant validity of factors was confirmed through HTMT, whereby the values were found to be less than the proposed value of 0.90 [91] (see Table 3).

4.2. Common Method Bias

Following the first check, we tested the constructs for common method bias in SPSS by executing "Harman's single factor test" [83]. About 34.227 percent of variation in the initial components was less than the suggested value of 50% [92]. This proves that AI-chatbots' data set lacked common method bias. Finally, we re-confirmed the CMB issue through the marker variable technique; herein, too, the results highlighted that our study was free from any CMB issues.

Table 3. Discriminant validity.

Variables	1	2	3	4	5	6	7
Perceived usability	0.79						
Interactivity	0.47	0.82					
Perceived intelligence	0.44	0.58	0.80				
Anthropomorphism	0.51	0.36	0.47	0.75			
Affective attitude	0.58	0.45	0.52	0.57	0.87		
Cognitive attitude	0.47	0.42	0.39	0.36	0.43	0.76	
Intention to adopt chatbots	0.39	0.31	0.37	0.28	0.59	0.57	0.85

4.3. Structural Model

The structural model enabled us to conceptually build relations to reflect the proposed hypotheses and statistically test them [93]. We confirmed the fitness of the model through "standardized root mean square residual" (SRMR), "unweighted least squares discrepancy" (dULS), and "geodesic discrepancy" (dG). Herein, it may be noted that the values obtained for each measure must be lower than those in HI99 [94]. Thus, as per recommendation of Henseler [94], the fit indices in the structural model were found to be satisfactory (SRMR = 0.081, dULS = 1.242, dG = 0.352) (see Table 4).

Table 4. Model Fit Values.

	Observed Value	HI195	HI199	Recommended Values
SRMR	0.081	0.099	0.141	<0.080 [95] and <HI99 [94]
d_{ULS}	1.242	1.766	4.052	<HI99 [94]
d_G	0.352	0.453	0.645	<HI99 [94]

Further, the findings revealed that perceived usability positively influenced consumers cognitive attitude (H1: ß = 0.47, $p < 0.001$) and affective attitude towards (H2: ß = 0.22, $p < 0.01$) AI-chatbots. Similarly, the coefficient values of other factors that lead to cognitive and affective attitude include interactivity (H3: ß = 0.48, $p < 0.001$), (H4: ß = 0.46, $p < 0.001$), perceived intelligence (H5: ß = 0.58, $p < 0.001$), (H6: ß = 0.37, $p < 0.001$), and anthropomorphism (H7: ß = 0.52, $p < 0.001$), (H8: ß = 0.44, $p < 0.001$); thus, even they were found to be positively significant. Further, cognitive attitude (H9: ß = 0.29, $p < 0.01$), and affective attitude (H10: ß = 0.26, $p < 0.01$) had positively and significantly influenced consumers' chatbot adoption intention (see Table 5). Therefore, all hypotheses considered under the current study were supported.

Table 5. Hypotheses results.

Number	Path	Estimate	*p*-Value	Supported?
H1	PU → CA	0.47	<0.001	Yes
H2	PU → AA	0.22	<0.01	Yes
H3	INT → CA	0.48	<0.001	Yes
H4	INT → AA	0.46	<0.001	Yes
H5	PIE → CA	0.58	<0.001	Yes
H6	PIE → AA	0.37	<0.001	Yes
H7	ANH → CA	0.52	<0.001	Yes
H8	ANH → AA	0.44	<0.001	Yes
H9	CA → INA	0.29	<0.01	Yes
H10	AA → INA	0.26	<0.01	Yes

R^2 value for CA (51.7%), AA (48.1%), and INA (39.4%).

5. Discussion

The findings show that the S-O-R approach for chatbot adoption intention is a suitable theoretical approach with a bi-dimensional attitude. Furthermore, all ten proposed hypotheses were supported in the structural model, validating the suggested directions of substantial impacts.

Hypotheses 1 and 2 examine the association between perceived usability and attitude toward chatbot adoption. The significant association between usability and attitude indicates that AI-chatbots with high usability generate a personalized experience, address customers' concerns, make consumers feel secure and respected, and cause consumers to recognize retail organizations that utilize AI-chatbots as innovative. Furthermore, according to Seffah and Metzker's [96] effectiveness usability criteria, respondents desire a technology to be useful, which measures how well it aids respondents in achieving and completing their goals or tasks with AI technology [96].

Testing hypotheses 3 and 4 reveals a positive association between interactivity and attitude, showing that interactivity can impact consumers' favorable reactions and, as a result, strengthen their attitude and intent to use chatbot services. Our findings agree with Park and Yoo [52], who underlined the importance of interaction in enhancing consumers' attitudes and reactions to smart devices.

Hypotheses 5 and 6 examine the relationship between perceived intelligence and chatbot adoption attitudes. Despite the lack of a concrete theoretical basis for such an argument, the finding of this study suggests that perceived intelligence is a crucial AI element that influences consumers' attitudes toward AI-chatbots. Though several studies have supported the idea that perceived intelligence is a key component of AI, more research is needed [67].

The association between anthropomorphism and attitude toward chatbot aim was tested with hypotheses 7 and 8. The influence of anthropomorphism on attitude in the AI chatbot's service was significant, indicating that consumers will have a more positive attitude to AI chatbots and will utilize them if they are more human-like. The results of the current study are similar to those of previous studies that conclude anthropomorphism-based services can improve consumers' attitudes and behavioral intentions [97].

Furthermore, according to hypotheses 9 and 10, consumers' affective and cognitive attitudes were significant predictors of AI-chatbot adoption. The findings indicate that consumers are not only fascinated with the technical aspects of chatbots, but are also interested in the product's functional benefits. Based on these findings, it was confirmed that the S-O-R model was effective at predicting consumer chatbot adoption intentions and the dominance of cognitive assessments of AI chatbots over affective assessments. As a result of the current study, chatbot qualities (perceived usability, interactivity, perceived intelligence, and anthropomorphism) are significant predictors of consumer attitudes, influencing their adoption intention toward AI-chatbots in tourism. Furthermore, the current study's findings indicate that when using AI-chatbots for vacation planning, consumers make rational and functional decisions rather than emotional ones. Thus, the S-O-R approach and bi-dimensional perspective to attitude, i.e., affective and cognitive attitude, lead to a greater understanding of consumers' adoption intention of AI-chatbots.

6. Implications

6.1. Theoretical Contribution

Theoretically, this work adds to the extant literature in several ways. Firstly, using the S-O-R approach as a theoretical framework in the current study expands the present understanding of AI-chatbots. Implementing the S-O-R model provides meaningful insight into the literature by taking a step-by-step approach to forecast consumer's AI-chatbots adoption intention, with chatbot attributes serving as stimuli, cognitive and emotional attitude serving as an organism, and adoption intention serving as a response. This study in particular adds to our compendium of knowledge on how AI attributes such as perceived usability, perceived intelligence, interactivity, and anthropomorphism operate as stimuli to influence consumer's AI-chatbot adoption. This study pioneers identifying AI-chatbot key factors as substantial triggers that influence consumers' internal states to determine AI-chatbot adoption.

Furthermore, the study attempts to identify certain attributes of chatbots as significant influences on consumers' internal feelings and perceptions of AI technology, which is distinct from traditional data systems in terms of consumer perception. As a result, the current study adds to the existing knowledge about AI technology in AI-chatbots and other automated robots and devices. Secondly, by introducing attitude elements into the structural model, the current study contributes to a deeper understanding of consumers' rational and emotional assessments of chatbot adoption intention. Finally, by developing a conceptual model for chatbot adoption, this study responds to a call for more empirical studies on AI technology in the tourism sector, as there are limited studies in the literature that examine how tourism is transforming due to the intervention of evolving technologies such as AI and automation [4].

6.2. Managerial Implications

The current study provides invaluable insights for practitioners and managers by identifying the factors influencing consumers' intentions to adopt AI-chatbots in tourism. AI-chatbot marketers and developers must guarantee consumers' that AI-chatbots are both beneficial and simple to use for booking trips online. Regarding interactivity and perceived intelligence, developers of AI-chatbots must ensure that AI-chatbots give relevant information and rationally regulate the tourism business by giving actual solutions. Interactivity is a distinct attribute of AI-chatbots that stimulates positive consumer attitudes toward AI-chatbots adoption. Therefore, service providers must create simple, controlled, intuitive, creative, and interesting AI-chatbots so that customers can easily connect with them. They must design a chatbot with a high capacity for engagement and inspiration, allowing users to interact promptly, manage effectively, manipulate, and engage with information.

Since anthropomorphism and perceived usability are predictors of adoption intention [7], developers of AI-chatbots must also ensure that AI-chatbots have anthropomorphous attributes so that users perceive AI-chatbots to be realistic, alive, and human-like. Therefore, managers can ensure that AI-chatbots interact in multiple languages, providing clients with an easily operated interface. The implications of this study for managers are simple: people utilize AI-chatbots primarily because they anticipate them to perform effectively. In this regard, early chatbot deployments are recommended to be as basic as possible; otherwise, potential consumers may be hesitant to adopt AI-chatbots if their early experiences were unsatisfactory.

7. Limitations and Future Research Directions

Although the current study adds to theoretical and practical aspects, it has significant limitations, suggesting that further research should be conducted to fill those gaps. First, the scope of the present study is limited to the adoption intention of AI-chatbots in the tourism industry. Therefore, future studies should examine consumers' actual adoption or continued intention of using AI-chatbots. Second, since we surveyed AI-chatbot consumers in India, the current study has geographic constraints. Therefore, future researchers must replicate this study in several developed and developing nations within the same or different contexts.

Further, to uncover other elements impacting human–chatbot interactions, future research should examine consumers' chatbot adoption intention by increasing the sample size and employing alternative theoretical frameworks and methodological approaches. Third, this study employed a non-probability purposive sampling method for data collection. Consequently, to have a better understanding of research, future studies should employ the probability sampling method. Fourth, in the AI industry, privacy and security are serious concerns. Future research should look at what organizations and end consumers believe about these challenges to develop solutions that address their concerns. Finally, while the current study did not contain any moderating variables, future studies can incorporate moderating variables (such as gender, experience, industry type, and trust).

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Appendix A

Table A1. Measurement Scale.

Variable	Items Code	Items
Perceived usability	PU1	Learning to navigate through e-commerce websites is simple with assistance from the chatbot
	PU2	Searching with assistance from the chatbot saves me time
	PU3	The chatbot makes e-commerce websites easy to use and effortless
	PU4	The chatbot is able to initiate conversation for further discussion (e.g., by offering suggestions or presenting the functionality of products or services on e-commerce websites)
	PU5	The chatbot provides customers with specific, preferred information
	PU6	The chatbot provides clear, easy-to-read information
	PU7	The chatbot provides a complete solution to my problems
	PU8	The chatbot is aware of the context during a conversation
	PU9	The chatbot is able to solve my problems
Interactivity	INT1	I was in control of my conversation through the chatbot
	INT2	I had some control over the results of the chatbot that I wanted to see
	INT3	I was in control over the pace to get information
	INT4	Chatbot had the ability to respond to my specific needs quickly
Perceived intelligence	PIE1	I feel that chatbots for tourism are competent
	PIE2	I feel that chatbots for tourism are knowledgeable
	PIE3	I feel that chatbots for tourism are responsible
	PIE4	I feel that chatbots for tourism are intelligent
	PIE5	I feel that chatbots for tourism are sensible

Table A1. *Cont.*

Variable	Items Code	Items
Anthropomorphism	ANH1	It is important that the conversation with a chatbot resembles one with a human being
	ANH2	Conversations with chatbots should be natural
	ANH3	Chatbots should seem as if they understand the person with whom they are interacting
	ANH4	Conversation with a chatbot should not be artificial
Affective attitude	AA1	Using chatbots for tourism is effective
	AA2	Using chatbots for tourism is helpful
	AA3	Using chatbots for tourism is functional
	AA4	Using chatbots for tourism is necessary
	AA5	Using chatbots for tourism is practical
Cognitive attitude	CA1	Using chatbots for tourism is fun
	CA2	Using chatbots for tourism is exciting
	CA3	Using chatbots for tourism is thrilling
	CA4	Using chatbots for tourism is enjoyable
Intention to adopt chatbots	INA1	I intend to use or to continue using chatbots in the future
	INA2	When required, I will use chatbots
	INA3	I intend to use chatbots in the future
	INA4	I think that more and more people will use chatbots

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