Customer Acceptance of Use of Artificial Intelligence in Hospitality Services: An Indian Hospitality Sector Perspective

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Abstract
This research endeavour tested and validated the artificially intelligent device use acceptance (AIDUA) three-stage AI acceptance framework in the context of the Indian hospitality sector. For this purpose, data on the constructs that captured primary appraisal (i.e., social influence, hedonic motivation and anthropomorphism), secondary appraisal (i.e., performance and effort expectancy), emotion, willingness to use AI devices and objection to use AI devices were captured from 210 guests/customers from 14 luxury hotels spread across the union territory of New Delhi and the state of Chandigarh in India. Findings that emerge from this study validate the fact that customers do indeed go through three stages of decision-making process before they demonstrate their proclivity to use AI devices or exhibit objection to use AI devices. In particular, the study found that both performance and effort expectancy influenced customer emotion which, in its turn, exercised its effect on the construct of willingness to use AI devices and objection to use AI devices among hotel customers. Accordingly, drawing from the findings of this study, implications for practitioners, decision-makers, and academic researchers are discussed in the article.

Keywords
Artificial intelligence (AI), hospitality, India, artificially intelligent device use acceptance (AIDUA) model, technology acceptance

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Introduction

The hospitality sector across the world continues to witness an exponential growth in the usage of artificial intelligence (AI)-driven technologies and robots, as many hospitality organizations are seen consolidating AI into their core service delivery models so as to offer seamlessly robust service experiences to their respective customers (Lin et al., 2019; Murphy et al., 2017). Scholars and practitioners alike, backed by strong empirical evidence, attribute this rising trend in the use of AI-related technologies to the fact that AI-driven applications and robots demonstrate superior information processing and enhanced, cognitive and task capabilities when compared to the ones that are demonstrated by traditionally used mechanisms (Ivanov et al., 2019). In fact, AI concerns intelligence as demonstrated by machines, that reacts and responds to its surrounding environment and customer requirements by using deep learning algorithms, offering robust services that are considered relatively superior to the ones that are offered by its human counterparts (Huang & Rust, 2018). As regards the hospitality sector, AI-driven devises essentially- clarify customer queries, offer relevant information and recommend suggestions in real-time, allow guests to manipulate and control their room’s physical atmosphere (e.g., using ALEXA), and offers robust end-to-end customer services (e.g., virtual check-in and check-outs, laundry, room-keeping, travel/tour planning and execution, food services, etc.) using robots and robotic technologies (Bellini & Convert, 2016; Osawa et al., 2017; Raz, 2016).

Perceived benefits of AI notwithstanding, the question of what drives customer acceptance of AI are of great concern to the hospitality organizations; the answer to which would allow hospitality organizations to conceptualize, design and adopt relevant, useful and robust AI devices and technologies that would elicit favourable response from the customers in terms of its acceptance and usage. Insights, however, on the factors that essentially drive customers’ AI acceptance decisions in the hospitality sector remain inadequately explored. Our motivation for this study, therefore, is essentially driven by two specific factors. The first relates to the conceptual gaps that emerge from the past empirical research, broadly highlighting the limitations of using traditional technology acceptance models in the domain of AI technology acceptance and adoption, further mandating the use and empirical validation of artificially intelligent device use acceptance (AIDUA) model (Gursoy et al., 2019), in this regard. The second relates to the need for such a study in the context of the Indian hospitality sector.

As regards consumer behaviour, current literature has demonstrated the presence of a possible antecedent-consequent relationship between an individual’s behavioural intentions or willingness and his or her actual demonstrated behaviour (Cronan et al., 2018; Fishbein & Ajzen, 1975). Though the past research has shown that customer willingness is a strong predictor of actual behaviour, scholars have demonstrated the presence of complexity among the antecedents of technology acceptance and adoption relating to AI devices and related technological devices (Gursoy et al., 2019; Lin et al., 2019). For example, past studies have shown that the factors such as customers’ service quality features, frontline assistance, customers’ expectations of AI devices (Stock & Merkle, 2017), device aesthetics, appearance, perceived usefulness of AI devices and service robots and social capability (Song, 2017) influence the acceptance and adoption of AI devices and the related technologies.

Although these studies mentioned above offer crucial insights on the willingness–behaviour relationship with regard to AI and associated tools, they draw their conclusions from the empirical findings that emerge from the traditional technology acceptance models. Traditional technology acceptance models predominantly situate technology—ease, usefulness, usability and anxiety; individual attitudes, self-efficacy beliefs, cognition and performance—effort expectancy; social influence; and facilitating conditions as key correlates of customers’ technology acceptance (Taherdoost, 2018). There
exists, however, a robust theoretical debate among scholars regarding the conceptual adequacy of the traditional technology acceptance models to explain the phenomenon of the acceptance and usage of AI. For example, scholars such as Lu et al. (2019) and Song (2017) contend that traditional technology acceptance models are inadequate in their ability to examine AI devise acceptance and usage. There are a few reasons for the perceived inadequacy of the conventional technology acceptance models in explaining the benefits of AI.

First, customers are likely to accord much importance to the process of appraising AI devices and related technologies by comparing them with the services that human employees are likely to deliver (Chi et al., 2020; Lin et al., 2019). In essence, AI-driven technologies are considered to be *intelligent* devices; therefore, customers exposed to AI are not expected to learn many new aspects of these devises upfront so as to operate them effectively. Further, as mentioned earlier in this section, AI-related technologies and devices are robustly built so as to function just like front-line employees by disseminating reliable information, clarifying customer questions and queries, and offering continued assistance in customer services. Against the background of the afore-mentioned observations, Lu et al. (2019) posit that the constructs of perceived ease of use and usefulness, as used in traditional technology models, may not be relevant in the context of AI acceptance frameworks (Gursoy et al., 2019). Further, as the appraisal of AI is contingent on its comparison with human performance, factors such as hedonic motivations and social influence (e.g., Morgan-Thomas & Veloutsou, 2013; Venkatesh & Davis, 2000; Wang et al., 2018) are expected to significantly influence the process of comparing the relative benefits of AI with other traditional mechanisms more when compared to other factors, especially in the hospitality sector. This is also because hospitality customers do demonstrate relatively higher levels of hedonic benefit expectations, in terms of fun and indelible stay experiences, when compared to the customers from other service sectors (Lin et al., 2019).

Second, traditional technology acceptance models do not account for the influence that the levels of AI anthropomorphism may exercise on performance and effort expectancy of customers. The Uncanny Valley Theory (UVT) offers some insights on the underlying mechanisms through which the construct of anthropomorphism operates. In particular, UVT presupposes a non-linear association between the levels of AI anthropomorphism and customers’ AI use intentions. Unlike non-intelligent systems, many AI devises and related technologies are designed to ape human features and attributes. While, at lower levels of anthropomorphism, the construct exercises its positive significant influence on customers’ AI usage intentions, at moderate to higher levels of anthropomorphism, the construct demonstrates a significant negative relationship with customers’ AI usage intentions. Therefore, situating anthropomorphism as a key construct in the AI acceptance conceptual framework is considered important because evidence from past research points towards the possibility of differential levels of AI anthropomorphism eliciting distinct behavioural attitudes, emotions and responses from consumers (Fan et al., 2020).

Finally, customers’ emotions, based on the cognitive appraisal of a stimulus (Breitsohl & Garrod, 2016), are also expected to play a significant role in their acceptance of or their refusal to use AI devices and related technologies (Kuo & Wu, 2012), which is not accounted for in the traditional technology acceptance models (Taherdoost, 2018).

Against this background, Gursoy and his colleagues conceptualized and developed the AIDUA model to measure customers’ willingness, and to capture objections to using AI devices and related technologies. Drawing extensively from cognitive appraisal theory and Lazarus’s framework (Lazarus, 1991a, 1991b), Gursoy et al. (2019) argue that customers are likely to engage in three stages of primary, secondary and outcome appraisals during their decision-making process. The primary appraisal refers to customers’ evaluation of AI devices. Social influence, hedonic motivation and anthropomorphism contribute to the
customers’ primary evaluation. However, the secondary appraisal captures the assessment of performance and effort expectancies. These expectancies influence the emergence of emotions towards AI’s usage. This, in turn, is expected to influence, favourably or unfavourably, the customers’ willingness to adopt AI devices and related technologies during their service transactions (Chi et al., 2020; Lu et al., 2019).

Against the rapid growth of AI adoption in the hospitality sector across the world and the presence of some conceptual fallacies in the traditional technology acceptance models in its ability to predict customers’ acceptance of AI, it becomes more so important to empirically validate the AIDUA framework in the hospitality context, given that such studies in the hospitality context have been very rare at best (see Lin et al. 2019 for an exception).

Moreover, as regards the Indian hospitality sector, the adoption of AI is still at an embryonic stage. However, the Indian hospitality sector is volatile, competitive and dynamic. Therefore, it has resulted in heightened levels of customer awareness and expectations. Accordingly, the need for Indian hospitality organizations to remain relevant has been on the rise (Roy, 2011). Consistent with these developments, the Indian hospitality sector is slowly embracing AI and related technologies to offer improved customer experiences. Notwithstanding the benefits of AI, it is also probable that an ill-planned transition into AI will lead to unprecedented levels of disruption in the sector if such transition happens without a clear understanding of what facilitates customers’ willingness to accept AI. Therefore, this research responds to the growing appeals for investigating the factors that influence the adoption of AI in the context of the Indian hospitality sector. Accordingly, all stakeholders and policy decision-makers in the Indian hospitality sector can gain critical insights from the findings of this research endeavour. Accordingly, this would facilitate the process of devising robust mechanisms that augment and facilitate the willingness to use AI among Indian hotel customers.

This research article is structured as follows: The ensuing ‘review of literature section’ offers in-depth insights on the theoretical underpinnings that situate the current study in its context. In particular, the section lists and expounds the relevant literature on primary appraisal, secondary appraisal and outcome stage and briefly outlines the empirical findings from past studies that have adopted the AIDUA model. We then present the study ‘objectives’ and ‘theoretical framework’ that logically emanate from the ‘review of literature section’. The section on ‘methods and procedures’ follows, which provides a detailed account of sampling, data collection, respondent profiles, measures used in this study and methods adopted for data analysis. The section on ‘results and discussion’ offers crucial insights into the empirical findings and the consequent theoretical implications of this study. We then present the implications, which emanate from the findings of this study, for industry practitioners and academic researchers.

**Review of Literature**

The technology of AI devices differs fundamentally from the technologies addressed by the traditional technology acceptance models on two counts (Lu et al., 2019). First, customers of AI technological devices would like to understand whether the underlying technology of AI devices provides similar or higher customer service in comparison with the service provided by human beings. This element of comparison of technology with human beings, as regards the service delivery, is the distinctive element in determining the customers’ acceptance of AI devices. Second, the acceptance of AI devices is dependent upon the processes of cognitive appraisal that aim at evaluating whether there is anything at stake for the consumer in the encounter with the AI technology. Scholars define cognitive appraisal as ‘a process through which the person evaluates whether a particular encounter with the environment is
relevant to his or her well-being, and if so, in what ways’ (Folkman et al., 1986, p. 992). If the use of AI potentially harms or benefits the user of the AI technology, the customer would wish to know what he or she can do to avert the threat of harm or improve the prospects of benefits. By implication, the process of customer acceptance of AI entails the stress coping mechanism as against the emphasis on the ease of and perceived usefulness in technology acceptance models. This is the rationale for the adoption of a completely different theoretical perspective of the cognitive appraisal theory to explain the adoption of AI technologies.

**Stage I: Primary Appraisal—Social Influence, Hedonic Motivation and Anthropomorphism**

**Social Influence**

The AIDUA model situates the construct of ‘social influence’ (e.g., Chou et al., 2015) as a significant component of customers’ primary appraisal and assessment of the relevance and importance of the services offered by AI devices and related technologies (Lin et al., 2019). Previous studies mostly defined social influence as ‘the degree that a customer’s social group (e.g., family and friends) believes that using AI devices in service delivery is relevant and congruent with group norms’ (Gursoy et al., 2019, p. 159). Group norms (Latané, 1981) decide the level of importance that one attaches to the social network’s opinion, critique and attitudes. There are three processes of social influence, that is, compliance, identification and internalization (Kelman, 1961), that determine how individuals receive and accept group influence. If individuals wish to receive a favourable outcome or avoid an unfavourable outcome, they are under the compliance process of social influence. If they accept the group norms for improving their self-image, the identification process of social influence would have motivated them to abide by the group norms. However, if individuals feel that their value system is in tune with the group’s expectations, one can conclude that they are under the influence of the internalization process of social influence. Accordingly, social network’s influence will play a significant role in the determination of behavioural intentions and willingness (Gursoy et al., 2017; Rather, 2018) to adopt AI devices and related technologies.

Scholars (e.g., Althuizen, 2018; Jeon et al., 2018) also posit that customers rely on their social group when they lack adequate knowledge and information to make informed decisions. Since the adoption of AI devices and related technologies is still new, the majority of customers in the Indian hospitality and tourism sector may demonstrate inadequate knowledge and skills to judge the suitability of accepting and adopting AI services. Because of this, many scholars hold the view that customers base and position their perceptions and attitudes towards AI services by relying heavily on the opinions, judgements and attitudes of their social group (Gursoy et al., 2019; Lin et al., 2019). As a result, recent research has suggested that customers show favourable opinions and perceptions about AI and associated services if the customers’ social network demonstrates a favourable attitude towards the use of AI devices and related technologies. Accordingly, it has been argued that social influence exercises its significant impact on customers’ perception of performance and effort expectancy.

**Hedonic Motivation**

As regards the other dimensions of primary appraisal in the AIDUA model, the construct of ‘hedonic motivation’ captures the ‘perceived fun or pleasure an individual expect to receive from using AI devices
in service delivery’ (Gursoy et al., 2019, p. 160). This definition situates hedonic motivation as a significant precursor to technology acceptance and related behaviours (e.g., Law et al., 2018). Hedonic motivation is an essential factor that augments intrinsic motivation among customers to accept and adopt new technologies and associated products (Venkatesh et al., 2012).

The importance of the role of hedonic motivation finds support in AI literature as well (Niemelä et al., 2017). Those individuals who demonstrate higher levels of hedonic motivation towards AI would probably view AI devices as the means to satisfy their needs for entertainment, novelty seeking and fun (Fryer et al., 2017). Individuals predominantly demonstrate favourable attitudes towards using AI devices by emphasizing the benefits of using AI devices and related technologies, notwithstanding the expected efforts or the task difficulties (e.g., Capa et al., 2008; Hockey, 1997). Many scholars hold the view that (e.g., Miao et al., 2014) customers place more importance on the hedonic value in the context of hospitality services than the utilitarian value of experienced services (Nunkoo & Ramkissoon, 2009). Therefore, in the hospitality and tourism domain, it is highly probable that those customers who perceive AI devices and services as the means to fulfil hedonic needs and opportunities would also demonstrate strong favourable emotions towards AI acceptance and adoption.

Anthropomorphism

Anthropomorphism (Kim & McGill, 2018) is the third dimension of the primary appraisal. It refers to ‘the level of an object’s human-like characteristics such as human appearance, self-consciousness, and emotion’ (Gursoy et al., 2019, p. 160). Scholars (e.g., Lu et al., 2019) situate anthropomorphism as a critical precursor to customers’ AI devise usage intentions and behaviours (Gursoy et al., 2019). Higher levels of anthropomorphism of AI devices would compel customers to consider such AI devices as a threat to their distinctiveness as humans, self-identity and self-relevance (Ackerman, 2016; Goudey & Bonnin, 2016). As AI devices and related technologies are fundamentally designed to replicate and reproduce human behaviour and responses, a more robust perception of anthropomorphism among customers would probably restrain customers’ behavioural intentions to adopt AI devices (Ackerman, 2016; Gursoy et al., 2019). Therefore, the probability that anthropomorphism would augment the performance expectancy of AI devices in the context of the hospitality sector among customers’ is limited at best. On the other hand, the construct of anthropomorphism is prone to result in higher effort expectancy (i.e., interaction with humans vs. interaction with AI devices) among its customers.

Stage II: Secondary Appraisal—Performance Expectancy, Effort Expectancy and Emotion

There is a strong possibility that customers’ attitudes and perceptions towards using advanced technologies (Baishya & Samalia, 2019), including AI devices (Gursoy et al., 2019), influence performance expectancy and effort expectancy (Gursoy et al., 2019). The process of formation of customers’ attitudes towards AI devices emanates from their primary appraisal, which seeks to identify the relevance and importance (i.e., perceived benefits and costs) of using AI devices and technologies (Lin et al., 2019). A negative primary appraisal would suggest higher effort expectancy (Lazarus, 1991b; Thompson et al., 1991) from customers and lower performance expectancy in subsequent stages of the decision-making process. A positive appraisal, on the other hand, would augment higher performance expectancy and lower effort expectancy (Gursoy et al., 2019). Further, it is highly probable that customers evaluate AI devices in
terms of service accuracy and reliability, quality and consistency. Furthermore, it is plausible that customers appraise the need to use AI devices by assessing the degree of psychological efforts needed to interact with technology-driven AI devices. It is also equally plausible that these expectancy (i.e., both performance and effort) evaluations shape customers’ positive or negative emotions towards AI devices (Gursoy et al., 2019; Lu et al., 2019; West et al., 2018).

**Stage III: Outcome Stage**

Prior research recognizes the presence of a strong possibility that the emotions exercise their significant influence on customers’ intentions and willingness to use AI devices and related technologies (Gursoy et al., 2019; Lin et al., 2019). While positive emotions may trigger willingness among the customers to use AI devices, negative emotions may elicit objections to using such AI devices. It is highly plausible that the use of AI devices would give rise to several benefits, such as a high degree of accuracy, reliability, superior operational efficiency and fewer service encounters. However, prior research points towards hotel customers’ overemphasis on the need for human-to-human interactions for superior service transactions and experiences (Ackerman, 2016; Zhang et al., 2017). Hotel customers may show a favourable attitude towards the use of AI due to their novelty, utilitarian benefits and newness (Fryer et al., 2017; Zalama et al., 2017). Notwithstanding these benefits, the same customers may object to using AI devices due to lack of quality human-to-human interactions and loss of social identity that stem from using AI devices and related technologies (Ackerman, 2016; Murphy et al., 2017).

During the stage of primary appraisal, there is a strong possibility that customers assess the relevance of the use of AI devices and related technologies from the standpoints of social influence, hedonic motivation and anthropomorphism. The appraisal [cost and benefit] analysis of the three aspects mentioned above is likely to influence performance and effort expectancy, which, in turn, is expected to exercise its effect on emotion. Subsequently, customers’ positive emotions would probably augment willingness to use AI devices and alleviate objection to use AI devices among the customers.

**The Empirical Validity of the Artificially Intelligent Device Use Acceptance Framework**

Gursoy et al. (2019) tested the three-stage AIDUA model on 439 potential customers of AI from the USA. The empirical results from this study did find support for the idea of a three-stage acceptance generation process that subsequently decides whether the customers would prefer using AI devices in their service interactions. In particular, in the primary appraisal stage, the dimensions of social influence and hedonic motivation exercised their significant positive effects on performance expectancy. In contrast, the aspect of anthropomorphism exercised its considerable negative impact on effort expectancy. Further, the constructs of performance and effort expectancy significantly related to emotion, in turn, predicted customers’ willingness or otherwise used AI devices in service interactions.

In a similar study, Lin et al. (2019) adopted the AIDUA framework to examine the role of precursors to full-service and limited-service hotel customers’ willingness and objection to use AI-driven robotic services. Drawing data from 605 potential customers in the USA, their study found empirical support to validate the AIDUA framework and for situating social influence, hedonic motivation, anthropomorphism, performance and effort expectancy and emotion as the significant precursors to the customers’ willingness.
or objection to use AI devices. Further, their study also found empirical support for the presence of a significant positive relationship between hedonic motivation and emotion.

**Objectives of the Study**

The purpose of this study is to attempt the task of validating the three-stage AIDUA acceptance framework, which was proposed by Gursoy et al. (2019). We investigate the validity of this model in the context of the Indian hospitality sector using multiple pathways. First, we examine the influence that the constructs of social influence, hedonic motivation and anthropomorphism exercise on the constructs of performance expectancy and effort expectancy. Second, in line with Lin et al.’s (2019) proposition, we examine the nature and magnitude of the relationship between hedonic motivation and emotions. Third, we examine the effects of performance and effort expectancy on emotions. Finally, we empirically examine the role that the construct of emotions play in eliciting willingness to use or objection to use AI devices among Indian hotel customers.

**Theoretical Framework**

Three theoretical postulates of the cognitive appraisal theory have enabled the development of the theoretical framework of this study. First, in line with the tenets of AIDUA model (Gursoy et al., 2019; Lin et al., 2019), customers evaluate the importance and relevance of AI devices based on three factors during the stage of primary appraisal, that is, social influence, hedonic motivation and anthropomorphism. In this process, as argued by the social identity theory, customers might perceive that the use of AI devices would strengthen their social identity. As a result, they would cultivate a favourable attitude towards the use of AI devices. The social influence to use AI devices would inspire customers to think in terms of the probable benefits instead of costs. Second, customers evaluate the performance expectancy and effort expectancy during the secondary appraisal stage. Such an appraisal would help customers’ emotions towards the use of AI devices. Third, customers’ emotions determine the degree of customers’ behavioural intentions during the outcome stage. These three theoretical postulates have influenced the evolution of the theoretical framework shown below:

Through the conceptualized framework (refer Figure 1), we propose that customers’ primary appraisal of the use of AI devices through social influence, hedonic motivation and anthropomorphism would significantly influence their respective performance expectancy and effort expectancy. It is highly probable that social influence and hedonic motivation positively relate to performance expectancy. In a similar vein, there is a strong possibility that anthropomorphism negatively relates to performance expectancy. In contrast, it is thought that higher levels of social influence and hedonic motivation attenuate customers’ perception of effort expectancy. However, according to many in the field of cognitive appraisal theoretical research, anthropomorphism augments the sense of effort expectancy among the hotel customers’.

Further, hedonic motivation probably exercises its positive influence on positive emotion. Consequently, the secondary appraisal of performance expectancy and effort expectancy is posited to influence the positive emotion of customers. There is some evidence to suggest that higher performance expectancy augments positive emotion. Besides, it is a widely held view that higher effort expectancy alleviates positive emotions among customers. Moreover, there is a strong possibility that while positive emotion positively relates to the willingness to use AI, it would negatively relate to objections to use AI.
Research Methods

Sampling, Data Collection and Respondent Profiles

We adopted a cross-sectional research design to capture hotel customers’ perceptions regarding the constructs considered for this study in accordance with the AIDUA model. We captured these constructs through a survey instrument at an individual level (i.e., hotel customers/guests). For this purpose, we approached 14 luxury hotels situated in the union territory of New Delhi and the state of Chandigarh. The list and details of all-star hotels in all the states and union territories in India are available on the Ministry of Tourism website of the Indian government, Union Territory (UT) of Delhi, and the state of Chandigarh. Notwithstanding the availability of the exhaustive list (tourism.gov.in;www.delhitourism.gov.in and www.chandigarhtourism.gov.in) of hotels in the respective locations, we approached 17 hotels based on our contacts and prior knowledge of them using AI to invite them to be a part of this survey. These hotels use myriad AI-driven technology-enabled services such as, mobile check-ins, ALEXA, self-service consoles and kiosks, Apple pay, laundry, robotic servers, etc. These hotels have been pioneers in adoption of AI devices in their operational services and were found to have been using different AI devices from at least past 5 years.

In all, 14 hotels (11 ‘four-star’ and three ‘five-star’ hotels; New Delhi—Seven ‘four-star’ and two ‘five-star’; Chandigarh—Four ‘four-star’ and one ‘five-star’ hotels) consented, in principle, to participate in this study. Accordingly, we captured responses from 210 respondents on the constructs of the AIDUA framework. The data collection lasted for 6 months. Further, we obtained the data through a structured survey instrument. Hotel customers’/guests’ participation in this research endeavour was completely voluntary. We treated the information shared by the respondents with complete confidentiality. As the data were captured from hotel customers at the individual level of analysis at a single point in time, after data collection, we tested the data for any possible presence of common method variance (CMV). Results of CMV analysis suggested that self-rating bias was not an issue with the data collected in this study.
In all, 129 (61.4%) male and 81 (38.6%) female respondents participated in this study. Further, the majority of the study sample (i.e., 170; 80.9%) were more than 40 years of age. The rest of the sample fell in the age group between 35 and 40 years. Also, 100 per cent of survey respondents were married (refer to Table 1). Furthermore, 100 per cent of survey respondents reported an average annual family income greater than 900,000. Moreover, 168 respondents (i.e., 80%) reported having visited luxury hotels between two and five times in the preceding 3 years. The rest (i.e., 42; 20%) reported having visited luxury hotels for more than five times in the preceding 3 years, and all comported to having knowledge of different AI devices being used in these hotels.

**Measures**

The survey instrument used in this study comprised two specific sections. The first section of the questionnaire captured data on respondents’ age, gender, average annual family income, marital status and frequency of customers’ visits to luxury hotels in the preceding 3 years. The second section of the survey instrument captured data on the eight latent constructs considered for this study. The items considered for this study were adapted from previously published articles on AI (e.g., Chi et al., 2020; Gursoy et al., 2019; Lin et al., 2019; Venkatesh et al., 2012; Wirtz et al., 2018). The latent constructs under consideration for this study included social influence (six items; e.g., *People who influence my behavior expect me to utilize AI devices where it is available, α = 0.801*), hedonic motivation (four items; e.g., *Interacting with AI devices would be enjoyable, α = 0.855*), anthropomorphism (four items; e.g., *AI devices will experience emotions, α = 0.797*), performance expectancy (four items, e.g., *AI devices provide more consistent hotel service than human beings, α = 0.911*), effort expectancy (three items, e.g., *Working with AI devices is so difficult to understand and use in hotel services, α = 0.863*), emotion (five items, e.g., *Despairing-Hopeful, α = 0.779*), willingness to use AI devices (three items, e.g., *I will feel happy to interact with AI devices in hotel services, α = 0.844*) and objection to use AI devices (three items, e.g., *Interaction with AI devices lacks social contact, α = 0.899*). As regards the construct of emotion, the items were captured on a 5-point bipolar scale (Gursoy et al., 2019; Lin et al., 2019). All the items considered for this study were captured on a 5-point Likert scale. The options on the 5-point scale ranged from 1 (strongly disagree) to 5 (strongly agree).

**Data Analysis**

We utilized SEM-AMOS to test the conceptualized AIDUA model in multiple stages. In the first stage, we carried out a ‘pooled’ confirmatory factor analysis (CFA) to assess composite reliability, construct validity, the fitness of the measurement model and to rule out CMV. In the second stage, we used CB-SEM (Hair et al., 2014; Sarstedt et al., 2016) to examine the direction and strength of the relationships between the eight latent factors considered for this study. Notwithstanding these two afore-mentioned steps, we also undertook outlier assessment by screening the data for missing values, abidance of data with normality assumption and the possible presence of multicollinearity even before using the data for CFA.
Results and Discussion

Data Screening: Table 2 exhibits the results of data screening phase. We found no values and/or information that were missing from the data set. Further, we examined the normality of the residuals by comparing the calculated skewness and kurtosis values against the standard threshold of ±2 (Field, 2009; Hair et al., 1998; Thompson, 2004). Skewness and kurtosis values of all the items belonging to the eight latent constructs fell in the range between −2 and +2, which suggested that the data did not violate the normality assumption. We assessed the possible presence of multicollinearity between the study constructs in two specific ways. First, we compared the bivariate correlation between the study constructs. In this connection, no value of the correlation between any two constructs was found to exceed 0.90 (Kline, 2005). Second, we calculated the variance inflation factor (VIF) for the study constructs. The VIF estimates ranged between 1.232 and 1.911, suggesting that multicollinearity was not an issue in this study (Marquardt, 1970).

Measurement Model

Reliability and Construct Validity

Table 3 exhibits the range of factor loadings, composite reliability (CR) scores, average variance extracted (AVE), and the square root of AVE compared with bivariate correlation estimates.

Table 1. Respondent Profiles.

| Parameter       | Categories                  | Frequency | Percentage | Cumulative Percentage |
|-----------------|-----------------------------|-----------|------------|-----------------------|
| 1. Gender       | Female                      | 81        | 38.6       |                       |
|                 | Male                        | 129       | 61.4       |                       |
|                 |                             | 210       | 100        |                       |
| 2. Age          | 20–25 years                 | 0         | 0          |                       |
|                 | 25–30 years                 | 10        | 4.7        |                       |
|                 | 30–35 years                 | 13        | 6.2        |                       |
|                 | 35–40 years                 | 17        | 8.1        |                       |
|                 | >40 years                   | 170       | 81.0       |                       |
|                 |                             | 210       | 100        |                       |
| 3. Income       | 300,000–500,000             | 0         | 0          |                       |
|                 | 500,000–700,000             | 0         | 0          |                       |
|                 | 700,000–900,000             | 0         | 0          |                       |
|                 | >900,000                    | 210       | 100        |                       |
|                 |                             | 210       | 100        |                       |
| 4. Marital status| Single                     | 0         | 0          |                       |
|                 | Married                     | 210       | 0          |                       |
|                 |                             | 210       | 100        |                       |

(Table 1 continued)
### Table 2. Means, Standard Deviations, Correlations, Normality and Multicollinearity Estimates.

| Variables         | Mean (SD) | SI   | HM   | A    | PE   | EE   | E    | WTUAI | OBTUAI |
|-------------------|-----------|------|------|------|------|------|------|-------|--------|
| Original sample size | 3.17 (0.81) | 1.00 | 0.43** | 0.61** | −0.02ns | 0.32** | −0.31** | 1.00 |
| Missing values    | Nil       | 3.15 (0.67) | 0.27** | 0.53** | −0.02ns | 0.53** | −0.31** | 1.00 |
| SI                | 3.63 (0.45) | 0.42** | 0.61** | −0.02ns | 0.32** | −0.31** | 1.00 |
| HM                | 3.67 (0.77) | 0.49** | 0.67** | 0.12* | 0.66** | −0.43** | 0.74** | 1.00 |
| A                 | 3.15 (0.67) | 0.27** | 0.17* | 1.00 |
| PE                | 3.44 (0.59) | 0.42** | 0.61** | −0.02ns | 0.32** | −0.31** | 1.00 |
| EE                | 3.26 (0.81) | −0.04ns | −0.33** | 0.32** | −0.31** | 1.00 |
| E                 | 3.43 (1.03) | 0.47** | 0.62** | 0.17* | 0.53** | −0.42** | 1.00 |
| WTUAI             | 3.67 (0.77) | 0.49** | 0.67** | 0.12* | 0.66** | −0.43** | 0.74** | 1.00 |
| OBTUAI            | 2.46 (1.12) | −0.32** | −0.39** | 0.03ns | −0.42** | 0.49** | −0.59** | 0.61** | 1.00 |
| Skewness<sup>a</sup> | ~ | ~ | ~ | ~ | ~ | ~ | ~ |
| Kurtosis<sup>a</sup> | 1.280 | 1.013 | 0.500 | 1.950 | 0.070 | 1.212 | 1.399 | 1.083 |
| VIF               | 1.232 | 1.238 | 1.437 | 1.812 | 1.432 | 1.765 | 1.911 | 1.589 |

**Source:** The authors.

**Notes:** * and ** Correlation is significant at 0.05 and 0.01 level respectively. SI—Social influence; HM—hedonic motivation; A—anthropomorphism; PE—performance expectancy; EE—effort expectancy; WTUAI—willingness to use AI devices; OBTUAI—objection to use AI devices; R—range; and NS—non-significance. Numbers in parentheses represent standard deviation.

<sup>a</sup>Represents the range of skewness and kurtosis values for the study constructs.
Table 3. Construct-wise Reliability and Validity Estimates.

| Comp | Factor Loadings | CR | AVE | SI | HM | A | PE | EE | E | WTUAI | OBTUAI |
|------|-----------------|----|-----|----|----|---|----|----|----|------|--------|
| SI 6 | 0.69–0.79       | 0.85| 0.555| 0.745|    |    |    |    |    |      |        |
| HM 4 | 0.71–0.82       | 0.88| 0.525| 0.431| 0.724|    |    |    |    |      |        |
| A 4  | 0.71–0.86       | 0.93| 0.723| 0.272| 0.174| 0.851|    |    |    |      |        |
| PE 4 | 0.88–0.93       | 0.87| 0.801| 0.424| 0.614| –0.020| 0.894|    |    |      |        |
| EE 3 | 0.81–0.90       | 0.89| 0.735| –0.040| –0.329| 0.319| –0.314| 0.857|    |      |        |
| E 5  | 0.78–0.91       | 0.84| 0.690| 0.473| 0.619| 0.170| 0.527| –0.421| 0.830|      |        |
| WTUAI (3) | 0.87–0.94 | 0.91| 0.810| 0.492| 0.673| 0.122| 0.660| –0.433| 0.741| 0.900|        |
| OBTUAI (3) | 0.68–0.84 | 0.86| 0.865| –0.322| –0.387| –0.031| –0.416| 0.485| –0.590| 0.600| 0.930 |

Source: The authors.

Notes: Values in italics evince the square-root values of AVE for the respective dimension. SI—Social influence; HM—hedonic motivation; A—anthropomorphism; PE—performance expectancy; EE—effort expectancy; WTUAI—willingness to use AI devices; OBTUAI—objection to use AI devices. *Represents the range of standardized factor loading scores.

The composite reliability scores (i.e., CR > 0.70) offered evidence for the presence of reliability. AVE scores greater than 0.50 for all the latent study constructs suggested the presence of convergent validity (Fornell & Larcker, 1981). The squared-root estimates of all the constructs were found to be greater than the bivariate correlations between the constructs, which suggested the presence of discriminant validity (Hair et al., 2014). Furthermore, CFA of the structural model comprising eight latent constructs offered satisfactory model fit indices (i.e., $\chi^2$/df = 1.396; CFI = 0.96; TLI = 0.94; NFI = 0.95; and RMSEA = 0.07) (Hu & Bentler, 1999; Kline, 2005).

Structural Model

As is evident from Figure 2, the construct of social influence related significantly and positively to performance expectancy ($\beta = 0.32, p < 0.001$). In a similar vein, the construct of hedonic motivation ($\beta = 0.64, p < 0.01$) was found to exercise its significant positive effect on performance expectancy. However, the observed relationship between the constructs of anthropomorphism and performance expectancy was found to be statistically non-significant ($\beta = –0.05, p > 0.05$). The construct of hedonic motivation was found to positively and significantly influence emotion ($\beta = 0.67, p < 0.001$) and negatively influence effort expectancy ($\beta = –0.43, p < 0.001$). The construct of anthropomorphism was found to exercise its significant positive effect on effort expectancy ($\beta = 0.43, p < 0.001$). Further, performance expectancy was found to be significantly and positively related to emotion ($\beta = 0.49, p < 0.001$), whereas effort expectancy was negatively and significantly related to emotion ($\beta = –0.18, p < 0.001$). Furthermore, emotion was found to significantly augment willingness to use AI devices among customers ($\beta = 0.73, p < 0.001$), whereas emotion was negatively related to objection to use AI devices among the hotel customers ($\beta = –0.60, p < 0.001$). Moreover, the constructs of social influence, hedonic motivation and anthropomorphism explained 56 per cent variance in performance expectancy ($R^2 = 0.56; p < 0.01$) and
29 per cent variance in effort expectancy ($R^2 = 0.29; p < 0.01$), respectively. Also, the constructs of performance expectancy and effort expectancy, together, explained 69 per cent variance in customers’ emotion ($R^2 = 0.69; p < 0.01$). In its turn, emotion was found to explain 78 per cent variance in willingness to use AI devices ($R^2 = 0.78; p < 0.01$) and 41 per cent variance in objection to use AI devices ($R^2 = 0.41; p < 0.01$) among the hotel customers.

This research examined the influence of crucial antecedents of customers’ willingness and objection to use AI devices and related technologies by testing the modified AIDUA framework (Lin et al., 2019) on a sample drawn from the hospitality sector in India. In this connection, the empirical findings that emerge from this study validate the AIDUA framework (Gursoy et al., 2019) in the hospitality sector (Lin et al., 2019).

The first finding of this study on the role of positive customer emotions is consistent with the tenets of the AIDUA framework (Gursoy et al., 2019). This study has found positive customer emotions (e.g., Goswami & Sarma, 2019) to be a crucial factor in the decision-making process that augments customers’ behavioural intentions to use AI devices in their service encounters. Therefore, one may argue that customers’ systematic emotional evaluation of AI devices triggers their willingness to use those devices (Lin et al., 2019). Higher levels of positive emotions towards AI would facilitate the alleviation of customers’ objections to using AI devices, whose magnitude and strength in this study may have emerged due to the lack of social interactions.

Second, the magnitude and strength of effort expectancy to predict emotion are relatively weak in comparison with those of performance expectancy. However, both the constructs of performance expectancy and effort expectancy exercise their influence on emotions. This finding is consistent with that of Lin et al.’s study (2019), which suggests that hotel customers demonstrate a propensity to invest time and discretionary efforts to use AI devices, provided they offer the desired utilitarian and hedonic benefits.
Third, the findings of this study also point towards the critical role that the social groups and network play in facilitating and influencing customers’ assessment of the perceived costs and benefits of using AI devices and related technologies (Gursoy et al., 2019; Lin et al., 2019; Venkatesh & Davis, 2000). This suggests that the more substantial the influence of the social group on the decision-making of customers, stronger would be the perceptions on positive benefits and lower would be the cost perceptions, notwithstanding the number of efforts required to use such AI devices. This would also explain the underlying reasons for the absence of a significant relationship between social influence and effort expectancy (Venkatesh & Morris, 2000).

Fourth, as regards the construct of hedonic motivation, it was found to affect performance expectancy positively and effort expectancy negatively. Individuals who demonstrate higher levels of hedonic motivation (i.e., novelty-seeking, fun-seeking, and entertainment-seeking behaviour) are also the ones who are more prone to exploring and experiencing new technology (Froehle & Roth, 2004). In the context of AI, it may so happen that their levels of knowledge and AI readiness lessen the efforts required to use such AI devices (Gursoy et al., 2019).

Finally, the findings that emerge from this study suggest that those individuals who demonstrate higher levels of anthropomorphism would perceive the need for more significant efforts to use AI devices. This is because not only would the individuals require discretionary efforts to interact with human-like AI devices, but they also have to exert considerable efforts to learn more about the technology-driven AI devices (Ackerman, 2016). In this context, the non-significant relationship between the constructs of anthropomorphism and performance expectancy is similar to the findings of Gursoy et al. (2019) and Lin et al. (2019). Against the backdrop of this finding, it would be reasonable to infer that hotel customers’ anthropomorphism of AI devices will result in negative attitudes towards these devices due to the perceived threat of self-identity.

Conclusion

As is evident from the observed industry trends, a majority of the hospitality organizations across the world are now seen integrating AI into their service delivery mechanisms so as to offer services that are relatively more reliable, timely and efficient when compared to the traditional modes that rely heavily on human capabilities. Success, however, of any technology adoption intervention by hospitality organizations is expected to be significantly contingent on customers’ proclivity and intentions to use such devices, given the fact that customers differ in their needs, service preferences and also their levels of willingness to forego traditional methods and adopt novel technologies. Though benefits of AI are unprecedented, investing in AI devices and related technologies without having a clear understanding of ‘what’ factors actually drive customers’ willingness to these devices will result in ineffective integration to AI into service delivery mechanisms, leading further to probable loss of customers. This study, therefore, attempted to identify the key antecedents to the customers’ willingness and objection to use AI in the Indian hospitality sector by using the AIDUA model from the data collected from 210 customers from 14 Indian luxury hotels. Accordingly, this study found strong empirical support to situate hedonic motivation and social as significant correlates of performance expectancy. In a similar vein, the results of the study position hedonic motivation and anthropomorphism as significant precursors of effort expectancy. Further, while performance expectancy was found to relate positively and significantly to customers’ positive emotions, effort expectancy alleviated customers’ positive emotion perceptions. Moreover, while customers’ positive emotions were found to increase their willingness to accept AI, they lessened their objections to use AI during their service encounters. Accordingly, this research endeavour
articulates the underlying role of customers’ positive emotions and situates the same as a possible intervening variable between the stages of primary appraisal and outcome in the customers’ decision-making process towards acceptance of AI.

**Implications for Managers**

The empirical findings of this study offer critical insights to AI developers and the hospitality sector’s managers, practitioners and decision-makers.

First, AI developers are cautioned not to lay overemphasis on anthropomorphic (human-like) design features while designing AI devices. By implication, customers are likely to perceive AI devices to be a direct threat to their self-identity at higher levels of anthropomorphism, though low to medium levels of anthropomorphism will augment and facilitate customers’ propensity to use AI devices. Therefore, such attitudes are likely to alleviate behavioural intentions to use AI devices among hotel customers. To this end, service delivery processes in the hospitality sector are essentially driven by high levels of human/interpersonal interactions, conversations and contacts. Over-reliance on AI with human-like features and intelligence may be detrimental to the customers’ willingness to use AI.

Second, the empirical findings of this study found hedonic motivation to be a stronger antecedent of performance expectancy, effort expectancy and customers’ positive emotions when compared to social influence and anthropomorphism. Given these findings, hospitality managers and decision-makers are encouraged to highlight and demonstrate the novelty, fun and entertainment features of AI devices instead of overemphasizing the efficiency and effectiveness features of such devices.

Finally, as the construct of social influence is found to affect performance expectancy, hospitality managers and practitioners can encourage active AI users to share their testimonials and opinions about their service encounters with AI devices on social media. The objective of this sharing of one’s views on social media is to increase traction and publicity about the benefits of using AI among those who are still reluctant to try AI devices. Active users of AI devices may be utilized as key influencers for the ones who are laggards.

**Limitations of the Study and Research Implications**

The findings of this study should be considered against the background of some methodological and conceptual limitations. First, this is among the first studies in India that has adopted the modified AIDUA model to test its validity in the hospitality sector. Though the empirical findings of this study offer compelling evidence to support the framework of the model, more research using the AIDUA model in different industries is required to pronounce any final verdict on the universality of the model.

Second, this study adopted a cross-sectional design. Future studies can choose longitudinal designs to establish causality between the constructs. As the adoption of AI is still in an embryonic stage in India, less is known as to what other contextual factors can influence customers’ behavioural intentions to use AI. Future studies in this regard can adopt multi-actor designs and mixed-method approaches to gain more significant insights from different stakeholders involved with AI to identify the key factors that may be used to revise the existing AIDUA model.

Third, researchers can also integrate socio-demographic variables (e.g., age, gender, experience, etc), individual personality traits and regulatory focus (i.e., approach-orientation, avoidance-orientation) in the AIDUA framework so as to explore their possible moderation effects on various criterion variables.
Finally, given the fact that some relationships in the AIDUA model considered for this study were found non-significant even though they are grounded in theory, future studies can test these relationships to examine whether they are context-specific.

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