INVESTIGATING THE ACTUAL ADOPTION OF AIVA SERVICES IN THE TOURISM INDUSTRY USING PLS-SEM

Neetima Agarwal, Jaypee Institute of Information Technology, Noida
Neha Sharma, Indian Institute of Management–Sirmaur (IIM–Sirmaur)
Mohd Naved, Jaipuria Institute of Management Noida

ABSTRACT

Tourism Industry has moved to a customer-centric approach from a firm-centric. In its continuous quest for value creation and delivery, AIVA has been adopted for reconfiguring customer expectations and experience. Building on the Integrated framework of UTAUT2 and HMSAM, the study has investigated the Actual Adoption of AIVA services by Generation Z using SEM- PLS 4. The paper has investigated the effect of the actual adoption of AIVA services. The findings suggest that Anthropomorphism has an insignificant impact on the "Actual Adoption" of AIVA. The effect on "Actual Adoption" is amplified when a serial mediation exists due to the Perceived Responsiveness and Perceived Hedonic Value. This study is one of the few empirical investigations relating to AIVA and its Actual Adoption in the Tourism Industry.

Keywords: Artificial Intelligence, Virtual Assistance, Anthropomorphism, Responsiveness, Hedonic Value, Actual Adoption.

INTRODUCTION

Acceptance of Artificial Intelligence Virtual Assistant (hereafter AIVA) services has led to a paradigm shift in the Tourism Industry. These virtual assistants are also called Intelligent Personal Assistants (Canbek & Mutlu, 2016; Loureiro, 2022; Buhalis & Moldavska, 2022), Artificial Intelligent Virtual Artist (Zulic, H., 2019), Artificial Intelligent Voice Assistants (Dellaert et al., 2020; Malodia et al., 2021; Zwakman et al., 2021), or Artificial Intelligence enabled Virtual Assistants (Kamoonpuri & Sengar, 2023) in the previous studies. As the world is heading towards the adoption of AI in all the realms of business and society, our interaction with machines is increasing for quick solutions are provided by calling "Hey Siri" (Hasan et al., 2021), "Hey Google" (Pandey et al., 2020), "Tell me Alexa" (Malodia et al., 2021), and other virtual assistant tools. AIVA is rapidly being adopted in the business for providing quick and trustworthy services (McLean & Osei-Frimpong, 2019). They are becoming the front-line executives of the organizations interacting with the customers and providing a wide range of services from information finding, initiating transactions, and open-handed advice (Marinchak et al., 2018).

This AIVA is a diverse class of information systems, that operate adaptively, autonomously, proactively, and reactively (Silva et al., 2020). They are penetrating everyday lives because of their names, physical attributes, emotional cues, and intelligence (Hu et al., 2021; Li et al., 2022). AI is leaving an impression greatly in the Tourism, Hospitality, and Retail Industries (Wang et al., 2023; Hsu & Lin, 2023), however, its dominance is growing in other industries such as digital marketing, advertising, healthcare, education, and E-commerce. There is evidence that AIVA has also failed at times like the most advanced chatbot-Microsoft Tay, Amazon AI recruitment system, Luda Lee of Scatter's Lab, BabyQ, and many others (Bird et al., 2019; Canhoto & Clear, 2020; Hwang et al., 2020, Cho et al., 2022) due to inadequate

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26.

configuration, optimization, and training (Marcondes et al., 2020; Sands et al., 2022).

This growing attention of academicians and practitioners in the area of AIVA in the Tourism Industry has utilized many significant models such as TAM (Dasgupta et al., 2002; Gillenson & Sherrell, 2002), TRA (Hsiao & Chen, 2022), UTAUT (Gansser & Reich, 2021; Samila et al., 2022; Balakrishnan et al., 2022), Service-Robot-Acceptance-Model (sRAM) (Aslam et al., 2022), Social cognitive Theory (Chong et al., 2021), HMSAM (Lovely & Wicaksana, 2021; Wicaksono & Zahra, 2022), and others. Most of the models are used in different studies to explore the acceptance of virtual assistant tools by analyzing the functional, relational, emotional, and social elements of interaction (Coccia & Watts, 2020). Few studies in the past are conducted comparing the performance of AIVA in replacing human assistants in the Tourism Industry. Some of the studies have highlighted that users prefer human assistants over AIVA, citing “human touch” as an important variable (Cheng et al., 2022; Zhou et al., 2023. However, few studies have quantitatively proved AIVA is better than human assistants because of their thread competence in handling multiple complaints at one time and not having a feeling of frustration, boredom, or exhaustion (Luo et al., 2019). Tourism Industry is adopting AI-based business models to ensure the success of value creation (Schneckenberg et al., 2021), value delivery (Heath et al., 2022), and value capture (Rohn et al., 2021).

In the Tourism Industry customer response and experience is a differentiating factor of organizational service quality. To measure the effect of AIVA researchers have proposed different determinants in their respective studies (Li et al., 2019; Kim et al. 2023). Researchers have proposed anthropomorphism, technical mechanism, social mechanism, and intention to use service robots in the tourism industry. Further, they proposed user and agent features as important antecedents influencing perceptions of anthropomorphism (Kim et al, 2019). Hsu & Lin (2023) proposed e-service quality with conversational AI bots to predict customer loyalty and satisfaction. Jiang et al., (2022) analyzed the effect of responsiveness in dialogic chatbot communication directly affects user satisfaction. Many studies have claimed Hedonic value influences the acceptance of AIVA either directly (Li et al., 2022; Fan et al., 2023) or as a mediator/moderator (Chi et al., 2022; Dinch and Park et al., 2023; Yuan et al., 2022). Previous studies have discussed the issues of system architecture (Chong et al., 2021; Ngai et al., 2021), human-machine interaction (Cheng et al., 2022), and service quality management (Akdim et al., 2022) both contextually and empirically.

Previous studies conducted in Tourism and Hospitality Industry have claimed that experiential constructs such as Perceived Responsiveness or Perceived Hedonic Value should be captured through introspective and phenomenological studies (Solakis et al., 2022; Sidaoui et al., 2020; Gentile et al., 2007). They believed that the expression of feelings of love, hatred, joy, or pain stimulating the critical success factors of AIVA can be expressed in narrative form. Some of the studies conducted in the past have been considered as a moderator (Uzir et al., 2021; Manyanga et al., 2022), as they believe that age has a significant impact on the choice and intent of users of utilizing AIVA services. Since previous studies have established age as a significant variable affecting the intention of adoption, so in this study, the data is collected only from Gen Z, to analyze the AIVA services adoption by the largest technology users. Another important research gap analyzed from previous research is the difference between intention and actual adoption. Previous studies have only examined the users’ intention to utilize AIVA services. However, the intention does not constantly lead to actual adoption (Rahim et al., 2022; Dhiman & Jamwal, 2022). This study is conducted to examine the actual adoption behaviors of Generation Z. data is collected from those respondents who are engaged with AIVA services at least 5 times a week and prefer AIVA over human assistance.

Thus, the study is aimed to reduce the research gaps by answering the following research

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26**.**

questions:

RQ1: Exploring the needs of Generation Z for the Actual Adoption of AIVA services in the Tourism Industry.

RQ2: The determinants affecting the actual behavior of users to reduce the gap between intention-actual adoption gap in the Tourism Industry.

To validate the impact of AIVA services, a measurement model is developed for examining humanness, responsiveness, intent to use, compatibility, privacy issues, interaction, and adoption of services (Pillai & Sivathanu, 2020). The study is conducted to analyze the relevance of Perceived Hedonic Value by Generation Z while engaging with AIVA services. The measurement scale adopted for the study is examined by conducting a pilot study on 45 respondents to reduce social desirability and participant-induced biases (Larson, 2019). The paper is structured as follows. Section 2 offers the literature on AIVA, using different determinants and theories. Based on the research gaps a research model is developed. Section 3 and 4 covers research hypothesis development and research methodology. The analytical procedure, discussion, and implications are then presented.

Related Work and Research Model

Table 1, illustrates the sources and prime studies used for the development of the research model after conducting an extensive literature review on measuring the service quality of AI chatbots/PVA and the Actual Adoption of the technology with the mediating effect of Perceived Hedonic Value. For conducting the literature review a combination of different keywords (approx 63) was used, where the primary keyword is "Artificial Intelligence". The secondary keywords constitute "chatbots", "PVA", "PVAs", "Virtual Assistants", "Siri", and "Conversational bot". Some of the other combinational keywords consist of "Perceived Satisfaction", "Perceived Usefulness", "Perceived Value", "Satisfaction", "Usefulness", "Intent to Use", "Continuance of Use", "Utility Value", "Anthropomorphism", "Service Quality", "Pleasure", "Emotion", "Happiness", "Intelligence", "Experience", "Trusts", "Hope", "Hedonic", "Motivation", and "Human". All these keywords were supported by "Tourism Industry", "Hospitality Industry", "Tourism and Hospitality", and "Service Industry"., To accomplish the purpose of this study, preceding studies from 2018 to 2023 of various prevalent databases, including Web of Science, Scopus, IEEE, and ScienceDirect are scrutinized. Conference proceedings, trade publications, and book series were not included in the study.

Table 1
RELATED STUDIES

Study	Methodology	Main Objectives, and Independent Variables	Dependent Variable	Sample Size	Context/ Setting	Industry
Gkinko & Elbanna, 2022	Interpretive case study approach and an Inductive analysis	The paper highlighted the effect of emotions while working with technology. Variables used for the study include Connection Emotions, Contentment	Technology Acceptance	39	AI Chatbot	Financial

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26.

		Emotions, Amusement Emotions, and Frustration Emotions.				
Zhu et al., 2022	Experimental Study	The paper examined the effect of the Certainty of Consumer Needs on the Acceptance of AI chatbots in the online pre-purchase stage. The study is further mediated by Perceived Effectiveness and moderated by Product type,	Acceptance of AI Chatbots	156	AI chatbot	E-commerce
Shin et al., 2022	Experimental Study	The Study claims that if a chatbot uses humour in communicating with customers service satisfaction increases. The full mediating effect of anthropomorphism and the interestingness of the interactions are also analyzed.	Service Satisfaction	117		Telecommunication Services
Cheng et al., 2022	Mixed-Method Approach	The study has highlighted the effect of Anthropomorphic attributes of chatbots on Trust in using chatbots. If the trust is higher Intention to Switch to human agents will be lower. The moderating effect of Communal and Exchange Relationships is also studied.	Intention to Switch	302	Text-Based Chatbots	E-commerce
Kim et al., 2023	EVM	The study examined the effect of interactive relationships between the Physical and Psychological dimensions of service robots and their impact on Consumer Acceptance	Intention to Use Service Robots	402	Service Robots	Hospitality

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26**.**

Lou et al., 2022	Experimental Study (online)	The paper has highlighted two independent variables: Emotional Intelligence and Message Contingency. The result of the paper rated human employees to be competent and warmer than a chatbot.	Human vs Chatbot	357	AI-powered Bots	Apparel
Akdim et al., 2022	Cross-sectional Survey	The study establishes that both utilitarian (perceived ease of use and perceived usefulness) factors and hedonic factors (perceived enjoyment) exert a significant positive influence on users' satisfaction with social mobile Apps. Satisfaction is the strongest predictor of continuance intention to use social mobile Apps	Continuance Intention to Use	397	Mobile Apps (Instagram & Trip Advisor)	Social Mobile Apps
Zhai & Wibowo, 2022	Systematic Review	The effect of the Cultural, Empathetic, and Humorous dimensions of chatbots on the Learning and Retention of L2 learners is analyzed.	Retention		Conversational Chatbots	L2 Learners
Blut et al., 2021	Meta-Analysis	The effect of Anthropomorphism on Customer Intention to use is analyzed. The robotic characteristics, usefulness, and ease of use as mediators have shown a positive effect. The type of Robot-male or female- has been studied as a moderator	Intention to Use		Service Robots and Chatbots	Service Industry
Jin & Youn,	Experimental Study	The study is conducted in two	Acceptance of Chatbot	273	Customer Service	Apparel

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26**.**

2021		parts. Firstly, the effect of chatbot Anthropomorphism and Consumer Social Phobia is analyzed. Secondly, interface effects amid anthropomorphic chatbot-consumer personality matching and consumers' social phobia of chatbot-and brand-related outcomes are measured.	and Brand		Chatbot Emily	
Ruan & Mezei, 2022	Scenario-based Online Experiment	The study focuses on the Service Agent type and Product Attribute type and their effect on Customer Satisfaction.	Customer Satisfaction	567	Online Shopping Assistance	E-commerce
Chong et al., 2021	Social-Cognitive Theory	The study focuses on the relationship between AI Chatbot Design on Customer Outcomes. The moderating effect of Customer Characteristics and the Nature of Service is also analyzed.	Customer Outcomes			Retail
Chen et al., 2021	TAM and ISSM	The study was conducted to measure the effect of Chatbot Adoption, Online Customer Experience on Customer Satisfaction with the moderating effect of Personality.	Customer Satisfaction	425	Chatbot	E-retailing
Tsai et al., 2021;	Experimental Study	The study examines chatbots' high social presence communication on consumer engagement outcomes are mediated by perceived parasocial interaction and dialogue	Consumer Engagement Outcomes	155	AI-powered Chatbot	Redbull (brand)
Ashfaq et al.,	Cross-sectional	The study has examined the effect	Continuance Intention	370	AI-powered Service Agents	Service Industry

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26**.**

2020	Study	of Perceived Enjoyment, Perceived Ease of Use, Perceived Usefulness, IQ, and SQ on the Continuance Intention of using AI-powered service agents. The IQ and SQ are mediated by Satisfaction.				
Meyer-Waarden et al., 2020	Cross-sectional Study	The study has examined the effect of Service Quality dimensions (SERVQUAL) on the Intention to Reuse. The mediators in the study include Perceived Usefulness, Perceived Ease of Use, and Trust	Intention to reuse	146	Chatbot	Tourism

Development of the Research Model

The article aims to highlight the Actual Adoption of AIVA by Gen Z for enriching the travel experience. The comprehensive research model has been designed using the UTAUT2 (Venkatesh et al., 2012) and HMSAM Models to investigate the Actual Adoption of AIVA by the users. The UTAUT2 model is designed to evaluate the “Behavior Intention of users toward technology”. This behavior is influenced by “Performance Expectancy”, “Effort Expectancy”, “Social Influence”, and “Facilitating Conditions”. The moderators used in the model are age, gender, and experience. Most of the studies conducted on “AI chatbots” or “AI enable Virtual Assistants” have utilized this model to test the “Use Behaviour” in different contexts and settings. Although UTAUT2 comprises Hedonic value, for testing cognitive absorption of AIVA by Gen Z the study has also included Hedonic-Motivation-System-Adoption Model (HMSAM) by Lowry et al., 2012. As the model is used to measure the intrinsic motivation of the users. Thus, for this study, a research model Figure 1 is created to analyze the effect of Anthropomorphism and Perceived Responsivenss of AIVA on the Actual Adoption behavior of Gen Z with Perceived Hedonic Value as a mediating factor Table 2.

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26**.**

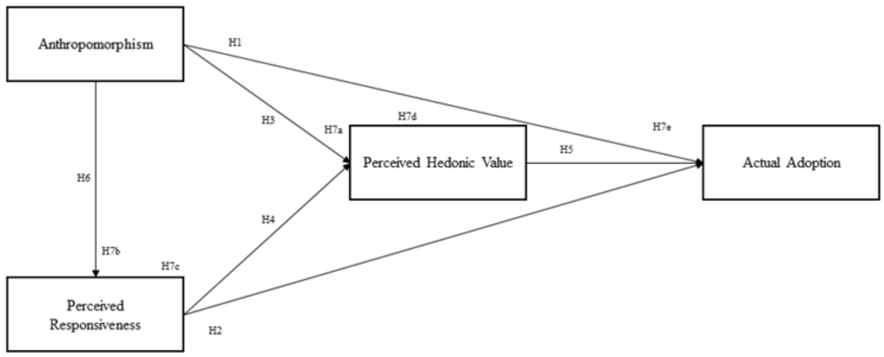

FIGURE 1
RESEARCH MODEL FOR EVALUATING ACTUAL ADOPTION OF AIVA IN THE TOURISM INDUSTRY BY GEN Z

Table 2
WORKING DEFINITION OF CONSTRUCTS

Constructs	Working Definition	References
Anthropomorphism	The physical and psychological traits displayed by the AIVA for enhancing human-machine communication. Such as appearance, humor, consciousness, and free will.	Blut et al., 2021; Cheng et al., 2022; Adam et al., 2021; Shin et al., 2022; Jin and Youn, 2021; Kim et al., 2023
Perceived Responsiveness	It is associated with ease of use, autonomy, task-solving competence, efficacy, risk handling, and satisfaction provided by the AI virtual assistants.	Ruan & Mezei, 2022; Chong et al., 2021; Chen et al., 2021; Tsai et al., 2021; Zhu et al., 2022
Perceived Hedonic Value	The cognitive, empathetic, compassionate, social, and contingent connections created by virtual assistants with humans.	Lou et al., 2022, Cheng et al., 2021; Jiang et al., 2022 a; Tsai et al., 2021; Yuan et al., 2022
Actual Adoption	It reflects the gap between intention-adoption. It accommodates the following aspects such as re-use, continue to use, recommend, and patronage of existing or new virtual assistant tools.	Farzin et al., 2022; Pillai & Sivathanu, 2020; Zhu et al., 2022; Borau et al., 2021; Blut et al., 2021; Ashfaq et al., 2020; Meyer-Waarden et al., 2020

RESEARCH HYPOTHESIS DEVELOPMENT

Anthropomorphism and Actual Adoption

Anthropomorphism is the degree to which AIVA such as chatbots are morphed into human-like appearances, voices, and emotions (Blut et al., 2021). The extant literature has identified the determinants affecting the users' behavior while interacting with AIVA and advocated the inclusion of humanness attributes in AIVA. The anthropomorphic characteristics are stimulating the response and actions of users as it affects the perceived interactivity of AIVA (Sheehan et al., 2020; Cheng et al., 2022; Shin et al., 2022). Few studies have also rejected the effect of anthropomorphism on users' intention to adopt the AIVA, as the results were either negative or insignificant (Cheng et al., 2022). Since most of the previous studies have indicated Anthropomorphism as a positive predictor of adopting AIVA (Sin et al., 2022; Jin and Youn et al., 2021), hence the hypothesis for the study created as.

H_1: *Anthropomorphism positively influences the Actual Adoption of AIVA in the Tourism industry*

Perceived Responsiveness and Actual Adoption

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26.

Perceived responsiveness is the willingness and the ability to deliver trustworthy and quick services to the users (Dinh & Park, et al., 2023). AIVA has often assumed a decision support system with the job of providing unique and engaging relationships with customers (Akdim et al., 2022). They are believed to provide an interactive platform ensuring privacy and multiplying task-solving competence (Yuan et al., 2022). If the user experiences higher utilitarian value while using the AIVA it enhances value creation (Jiang et al., 2022 a; Tsai et al., 2021). Previous research has utilized extended scales of measurement and considered responsiveness, reliability, and assurance as different latent variables (Lou et al., 2022; Cheng et al., 2021; Lai et al., 2021). However, for this study, reliability and assurance are considered items of the Perceived Responsiveness construct (Hsaio et al., 2022). The decision of including them as items in the single construct was mutually agreed upon by three independent experts and a consensus was built based on the definitions and usability. Previous studies have proven the importance of Perceived Reposnivenes as an important predictor (Adam et al., 2021; Hsaio and Chen, 2022) so the hypothesis is created as

***H_2**: Perceived Responsiveness will positively influence the Actual Adoption of AIVA in the Tourism industry*

Anthropomorphism and Perceived Hedonic Value

The affinity and compatibility of AI assistants are also exhibited by their physical appearance (Marjerison et al., 2022). Designing AIVA with human-like physical appearance and psychological attributes to convince the users to increase their excitement, happiness, joyfulness, and usefulness depends on many other social and cognitive factors (Baumbach et al., 2023, Kim et al., 2023). Users' irrational emotional value perception is affected by the psychological cues provided by AIVA (Bao et al., 2022; Pentina et al., 2023). Some of the studies believe the social anxiety of the users while interacting with AIVA can be optimized (Yuan et al., 2022) by including human cues such as Names like Alexa, Disha 2.0, and Elle. Instilling pictures, emoticons, Natural language and other human attributes in AIVA will motivate the users (Song et al., 2022). Hence, the researchers were interested to capture the positive relation between Anthropomorphism and Perceived Hedonic Value

***H_3**: Anthropomorphism will positively influence the Perceived Hedonic Value of AIVA in the Tourism industry*

Perceived Responsiveness and Perceived Hedonic Value

Studies conducted in the past have proven the usage of AIVA in the Tourism Industry is growing organically and an upward trend is visible in its acceptance by users (Huang & Rust, 2021; Venkatesh et al., 2012). Since these computer-mediated virtual assistants are providing higher interactivity, bi-direction transaction of communication, and strong social presence evoking higher satisfaction in the users (Van Doorn et al., 2017; Biocca, 1997). As illustrated in dual process theory (Zhou et al., 2022; Fan et al., 2023) both intuitive and deliberate thinking are affected by cognitive and empathetic skills (Duckitt et al., 2002). The researchers believed that the responsive factor of AIVA has a significant positive effect on cognitive, affective, and compassion as perceived by the customers while utilizing the AI tools (Li et al., 2022). Previous research has analyzed that the “pleasure” experienced by the users with the AI tools can be greatly increased by tailored responses and the task-solving capacity of the tools (Sidaoui et al., 2020). Researchers believed that the Perceived Responsiveness of utilizing AI tools affects the

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26.

Perceived Hedonic Value.

> ***H*$_4$**: *Perceived Responsiveness will positively influence the Perceived Hedonic Value in the Tourism industry*

Perceived Hedonic Value and Actual Adoption

Perceived Hedonic Value is primarily driven by "sensory or experiential" pleasure (Longoni & Cian, 2022), and the outcomes are assessed in terms of cognitive, affective, compassionate, social, and contingent connection with the AIVA (Tsai et al., 2021; Yuan et al., 2022). Since it is a psychological construct being tested in almost all research fields - medical, clinical, animal models, and technical – highlighting its importance in different research studies as an independent, dependent, mediating, or moderating variable (Na et al., 2022). The success of high-quality customer-oriented services depends on the hedonic value as perceived by the user (Gkinko & Elbanna, 2022).

Prior research has established both quantitatively and qualitatively the effect of Hedonic Value on Satisfaction, Intent to Use, and Continuance to use the AIVA (Tran et al., 2021; Hu et al., 2021). For the study, researchers have analyzed 11 different attributes of Hedonic value as discussed in AI-based research papers (UTAUT2 & HMSAM Model) published from 2018-2023 (Jeyaraj, 2022; Arpaci et al., 2022; Rahim et al., 2022). The three independent experts selected 5 attributes highlighting cognitive, affective, compassionate, contingent, and social aspects of Perceived Hedonic value for the study. Based on the previous study researchers were interested to find the positive relationship between Perceived Hedonic Value and Actual Adoption of AIVA.

> ***H*$_5$**: *Perceived Hedonic Value will positively influence the Actual Adoption of AIVA in the Tourism industry*

Anthropomorphism and Perceived Responsiveness

Previous studies have proved both the significant and insignificant impacts of anthropomorphism on perceived responsiveness (Kim et al., 2020). Some studies have highlighted that the perception of users about the responsiveness of AIVA completely depends on its capabilities of task-solving in optimal time (Chong et al., 2021). Some studies have also highlighted that due to the presence of technical glitches in the morphic attributes of AIVA- natural language interaction failure- users irritate due to incorrect responses (Diederich et al, 2020). The "Assistance Power" of AIVA is also calculated through its design capabilities (Rafiq et al., 2022). The utmost use of AIVA is providing customer support to numerous businesses and engaging users by providing various cues (Kim and Im, 2023). The responsiveness of the AIVA depends on its interactive and arousal abilities along with its physical and social appeal. Thus the researchers are interested to test the following hypothesis.

> ***H*$_6$**: *Anthropomorphism will be positively influencing the Perceived Responsiveness of AI tools as perceived by the customers in the Tourism industry*

The Mediating Role of Perceived Responsiveness and Perceived Hedonic Value on Actual Adoption

The acceptance of AI virtual assistants is increasing in the tourism industry (Wilson et al., 2022). The chatbot revolution is visible almost everywhere. The Meta-world will be mutating the

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26.

customer experience in the growing era of AI/AR/VR (Buhalis et al., 2023). Blockchain has led to a paradigm shift in the banking and logistics industries. Most of the research conducted in the past has considered User Satisfaction, Behavioral Intention to Use, or Continuance Intention as the reflective variable (Jo, H., 2022; Kim et al., 2019). However, the relevance of "Use Behaviour" was valid till the time AIVA was in its natal stage in businesses. Now, when it is acting as a front-line executive, so the actual adoption behavior should be studied.

The Perceived Responsiveness and Perceived Hedonic Value of AI tools as a mediator are crucial determinants while studying the Actual Adoption of AI virtual tools in improving the customer experience in the Tourism industry. As analyzed in the previous research AI chatbot users' intention of use and experience has a significant relationship with customer satisfaction (Rahim et al., 2022). The needs of the customer should be well understood by the machine for developing effective rapport. A "bond of survival" should be developed between man and machine. Customers should experience that machine is relating to them and adjusting to their demands continuously. Researchers argued that Responsiveness and Hedonic Value have significant mediating effects affecting the Actual Adoption of AI virtual tools in the Tourism industry. The following hypothesis from H6a to H6e are tested for various mediating relationships.

H_{7a}: *The effect of Perceived Responsiveness on the Actual Adoption of AIVA will be mediated by Perceived Hedonic Value in the Tourism industry.*

H_{7b}: *The effect of Anthropomorphism on the Actual Adoption of AIVA will be mediated by the Perceived Responsiveness of AI tools in the Tourism industry.*

H_{7c}: *Perceived Responsiveness and Perceived Hedonic Value of AIVA will serially mediate the effect of Anthropomorphism on the Actual Adoption of Virtual Assistants in the Tourism industry.*

H_{7d}: *The effect of Anthropomorphism on Perceived Hedonic Value will be mediated by the Perceived Responsiveness of AIVA in the Tourism industry.*

H_{7e}: *The effect of Anthropomorphism on the Actual Adoption of AIVA will be mediated by Perceived Hedonic Value in the Tourism industry.*

RESEARCH METHODOLOGY

Sampling and Data Collection Process

The data was collected from management students at a private university in India. Since the user population of customers utilizing AI-based virtual assistants is not available, the non-probability sampling method was used. Using the purposive sampling method, those students were included having experience utilizing chatbots/PVAs/other tools for at least from last 12 months and at least 5 times a week for an itinerary, travel planning, hotel reservations, or complaints. The invitation for participating in the study was distributed to 603 students of the university enrolled in a full-time course. A total of 446 responses were received, resulting in a 73.9% of response rate. The participants were provided with the link to Survey Monkey for participating in the study. The confidentiality of the participants was maintained as only the IP address of the participants was recorded, and no other information other than gender and age was collected. In the end, 391 responses were retained and others were rejected during the data-cleaning process Table 3. The sample size used for the study has exceeded the suggested minimum sample size of 153 obtained from G*Power with an effect size of 0.3, and an alpha value of 0.05 with 0.90 statistical power (Verma et al., 2020).

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26**.**

Table 3 DEMOGRAPHIC PROFILE OF THE RESPONDENTS				
Category		**Number**	**Percentage**	**Mean**
Gender	Female	142	36.3	1.36
	Male	249	63.9	
Age (In years)	18-20	203	51.9	1.69
	20-22	107	27.3	
	22-24	78	19.9	
	Above 24	03	0.76	
Education	Under-Graduation	294	75.1	1.25
	Post-Graduation	97	24.8	
Annual Income (INR)	0-5,000	302	77.2	1.30
	5,000-10,000	59	15.1	
	10,000-15,000	29	7.41	
	Above 15,000	1	0.25	
Chatbot/PVA Experience	Yes	370	100%	
User Frequency	At least Five times within a week	147	37.6	1.88
	5-8 times within a week	159	40.7	
	8-10 times within a week	71	18.1	
	More than 10 times within a week	14	3.6	
Duration	Less than 10 min once	141	36.1	1.79
	10-20 min once	206	52.7	
	20-30 min once	34	8.7	
	Over 30 min once	11	2.8	
Used for	Queries on Products and Services (Itinerary)	61	15.6	2.01
	Complaints	277	70.8	
	Promotional offers and discounts	42	10.8	
	Travel planning and Hotel Suggestions	9	2.3	
	Others	2	0.5	

Measures and Scale –Development

For selecting the attributes of the scale, a deductive approach of the Scale Development

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26.

theory (Tian et al., 2001) was adopted for defining the initial constructs to assess the Actual Adoption of the AI chatbots/PVAs by the customers. To ensure the construct validity the items were extracted from the literature review and adapted to the context of Actual Adoption. The Researchers have analyzed 12 different measurement scales utilized in different studies. However, those scales were extended or too large. Finally, 34 references and 62 attributes proposed by researchers in the past were screened for the study. All 34 references studied were taken from the research papers published from 2018-2022. During the re-examination and screening of the literature, only those measurement attributes were retained having perceived characteristics to be used in the current study Table 4. A careful examination of each attribute was conducted during the screening process by the three experts - one from industry and another two from academics – to finalize the satisfactory scale for adequately measuring the experience of the customers. The measurement model utilized “a five-point Likert Scale” from “Strongly Disagree” to “Strongly Agree” for measuring the indicators. The researchers finalized the 5-point Likert scale to minimize the frustration and confusion levels of the respondents. Thus, the previously validated scales were modified to fit the context of the current study.

Table 4
MEASUREMENT SCALE

Constructs	Number of Items	Items ID	Survey Item	Source	Mean	S.D	Cramer-von Mises P-Value
Anthropomorphism	4	Anth1	*I am excited as AIVA looks like a living creature in visual features, language, and style*	Kim et al., 2019	3.7	0.827	0.00
		Anth2	*I feel that AIVA has a human-like mind with consciousness and free will*	Kim et al., 2023	4.2	0.807	0.00
		Anth3	*I am happy as AIVA provides verbal cues of humor, fillers, flattery, and praise displaying emotional disclosure like humans*	Kim et al., 2023	3.5	1.009	0.00
		Anth4	*AIVA mostly provides persuasive, courteous, and assertive messages*	Kim et al., 2023	3.5	0.943	0.00
Perceived Responsiveness	5	PR1	*I found AIVA easy to use for queries and other functions*	Akdim et al., 2022	3.1	0.915	0.00
		PR2	*AIVA makes me feel that it is talking to me personally*	Chen et al., 2021	3.2	0.905	0.00
		PR3	*AIVA helped me to enhance my experience by managing many tasks*	Akdim et al., 2022	3.5	0.959	0.00
		PR4	*AIVA is trustworthy and provides reliable services*	Hsaio & Chen, 2022	3.4	0.945	0.00
		PR5	*Overall I am satisfied with AIVA*	Chen et al., 2021	3.1	0.918	0.00
Perceived Hedonic	5	PHV1	*AIVA seems to*	Tsai et al.,	3.3	0.931	0.00

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26.

Value			*understand things I want to know*	2021			
		PHV2	*I am satisfied with the availability of quality emotional signals while using AIVA*	Liu-Thompkins et al., 2022	3.9	0.994	0.00
		PHV3	*I think AIVA is kind of cute, and I am happy to call them my AIVA*	Gkinko & Elbanna, 2022	3.4	0.984	0.00
		PHV4	*AIVA is like a continuous thread that records and recounts the relatedness of our earlier conversation*	Lin & Wu, 2023	3.9	0.887	0.00
		PHV5	*AIVA creates an impression of caring and concern toward the users*	Liu-Thompkins et al., 2022	3.8	0.858	0.00
Actual Adoption	3	AA1	*I will continue using the AIVA services*	*Dhiman & Jamwal, 2022*	3.2	1.023	0.00
		AA2	*I recommend AIVA tools to friends*	*Farzin et al., 2021*	3.6	0.951	0.00
		AA3	*I am happy to try the new AIVA*	*Farzin et al., 2021*	2.4	0.810	0.00

Control Variables

Many research studies – in technological contexts- have quantitatively proven the significant effect of demographic variables in the studies conducted previously (Croasmun & Ostrom, 2011). For conducting the study few demographic variables such as Age, Gender, Education, and frequency of using VA tools are controlled to confirm that the results obtained from the empirical analysis have not occurred because of variance caused by these demographic variables. These demographic variables may incur their moderating or partial effects during the study and might influence the results.

Common Method Bias (CMB

For analyzing the Common Method of Biasness principal component analysis with "Harman's one-factor test (Harman, 1976) using SPSS software (V.25) was utilized. As stated by Harman, CMB (Chang et al, 2019) exists in the data if the value of a single construct is greater than 50% of the variance. The EFA result indicated that the variance percent of a single construct was 32.12, below 50% of the variance, thus indicating there is no CMB (Fuller et al., 2016). The non-issue of CMB was further analyzed by performing a Common Latent factor Analysis on AMOS 25. Every indicator was changed into a single-item second-order construct (Hew and Kadir, 2017). The result displayed Table 5 that the method loadings are almost negligible or insignificant lesser than 0.2 (Lowry & Gaskin, 2014). Hence, CMB is not affecting the reliability and validity of the scale. Researchers have utilized different strategies such as the random ordering of questions and reverse scoring of the items to reduce the CMB (Galberth and Shum 2012). The dependent and independent variables of the study were also separated to reduce the biasedness.

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26.

Table 5
COMMON LATENT FACTOR ANALYSIS

Path			Actual Loading	Method Loading	Difference
Anth 1	<---	Anth	0.563	0.479	0.084
Anth 2	<---	Anth	0.656	0.502	0.154
Anth 3	<---	Anth	0.589	0.444	0.145
Anth 4	<---	Anth	0.648	0.532	0.116
PR1	<---	PR	0.58	0.478	0.102
PR2	<---	PR	0.622	0.544	0.078
PR3	<---	PR	0.748	0.631	0.117
PR4	<---	PR	0.788	0.503	**0.285**
PR5	<---	PR	0.683	0.486	0.197
PHV1	<---	PHV	0.436	0.381	0.055
PHV2	<---	PHV	0.492	0.459	0.033
PHV3	<---	PHV	0.405	0.316	0.089
PHV4	<---	PHV	0.696	0.705	-0.009
PHV5	<---	PHV	0.762	0.695	0.067
AA1	<---	AA	0.547	0.496	0.051
AA2	<---	AA	0.774	0.777	-0.003
AA3	<---	AA	0.6	0.416	0.184

RESULTS

Measurement Model Analysis

In the present study, at the initial stage, PLS-SEM was run to conduct model testing for the measurement model (Hair et al., 2014) and confirm the indicators' reliability of constructs in the proposed scale (Hair et al., 2013). The test produced factor loading values of more than 0.5 for all the indicated items demonstrating that the construct explains 50% of the variance Table 6. A standardized root mean square residual (SRMR) of 0.07 smaller than 0.08 as per the rule (HU and Bentler, 1999) explained goodness of fit, Chi^2 value of 515.6, and Normed Fit Index (NFI) 0.94 represented acceptance of the model. The current study's composite reliability (CR) values range from 0.79 to 0.87, showing strong internal consistency (Hair et al., 2011). Cronbach's alpha for all constructs is more than 0.7. (Hair et al., 2019) suggested reliability of constructs' measures.

To test the validity, convergent validity was first analyzed with an average variance extract (AVE) value which was near 0.5 (required level >5.0). This demonstrated that the items are part of the construct and have a strong association with the factor (Fornell and Larcker, 1981; Hair et al., 2011). Secondly, Discriminant validity was examined from Heterotrait–Monotrait (HTMT) ratios and values of the Fornell–Larcker criterion in Table 7. Fornell–Larcker's approach advised that the topmost value of each column must be higher than the subsequent values of the column after taking the square root of the AVE of each variable (Fornell and Larcker, 1981; Hair et al., 2016). Table 7 shows the required values and indicates how distinct the constructs are from each other. Further scholars recommended that the HTMT ratio should be less than 0.85(Henseler et al., 2015). Thus, the aforementioned approaches passed the discriminant validity and confirms the suitability of the model.

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26.

Table 6
FACTOR LOADING, CONVERGENT VALIDITY, COMPOSITE RELIABILITY, AND INDICATOR RELIABILITY

Constructs	Factor loading (Indicator reliability - threshold value > 0.708)	CR (threshold value > 0.7)	AVE (threshold value > 0.5)	Cronbach's alpha (CA> 0.7)	Q^2 (Greater than 0)
Anth	0.696	0.820	0.533	0.71	0.410
	0.769				
	0.703				
	0.749				
PHV	0.581	0.798	0.49	0.69	0.330
	0.613				
	0.564				
	0.757				
	0.794				
PR	0.665	0.871	0.576	0.81	0.480
	0.71				
	0.807				
	0.831				
	0.769				
AA	0.714	0.818	0.60	0.68	-
	0.851				
	0.755				

Notes: Anth: anthropomorphism, PHV- perceived hedonic value, PR: perceived responsiveness, AA: actual adoption, CR: composite reliability, AVE: average variance extracted,

Structural Model

The measurement model is confirmed to take the next step for assessing the structural model. R2 indicates the standard assessment criteria by explaining the coefficient of determination and their statistical significance (Hair et al., 2019). Table 9 depicts the value of R2 of "endogenous" constructs between 0.3-0.5. This explains good association among the variables and signifies a fair predictive model.

For all endogenous variables, Q2 values are above Table 6, explaining the significant fitness of the model (Hair et al., 2016; Sarstedt et al., 2014). Further to rule out the collinearity issues in the model, VIF values are accepted below 3 (Becker et al., 2015). Table 8 indicated the VIF value is within an acceptable range (1-1.72) that demonstrates no collinearity issues in the data set Hair et al., 2019). Another test of model fit is the f2 effect size which as indicated in Table 10, ranges from low to high. This also depicts the model's strength (Hair et al., 2016).

Hypothesis Testing

To examine the hypothesis significance, Smart PLS 4 software was used, where the PLS

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26.

algorithm and bootstrapping were conducted with 5,000 samples (Hair et al., 2016). This process generated Path coefficients to assess the relationships between the constructs (Hair et al., 2014). Structural paths were investigated by analyzing the standard beta value, t-statistics, and p-values as indicated in Table 10. Also, the effect of independent variables on the dependent variables was shown in Table 10.

Table 7
DISCRIMINANT VALIDITY

Forenell-Larcker Criteria				
Constructs	AA	PHV	PR	Anth
AA	0.775	-	-	-
PHV	0.514	0.669	-	-
PR	0.393	0.361	0.759	-
Anth	0.228	0.299	0.622	0.730
Heterotrait-monotrait ratio (HTMT)				
Constructs	AA	PHV	PR	Anth
AA	-	-	-	-
PHV	0.740	-	-	-
PR	0.524	0.458	-	-
Anth	0.330	0.432	0.803	-

Notes: Anth: anthropomorphism, PHV- perceived hedonic value, PR: perceived responsiveness, AA: actual adoption

Table 8
COLLINEARITY STATISTICS (VIF)

Constructs	**AA**	**PHV**	**PR**	**Anth**
AA				
PHV	1.162			
PR	1.725	1.631		
Anth	1.648	1.631	1	

Table 9
ADJUSTED R SQUARE

Construct	**Adjusted R Square**
AA	0.412
PHV	0.335
PR	0.485

Notes: Anth: anthropomorphism, PHV- perceived hedonic value, PR: perceived responsiveness, AA: actual adoption

In Table 10, PR and PHV bring a positive relationship with Actual Adoption (B = 0.289; t=4.317 $p < 0.00$) (B= 0.434, t=7.293 $p < 0.05$) respectively. Whereas Actual Adoption could not build a significant relationship with Anthropomorphism. Thus, H2 and H5 could be confirmed but H1 is not accepted. Further, Anth is also not significantly building a positive relationship with PHV (B=0.126,t=1.513) which rejected H3. However, it has significant and positive relations with PR (B=0.434,t=7.293), which confirms the acceptance of H6. Finally, a significant and positive relationship between PR and PHV is found (B=0.286, t=3.70) which supports H4.

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26.

Table 10
HYPOTHESIS TESTING

Hypothesis No.	Type of Effect	Total effect		Direct Effect		F2 effect sizes	Outcomes	Decision on Hypothesis
		Path Coefficient	T Statistics	Path Coefficient	T Statistics			
H1	Anth -> AA	0.233	3.703**	0.079	1.290	0.006	Insignificant direct effect	
H2	PR -> AA	0.412	5.407**	0.289	4.317**	0.069	Significant direct effect	Supported
H3	Anth -> PHV	0.305	4.867**	0.126	1.513	0.011	Insignificant direct effect	
H4	PR-> PHV	0.286	3.700**	0.286	3.700**	0.058	Significant direct effect	Supported
H5	PHV -> AA	0.434	7.293**	0.434	7.293**	0.237	Significant direct effect	Supported
H6	Anth -> PR	0.624	17.369**	0.624	17.369**	0.631	Significant direct effect	Supported

Notes: Anth: anthropomorphism, PHV- perceived hedonic value, PR: perceived responsiveness, AA: actual adoption

Table 11
INDIRECT EFFECT

Hypothesis No.	Type of Effect	Path Coefficient	T Statistics	VAF	Mediation level	Outcomes
H7a	PR -> PHV -> AA	0.123	3.910**	23.13%	Partial	Significant indirect effect
H7b	Anth -> PR -> AA	0.180	4.251**	52.44%	Full Mediation	Significant indirect effect
H7c	Anth -> PR -> PHV-> AA	0.076	3.851**	59.99%	Partial	Significant indirect effect
H7d	Anth -> PR -> PHV	0.178	3.706**	30.4%	Full Mediation	Significant indirect effect
H7e	Anth -> PHV -> AA	0.056	1.428	19.45%	No mediation	Insignificant indirect effect

Notes: Anth: anthropomorphism, PHV- perceived hedonic value, PR: perceived responsiveness, AA: actual adoption

In Table 11 a partial mediation of PHV between PR and AA is found significant (b= 0.123, t=3.9, $p < 0.05$, VAF:23.13%). An approach "Variance Accounted for" is also tested to analyze the effect of mediation (Bari et al., 2020a, 2020b), which mentions that VAF should be >80% to indicate full mediation, values >20% and < 80% is considered partial mediation and < 20% indicates no mediation. Thus H7a is supported here. Two full mediation cases have been reported in Table 11. A direct effect of Anthropomorphism on Actual Adoption is insignificant (B=-0.079, t =1.290, p>0.00) in Table 11, effect of Anth on Actual 'Adoption (B=0.289,t =4.251, p<0.00, VAF= 52.44%) is significant. This confirms that full mediation of PR exists between Anth and AA (Hair et al., 2021). Although in this case VAF value, of of 52.44% is less than a threshold level of 80%, however when the direct effect is significant and the indirect effect is significant, full mediation is considered (Hair et al., 2021). Thus H7 b is also

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26.

acknowledged. Similarly, PR fully mediates Anth and PHV with a significant indirect effect (b=0.178, t=3.706, p<0.05, VAF= 30.4%) and insignificant direct effect as indicated in Table 11. This supports H7d. Further, a serial partial mediation of PR and PHV between Anth and AA (b=0.076, t=3.851, p<0.05 VAF= 59.99%) has been found accepting H7c. However there is no mediation of PHV is found between Anth and AA (b=0.056, t=1.428, p>0.05, VAF: 19.13%), as VAF is below the threshold level and the t value also shows the insignificance of meditating relationship. This rejects H7e. Hence the strongest mediation of the effect of PHV between PR and AA as full mediator is acknowledged with the highest.

DISCUSSIONS

This study is amongst the few types of research that have investigated core attributes for customers' interaction with AIVA in the Tourism Industry. We particularly focused on the influence of anthropomorphism, perceived responsiveness, and hedonic value on the effectiveness of the actual adoption of AIVA by the users. A theoretical framework was created and a conceptual model was designed which was later tested. Results enriched the prevailing knowledge on the importance of human responsiveness and empathy while the interaction of human-machine and demonstrated conversation style and being compassionate can affect the length of adoption of AIVA services in the Tourism Industry.

The hypothesized relationship between Anthropomorphism and actual adoption was found insignificant as indicated by the results. However, perceived responsiveness was seen as bringing a vital and significant mediation role between relationships of anthropomorphism and actual adoption. This can be substantiated by the fact that AI that resembles humans is viewed as strange and unsettling by some, where discomfort can lead to a negligible influence on usage by consumers (Vlachos et al., 2016; Goudey and Bonnin, 2016; Yang et al., 2020). Thus, here, interpreting an AI entity with the presence of RR seems to have a positive influence on consumers' actual adoption of AIVA for selecting the destination or making reservations.

Next, a positive impact of perceived responsiveness on actual adoption was reported in the results. This insight is validated, as employee responsiveness, indicates their willingness to help and their ability to be responsive to customer requests. Customers have a better experience as a result of employee responses that displayed courtesy, social interaction, and empathetic exchanges, rather than AI-powered ones (Prentice and Nguyen, 2020). Further, the relationship between Anthropomorphism and Hedonic Value was not supported by the results, as, if AI adoption is not related to hedonic value, as previously discussed, the lack of relationship may instigate the non-adoption of AI devices by users (Pelau et al., 2021). Hedonic value requires feelings attachment and emotions that anthropomorphism alone does not provide. Thus it can be admitted that anthropomorphism does not impact directly the perceived hedonic value. The subsequent findings indicated a positive impact of perceived responsiveness on hedonic value. This was validated by analyzing the characteristics of perceived responsiveness, which allow them to be more empathetic more frequently during interaction with customers, with more cognitive, affective, and compassionate behavior (Prentice and Nguyen, 2020).

As discussed, a positive relation between hedonic value and perceived acceptance was confirmed by the results and these findings are in line with the findings of Pelau et al., (2021), who stated that empathy has to do with how people interact with one another and their social environment and can create a positive influence on by consumers' adoption of technology. Thus hedonic values positively stimulate customers' AI adoption. Next, a direct positive relation between anthropomorphism was found with perceived responsiveness. This conclusion is further supported by the fact that when a virtual assistant (VA) is sufficiently anthropomorphized, it may

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26.

activate the long-standing significance that attractive alternatives play in the relationship. This helps the AIVA better meet the needs of responsiveness (Koike & Loughnan, 2021).

The findings represent that hedonic value fully mediates the relation between perceived responsiveness and actual adoption. This is validated by the fact that a lack of personal touch and lack of empathy in technologies such as chatbots and AI, may be a concern to handle customer's reluctance to interact with them (Ashfaq, et al., 2020; Longoni & Cian, 2022). Additionally, partial mediation of perceived responsiveness between anthropomorphism and actual adoption was also confirmed by the results, which is also shared in insights by Koike & Loughnan (2021) that a chatbot appeared to be human when it shows perceived responsiveness (Ekiba, 2008) as a range of reactions where chatbots can use in comparison to a human, that is greatly constrained by this (Pelikan, 2015; Dhiman and Jamwal, 2022). Overcoming this responsiveness bottleneck would be a significant step forward in our ability to create AI partnerships, given the importance of responsiveness in maintaining a good customer relationship (Koike & Loughnan, 2021). Now in H7c, the mediating effect of both the Perceived Responsiveness and perceived hedonic value together was assumed between Anthropomorphism and Perceived Acceptance (Zhai & Wibowo, 2022). The analysis of hypothesis testing confirmed the significance of this relation and indicated the positive partial mediation. This finding is in line with the assertion of Koike & Loughnan (2021) that, perceived responsiveness enables people to be more empathic with increased compassionate behavior during interactions with consumers (Prentice and Nguyen, 2020), which further works as an essential component of a fulfilling relationship with caring about the other person and emotionally responding to them. When it comes to consumer adoption, anthropomorphic features alone do not matter as much as empathy and the ability to engage with consumers (Pelau, et al., 2021). Further perceived responsiveness was found partially mediate the relationship between Anthropomorphism and PHV in the findings. The analyzed data indicated a positive indirect effect and significant mediation. It was also supported by the fact that Anthropomorphism alone does not increase the adoption and trust towards AI devices unless the AI device can show empathy and interact with a focus on the consumer's needs and desires Pelau et al., (2021). By being responsive to customers' needs and adjusting to their demands, the features of empathy and hedonic bond in anthropomorphism can be strengthened. Finally, it was found that perceived hedonic value does not mediate the relationship between anthropomorphism and actual adoption. This advocates that hedonic value alone might not support Anthropomorphism to impact customers' adoption of AIVA unless the characteristics of perceived responsivenss (H7d) can perform here between the two for customers' adoption of Anthropomorphism. So, it should be possible to build an AI device to behave like an intelligent, empathic service agent if businesses can train their staff to exhibit empathy and communicate with customers in line with their desires.

Research Implications

The use of AIVA services is computer-mediated communication replacing human agents in Tourism Industry due to their 24*7 availability, cost-effectiveness, and self-learning. However, their performance outcomes vary with the perception of people. The intention to the adoption of AI assistants is mostly affected by perceived responsiveness and perceived hedonic value (Chen et al., 2022; Lou et al., 2022). Even if the responsiveness factor is achieved, the perceived hedonic value changes with the age, skill, context, and knowledge of the user. The intention-adoption gap is mostly influenced by responsive and hedonic factors. For academic research, the present study has made two important contributions: Firstly, the study has been conducted exclusively on Gen Z, who are the biggest user base of AIVA services. Most of the

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26.

previous research is conducted on the age group of 20-60 years (Zhou et al., 2023; Hsu et al., 2023; Kim et al., 2023b) The study examines that Gen Z is not influenced by the anthropomorphic attributes of AI-enabled tools, rather the consideration of usage is specific to the responsive factors of the AIVA. AIVA service quality is the differentiation factor for them. They can be converted into loyal customers if they enjoy the services and found the virtual assistants trustworthy. The biggest challenges are the risk of privacy invasion. The study also reveals that hedonic value mediates the relationship between responsiveness and adoption, as experience is the biggest driver in the Tourism Industry. This research highlights the intention to use and actual adoption of the AIVA should be visualized through the lens of age.

Secondly, most of the studies conducted in the past have highlighted the "Intention to Use" or "Continuance Intention" as the prime dependent variable. This created a gap between intention-adoption behavior. UTAUT2 model as used in many studies has Behavioural Intention or Use Behaviour as a dependent variable. However, this study is looking beyond "intention" to "adoption". Thus, future researchers should describe and validate a model with "Actual Adoption" as a dependent variable. "Intention" behavior is valid till the time AIVA services were in the generic state. Now that most organizations have adopted them as font line workers or executives future studies must focus on their acceptance. Therefore research should be conducted to design a validate a scale having "Actual Adoption" as a dependent variable.

Managerial Implications

Since the commercialization of AIVA tools is increasing, due to their demonstrated capabilities. There is an enormous demand for AI-based chat tools in businesses. Most of the demand is coming from industries like Hospitality, E-commerce, Tourism, Retail, Healthcare, and Banking & Insurance. As the business models are moving to provide dedicated personalized services to its customers, the dependency on the AIVA is increasing to save manpower costs in B2B, B2C, and D2C sectors. Our research is helpful for businesses as it is conducted on a special segment of users who are the biggest users. The study reveals that the adoption of AIVA services in the Tourism Industry has increased manifold because of the increasing cognitive and social connection with the AIVA. Gen Z finds AIVA has higher task competence and provides reliable services. Thus, more focus should be given to increasing the service quality with a personalized experience as this has the strongest impact on user satisfaction (Maier et al., 2023).

CONCLUSION AND LIMITATION

The paper has highlighted the technology-based factors as perceived by the users in the Tourism Industry. Post-covid the inclusion of technology has increased manifolds to multiply the users' experience and ensure collaborative value creation. Personalizing customer service can be achieved if the users develop faith and trust in AIVA services. The tourism Industry should strategies the adoption of AIVA for unique customer offerings and mutual reliance. The current research has many limitations that offer research gaps for future research. The study has done a careful selection of the respondents (Gen Z) but it may still produce the bias results, for which cross-sectional studies are often discouraged. The motivation experienced by the people while filling out the survey was not accounted for in the study. Secondly, the study has ignored the effect of gender, education, and the context of using AIVA. Future research should include these factors as they may have a significant impact on the actual adoption of AI-enabled virtual assistants. Third, the most important variable "culture" is not used in the study, which impacts the relationship building with the virtual assistants. It is important to study the effect of "cultural differences" on the adoption of AIVA by Gen Z. Although the study has included privacy risk as

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26.

one of the items in the Perceived Responsiveness construct, future research should take into account the effect of ethics, privacy, and legal problems on service quality of AIVA. In addition, future research should also focus on the effect of service failure on the hedonic value of Gen Z.

REFERENCES

Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, *31*(2), 427-445.

Akdim, K., Casaló, L.V. and Flavián, C., 2022. The role of utilitarian and hedonic aspects in the continuance intention to use social mobile apps. *Journal of Retailing and Consumer Services*, *66*, p.102888.

Arpaci, I., Karatas, K., Kusci, I., & Al-Emran, M. (2022). Understanding the social sustainability of the Metaverse by integrating UTAUT2 and big five personality traits: A hybrid SEM-ANN approach. *Technology in Society*, *71*, 102120.

Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telematics and Informatics*, *54*, 101473.

Aslam, W., Siddiqui, D.A., Arif, I., and Farhat, K., 2022. Chatbots in the frontline: drivers of acceptance. *Kybernetes*, (ahead-of-print).

Balakrishnan, J., Abed, S. S., & Jones, P. (2022). The role of meta-UTAUT factors, perceived anthropomorphism, perceived intelligence, and social self-efficacy in chatbot-based services? *Technological Forecasting and Social Change*, *180*, 121692.

Bao, Z., Chen, J., Luo, Y., & Reani, M. (2022). Convincing or odd: Anthropomorphic design cues in chatbots.

Biocca, F. (1999). The Cyborg's dilemma. Progressive embodiment in virtual environments. In *Human Factors in Information Technology* (pp. 113-144). Elsevier.

Bird, J. J., Ekárt, A., & Faria, D. R. (2019). Learning from interaction: An intelligent networked-based human-bot and bot-bot chatbot system. In *Advances in Computational Intelligence Systems: Contributions Presented at the 18th UK Workshop on Computational Intelligence, September 5-7, 2018, Nottingham, UK* (pp. 179-190). Springer International Publishing.

Blut, M., Wang, C., Wünderlich, N. V., & Brock, C. (2021). Understanding anthropomorphism in service provision: a meta-analysis of physical robots, chatbots, and other AI. *Journal of the Academy of Marketing Science*, *49*(4), 632-658.

Borau, S., Otterbring, T., Laporte, S., & Fosso Wamba, S. (2021). The most human bot: Female gendering increases humanness perceptions of bots and acceptance of AI. *Psychology & Marketing*, *38*(7), 1052-1068.

Buhalis, D., & Moldavska, I. (2022). Voice assistants in hospitality: using artificial intelligence for customer service. *Journal of Hospitality and Tourism Technology*, *13*(3), 386-403.

Buhalis, D., Leung, D., & Lin, M. (2023). Metaverse as a disruptive technology revolutionizing tourism management and marketing. Tourism Management, 97, 104724.

Canbek, N. G., & Mutlu, M. E. (2016). On the track of artificial intelligence: Learning with intelligent personal assistants. *Journal of Human Sciences*, *13*(1), 592-601.

Canhoto, A. I., & Clear, F. (2020). Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential. *Business Horizons*, *63*(2), 183-193.

Cheng, X., Zhang, X., Cohen, J., & Mou, J. (2022). Human vs. AI: Understanding the impact of anthropomorphism on consumer response to chatbots from the perspective of trust and relationship norms. *Information Processing & Management*, *59*(3), 102940.

Chi, O. H., Gursoy, D., & Chi, C. G. (2022). Tourists' attitudes toward the use of artificially intelligent (AI) devices in tourism service delivery: moderating role of service value seeking. *Journal of Travel Research*, *61*(1), 170-185.

Cho, W. I., Kim, S., Choi, E., & Jeong, Y. (2022, November). Assessing How Users Display Self-Disclosure and Authenticity in Conversation with Human-Like Agents: A Case Study of Luda Lee. In *Findings of the Association for Computational Linguistics: AACL-IJCNLP 2022* (pp. 145-152).

Chong, T., Yu, T., Keeling, D. I., & de Ruyter, K. (2021). AI-chatbots on the services frontline addressing the challenges and opportunities of agency. *Journal of Retailing and Consumer Services*, *63*, 102735.

Coccia, M., & Watts, J. (2020). A theory of the evolution of technology: Technological parasitism and the implications for innovation management. *Journal of Engineering and Technology Management*, *55*, 101552.

Croasmun, J. T., & Ostrom, L. (2011). Using likert-type scales in the social sciences. Journal of adult education, 40(1), 19-22.

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26**.**

Dasgupta, S., Granger, M., & McGarry, N. (2002). User acceptance of e-collaboration technology: An extension of the technology acceptance model. *Group Decision and Negotiation*, *11*(2), 87-100.

Dellaert, B. G., Shu, S. B., Arentze, T. A., Baker, T., Diehl, K., Donkers, B., ... & Steffel, M. (2020). Consumer decisions with artificially intelligent voice assistants. *Marketing Letters*, *31*, 335-347.

Dhiman, N., & Jamwal, M. (2022). Tourists' post-adoption continuance intentions of chatbots: integrating task–technology fit model and expectation–confirmation theory. *foresight*, (ahead-of-print).

Diederich, S., Brendel, A. B., & Kolbe, L. M. (2020). Designing anthropomorphic enterprise conversational agents. *Business & Information Systems Engineering*, *62*, 193-209.

Dinh, C. M., & Park, S. (2023). How to increase consumer intention to use Chatbots? An

Duckitt, J., Wagner, C., Du Plessis, I., & Birum, I. (2002). The psychological bases of ideology and prejudice: testing a dual process model. *Journal of personality and social psychology*, *83*(1), 75.

Fan, H., Gao, W., & Han, B. (2023). Are AI chatbots a cure-all? The relative effectiveness of chatbot ambidexterity in crafting hedonic and cognitive smart experiences. *Journal of Business Research*, *156*, 113526.

Fuller, C. M., Simmering, M. J., Atinc, G., Atinc, Y., & Babin, B. J. (2016). Common methods variance detection in business research. Journal of business research, 69(8), 3192-3198.

Gansser, O. A., & Reich, C. S. (2021). A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application. *Technology in Society*, *65*, 101535.Gentile, C., Spiller, N. and Noci, G. (2007), "*How to sustain the customer experience: an overview of experience components that Co-create value with the customer*", European

Gillenson, M.L., & Sherrell, D. L. (2002). Enticing online consumers: an extended technology acceptance perspective. *Information & management*, *39*(8), 705-719.

Gkinko, L. and Elbanna, A., 2022. Hope, tolerance and empathy: employees' emotions when using an AI-enabled chatbot in a digitalised workplace. *Information Technology & People*, (ahead-of-print).

Hasan, R., Shams, R., & Rahman, M. (2021). Consumer trust and perceived risk for voice-controlled artificial intelligence: The case of Siri. *Journal of Business Research*, *131*, 591-597.

Heath, M., Appan, R., & Henry, R. (2022). Value alignment's role in mitigating resistance to IT use: The case of physicians' resistance to electronic health record systems. *Information & Management*, *59*(8), 103702.

Hsiao, K. L., & Chen, C. C. (2022). What drives continuance intention to use a food-ordering chatbot? An examination of trust and satisfaction. *Library Hi Tech*, *40*(4), 929-946.

Hsu, C. L., & Lin, J. C. C. (2023). Understanding the user satisfaction and loyalty of customer service chatbots. *Journal of Retailing and Consumer Services*, *71*, 103211.

Hu, Q., Lu, Y., Pan, Z., Gong, Y., & Yang, Z. (2021). Can AI artifacts influence human cognition? The effects of artificial autonomy in intelligent personal assistants. *International Journal of Information Management*, *56*, 102250.

Huang, M. H., & Rust, R. T. (2021). Engaged to a robot? The role of AI in service. *Journal of Service Research*, *24*(1), 30-41.

Hwang, G. J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of Artificial Intelligence in Education. *Computers and Education: Artificial Intelligence*, *1*, 100001.

Jeyaraj, A. (2022). Models of Information Technology Use: Meta-Review and Research Directions. *Journal of Computer Information Systems*, 1-16.

Jiang, H., Cheng, Y., Yang, J., & Gao, S. (2022). AI-powered chatbot communication with customers: Dialogic interactions, satisfaction, engagement, and customer behavior. *Computers in Human Behavior*, *134*, 107329. b

Jiang, Q., Zhang, Y., & Pian, W. (2022). Chatbot as an emergency exist: Mediated empathy for resilience via human-AI interaction during the COVID-19 pandemic. *Information Processing & Management*, *59*(6), 103074.

Jin, S. V., & Youn, S. (2021). Why do consumers with social phobia prefer anthropomorphic customer service chatbots? Evolutionary explanations of the moderating roles of social phobia. *Telematics and Informatics*, *62*, 101644.

Kamoonpuri, S. Z., & Sengar, A. (2023). Hi, May AI help you? An analysis of the barriers impeding the implementation and use of artificial intelligence-enabled virtual assistants in retail. *Journal of Retailing and Consumer Services*, *72*, 103258.

Kim, J., & Im, I. (2023). Anthropomorphic response: Understanding interactions between humans and artificial intelligence agents. *Computers in Human Behavior*, *139*, 107512.

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26**.**

Kim, S.Y., Schmitt, B.H. and Thalmann, N.M., 2019. Eliza in the uncanny valley: Anthropomorphizing consumer robots increases their perceived warmth but decreases liking. *Marketing letters*, *30*(1), pp.1-12.

Kim, T., Lee, O.K.D. and Kang, J., 2023. Is it the best for barista robots to serve like humans? A multidimensional anthropomorphism perspective. *International Journal of Hospitality Management*, *108*, p.103358.

Kim, T., Sung, Y., & Moon, J. H. (2020). Effects of brand anthropomorphism on consumer-brand relationships on social networking site fan pages: The mediating role of social presence. Telematics and Informatics, 51, 101406.

Larson, R. B. (2019). Controlling social desirability bias. *International Journal of Market Research*, *61*(5), 534-547.

Lin, J. S. E., & Wu, L. (2023). Examining the psychological process of developing consumer-brand relationships through the strategic use of social media brand chatbots. *Computers in Human Behavior*, *140*, 107488.

Liu-Thompkins, Y., Okazaki, S. and Li, H., 2022. Artificial empathy in marketing interactions: Bridging the human-AI gap in affective and social customer experience. *Journal of the Academy of Marketing Science*, *50*(6), pp.1198-1218.

Longoni, C., & Cian, L. (2022). Artificial intelligence in utilitarian vs. hedonic contexts: The “word-of-machine” effect. *Journal of Marketing*, *86*(1), 91-108.

Lou, C., Kang, H., & Tse, C. H. (2022). Bots vs. humans: how schema congruity, contingency-based interactivity, and sympathy influence consumer perceptions and patronage intentions. *International Journal of Advertising*, *41*(4), 655-684.

Loureiro, S. M. C. (2022). Using immersive and artificial intelligence technologies to promote different industries. *Journal of Promotion Management*, *28*(2), 111-112.

Lovely, F. P., & Wicaksana, A. (2021). Rule-based lip-syncing algorithm for virtual character in voice chatbot. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, *19*(5), 1517-1528.

Lowry, P. B., & Gaskin, J. (2014). Partial least squares (PLS) structural equation modeling (SEM) for building and testing behavioral causal theory: When to choose it and how to use it. IEEE transactions on professional communication, 57(2), 123-146.

Lowry, P. B., Gaskin, J., Twyman, N., Hammer, B., & Roberts, T. (2012). Taking ‘fun and games’ seriously: Proposing the hedonic-motivation system adoption model (HMSAM). *Journal of the association for information systems*, *14*(11), 617-671.

Maier, C., Thatcher, J. B., Grover, V., & Dwivedi, Y. K. (2023). Cross-sectional research: A critical perspective, use cases, and recommendations for IS research. *International Journal of Information Management*, 102625.

Malodia, S., Islam, N., Kaur, P., & Dhir, A. (2021). Why do people use Artificial Intelligence (AI)-enabled voice assistants?. *IEEE Transactions on Engineering Management*.

Manyanga, W., Makanyeza, C., & Muranda, Z. (2022). The effect of customer experience, customer satisfaction and word of mouth intention on customer loyalty: The moderating role of consumer demographics. *Cogent Business & Management*, *9*(1), 2082015.

Marcondes, F. S., Almeida, J. J., & Novais, P. (2020). A short survey on chatbot technology: failure in raising the state of the art. In *Distributed Computing and Artificial Intelligence, 16th International Conference* (pp. 28-36). Springer International Publishing.

Marinchak, C. L. M., Forrest, E., & Hoanca, B. (2018). The impact of artificial intelligence and virtual personal assistants on marketing. In *Encyclopedia of Information Science and Technology, Fourth Edition* (pp. 5748-5756). IGI global.

Marjerison, R. K., Zhang, Y., & Zheng, H. (2022). AI in E-Commerce: Application of the Use and Gratification Model to the Acceptance of Chatbots. *Sustainability*, *14*(21), 14270.

McLean, G., & Osei-Frimpong, K. (2019). Hey Alexa… examine the variables influencing the use of artificial intelligent in-home voice assistants. *Computers in Human Behavior*, *99*, 28-37.

Meyer-Waarden, L., Pavone, G., Poocharoentou, T., Prayatsup, P., Ratinaud, M., Tison, A., & Torné, S. (2020). How service quality influences customer acceptance and usage of chatbots?. *SMR-Journal of Service Management Research*, *4*(1), 35-51.

Pandey, A., Vashist, V., Tiwari, P., Sikka, S., & Makkar, P. (2020). Smart voice based virtual personal assistants with artificial intelligence. *Artificial Computational Research Society*, *1*(3).

Pentina, I., Hancock, T., & Xie, T. (2023). Exploring relationship development with social chatbots: A mixed-method study of replika. *Computers in Human Behavior*, *140*, 107600.

Pillai, R., & Sivathanu, B. (2020). Adoption of AI-based chatbots for hospitality and tourism. *International Journal of Contemporary Hospitality Management*, *32*(10), 3199-3226.

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26**.**

Rafiq, F., Dogra, N., Adil, M., & Wu, J. Z. (2022). Examining consumer's intention to adopt AI-chatbots in tourism using partial least squares structural equation modeling method. Mathematics, 10(13), 2190.

Rohn, D., Bican, P. M., Brem, A., Kraus, S., & Clauss, T. (2021). Digital platform-based business models–An exploration of critical success factors. *Journal of Engineering and Technology Management*, *60*, 101625.

Ruan, Y., & Mezei, J. (2022). When do AI chatbots lead to higher customer satisfaction than human frontline employees in online shopping assistance? Considering product attribute type. *Journal of Retailing and Consumer Services*, *68*, 103059.

Samila, A. R., Shabrina, N. P., & Rokanta, S. A. (2022, August). Factors Affecting Behavioral Intention and Use Behavior of E-Commerce Users from Gen-Z Using UTAUT2 Model. In *2022 International Conference on Information Management and Technology (ICIMTech)* (pp. 262-267). IEEE.

Sands, S., Campbell, C., Plangger, K., & Pitt, L. (2022). Buffer bots: The role of virtual service agents in mitigating negative effects when service fails. *Psychology & Marketing*, *39*(11), 2039-2054

Schneckenberg, D., Benitez, J., Klos, C., Velamuri, V. K., & Spieth, P. (2021). Value creation and appropriation of software vendors: A digital innovation model for cloud computing. *Information & Management*, *58*(4), 103463.

Sheehan, B., Jin, H. S., & Gottlieb, U. (2020). Customer service chatbots: Anthropomorphism and adoption. Journal of Business Research, 115, 14-24.

Shin, H., Bunosso, I., & Levine, L. R. (2022). The influence of chatbot humour on consumer evaluations of services. *International Journal of Consumer Studies*.

Sidaoui, K., Jaakkola, M., & Burton, J. (2020). AI feel you: customer experience assessment via chatbot interviews. *Journal of Service Management*, *31*(4), 745-766.

Solakis, K., Katsoni, V., Mahmoud, A. B., & Grigoriou, N. (2022). Factors affecting value co-creation through artificial intelligence in tourism: a general literature review. Journal of Tourism Futures, (ahead-of-print).

Song, X., Xu, B., & Zhao, Z. (2022). Can people experience romantic love for artificial intelligence? An empirical study of intelligent assistants. *Information & Management*, *59*(2), 103595.

Tian, K. T., Bearden, W. O., & Hunter, G. L. (2001). Consumers' need for uniqueness: Scale development and validation. Journal of consumer research, 28(1), 50-66.

Tran, A. D., Pallant, J. I., & Johnson, L. W. (2021). Exploring the impact of chatbots on consumer sentiment and expectations in retail. *Journal of Retailing and Consumer Services*, *63*, 102718.

Tsai, W. H. S., Liu, Y., & Chuan, C. H. (2021). How chatbots' social presence communication enhances consumer engagement: The mediating role of parasocial interaction and dialogue. *Journal of Research in Interactive Marketing*, *15*(3), 460-482.

Uzir, M. U. H., Al Halbusi, H., Lim, R., Jerin, I., Hamid, A. B. A., Ramayah, T., & Haque, A. (2021). Applied Artificial Intelligence and user satisfaction: Smartwatch usage for healthcare in Bangladesh during COVID-19. *Technology in society*, *67*, 101780.

Van Doorn, J., Mende, M., Noble, S. M., Hulland, J., Ostrom, A. L., Grewal, D., & Petersen, J. A. (2017). Domo arigato Mr. Roboto: Emergence of automated social presence in organizational frontlines and customers' service experiences. *Journal of service research*, *20*(1), 43-58.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, 157-178.

Verma, J. P., Verma, P., Verma, J. P., & Verma, P. (2020). Determining sample size in experimental studies. Determining Sample Size and Power in Research Studies: A Manual for Researchers, 61-88.

Wang, X., Cheng, M., Li, S., & Jiang, R. (2023). The interaction effect of emoji and social media content on consumer engagement: A mixed approach on peer-to-peer accommodation brands. Tourism Management, 96, 104696.

Wicaksono, B. P., & Zahra, A. (2022). Design of the use of chatbot as a virtual assistant in banking services in Indonesia. *IAES International Journal of Artificial Intelligence*, *11*(1), 23.

Wilson, A., Stefanik, C., & Shank, D. B. (2022). How do people judge the immorality of artificial intelligence versus humans committing moral wrongs in real-world situations? Computers in Human Behavior Reports, 8, 100229.

Yuan, C., Zhang, C., & Wang, S. (2022). Social anxiety as a moderator in consumer willingness to accept AI assistants based on utilitarian and hedonic values. *Journal of Retailing and Consumer Services*, *65*, 102878.

Zhai, C., & Wibowo, S. (2022). A systematic review on cross-culture, humor and empathy dimensions in conversational chatbots: the case of second language acquisition. *Heliyon*, e12056.

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26**.**

Zhou, Q., Li, B., Han, L., & Jou, M. (2023). Talking to a bot or a wall? How chatbots vs. human agents affect anticipated communication quality. *Computers in Human Behavior*, 107674.

Zhou, Y., Fei, Z., He, Y., & Yang, Z. (2022). How human–chatbot interaction impairs charitable giving: the role of moral judgment. *Journal of Business Ethics*, *178*(3), 849-865.

Zhu, Y., Zhang, J., Wu, J. and Liu, Y., 2022. AI is better when I'm sure: The influence of certainty of needs on consumers' acceptance of AI chatbots. *Journal of Business Research*, *150*, pp.642-652.

Zwakman, D. S., Pal, D., & Arpnikanondt, C. (2021). Usability evaluation of artificial intelligence-based voice assistants: The case of Amazon Alexa. *SN Computer Science*, *2*, 1-16.

Received: 12-Nov-2024, Manuscript No. AMSJ-24-15444; **Editor assigned:** 13-Nov-2024, PreQC No. AMSJ-24-15444(PQ); **Reviewed:** 20-Dec-2024, QC No. AMSJ-24-15444; **Revised:** 26-Dec-2024, Manuscript No. AMSJ-24-15444(R); **Published:** 19-Jan-2025

Citation Information: Agarwal, N., Sharma, N., & Naved, M. (2025). Investigating the actual adoption of aiva services in the tourism industry using pls-sem. *Academy of Marketing Studies Journal, 29*(2), 1-26**.**