

Consumers acceptance of artificially intelligent (AI) device use in service delivery



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ABSTRACT

This study develops and empirically tests a theoretical model of artificially intelligent (AI) device use acceptance (AIDUA) that aims to explain customers' willingness to accept AI device use in service encounters. The proposed model incorporates three acceptance generation stages (primary appraisal, secondary appraisal, and outcome stage) and six antecedents (social influence, hedonic motivation, anthropomorphism, performance expectancy, effort expectancy, and emotion). Utilizing data collected from potential customers, the proposed AIDUA model is tested. Findings suggest that customers go through a three-step acceptance generation process in determining whether to accept the use of AI devices during their service interactions. Findings indicate that social influence and hedonic motivation are positively related to performance expectancy while anthropomorphism is positively related to effort expectancy. Both performance and effort expectancy are significant antecedents of customer emotions, which determines customers' acceptance of AI device use in service encounters. This study provides a conceptual AI device acceptance framework that can be used by other researchers to better investigate AI related topics in the service context.

1. Introduction

Development and utilization of artificially intelligent (AI) devices has been gaining momentum during the last few years (Duan, Edwards, & Dwivedi, 2019). From robots used in the assembly lines by the automotive industry to the clinical decision support systems utilized by hospitals, AI technology has become a critical component of doing business in a number of industries. Tasks that used to be performed by humans only, such as driving vehicles, processing human language, recognizing faces in photos, analyzing big data or conducting online searches, now can be easily accomplished by AI devices (Anthes, 2017). Companies that provide a variety of services have also started utilizing AI technologies in their service production and delivery processes. For example, in the hotel industry, Hilton Worldwide employs a robotic concierge named "Connie", who is responsible for personalizing guests' experience, providing information, and addressing guests' general needs (Tavakoli & Mura, 2018). In the airline industry, KLM Airlines uses an AI device named "Spencer" to answer travelers' queries and to enhance their travel experiences (West, Clifford, & Atkinson, 2018). In

the retail industry, the North Face utilizes an online AI application developed by IBM Watson's technology to help customers choose the most suitable jacket (Faggella, 2019). The application empowered by AI makes personalized recommendations to customers through an analysis of a huge multi-variance dataset. This AI based sales application does not only provide quick and accurate personalized suggestions to enhance customer-brand interaction, but also saves the firm a significant amount of human labor cost.

Recent advances in AI development and the speed of AI integration and applications into the service delivery process by service companies suggest that the adoption of AI devices in the service context is not a fad, but a rising trend since AI devices have several advantages over human employees. From the service delivery perspective, AI devices can provide not only more consistent and timely service, but also a higher quality of service compared to human employees due to the advanced data storage capabilities empowered by AI technology, high processing speeds, and accurate personalization features (West et al., 2018). From the operation perspective, AI devices can decrease cost by increasing operational efficiency and effectiveness by lowering human

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employees' workload (Cobos, Mejia, Ozturk, & Wang, 2016; Marinova, de Ruyter, Huang, Meuter, & Challagalla, 2017; West et al., 2018). Studies reveal that around 75% of customers believe that AI devices can enhance hotel service quality (Travelzoo, 2016) and approximately 86% marketing programs in the retail industry plan on adopting AI devices. The global market demand for AI device in the service industry is predicted to reach 1.5 billion US dollars in 2019. As a result, the adoption of AI devices in service delivery has started attracting a significant attention from researchers (Huang & Rust, 2018; Wirtz et al., 2018).

Previous studies have explored a number of issues regarding AI devices, their utilization in the service delivery, and their users (Duan et al., 2019). While some scholars have focused on practical issues related to AI device use in service delivery such as the role of service robots in service encounters (Wirtz et al., 2018), impacts of AI technology on frontline employee-customer interactions (Marinova et al., 2017), and challenges related to adoption of AI devices to enhance customer's experience (Bolton et al., 2018), others have attempted to conceptualize AI device use in service delivery and decision-making process (Duan et al., 2019; van Doorn et al., 2017) or have propose theories to explain AI technology development and human job replacement (Huang & Rust, 2018). Scholars have also developed a measurement scale to measure customer's willingness to use AI robots during service delivery (Lu, Cai, and Gursoy, (2019)).

However, studies that examined customers' intention to use AI devices during service delivery are mainly based on existing technology acceptance theories. For example, Sundar, Waddell, and Jung, (2016)'s study regarding AI robot adoption intention was based on the Technology Acceptance Model (TAM) developed by Davis, Bagozzi, and Warshaw in 1989. Fritz, Corbett, Vandermause, and Cook, (2016) study on senior residents' intention to use AI home monitoring devices utilized the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh, Thong, and Xu in 2012 and subsequently tested empirically across several contexts, sometimes with some modifications (Dwivedi, Shareef, Simintiras, Lal, & Weerakkody, 2016; Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2017; Oliveira, Faria, Thomas, & Popović, 2014; Rana, Dwivedi, Lal, Williams, & Clement, 2017; Rana, Dwivedi, Williams and Weerakkody, 2016; Williams, Rana, & Dwivedi, 2015). Even though traditional technology acceptance models, to a certain extent, explain the mechanism of users' intention to use AI devices, these models were originally developed to investigate the the adoption of non-intelligent technologies such as self-service technologies in service delivery (Im & Hancer, 2017; Lee & Cranage, 2018), whereas, AI devices possess humanlike intelligence powered by AI technology. As such, these devices do not require users to learn how to operate them, which makes the *ease-of-use* construct included in all technology acceptance models as a core construct, irrelevant to the examination of customer's willingness to accept the use of AI devices during a service encounter (Lu et al., 2019).

Furthermore, AI devices are designed to interact with customers like regular frontline employees, and thus the construct of *perceived usefulness* included in previous technology acceptance models is also not likely to be relevant to predict customers' willingness to accept the use of AI devices during service encounters (Lu et al., 2019). Using AI devices to replace frontline employees not only concerns task performance at the physical level, but also serves the social (i.e., AI used as automated social presence) and emotional meaning embedded in service interactions (van Doorn et al., 2017). However, none of existing technology acceptance research has captured a technology that characterizes the multi-faceted role of AI devices used in service encounters. Thus, there is a need for a comprehensive model delineating the psychological path-way that leads to customer's willingness to accept the use of AI devices during service encounters.

Using the Cognitive Appraisal Theory (Lazarus, 1991a; Lazarus, 1991b) and the Cognitive Dissonance Theory (Festinger, 1962), this study proposes a theoretical model of AI Device Use Acceptance

(AIDUA) that explains the multi-step process that customers utilize in determining their willingness to accept the use of AI devices during service encounters. Furthermore, this study empirically tests the proposed AIDUA model in order to identify the direction and the strength of the relationships among the constructs included in the proposed AIDUA model. Using AI devices to replace human presence has been a controversial subject such that most consumers do not hold a firm stance whether to accept or refuse AI devices and robots (Huang & Rust, 2018; Makridakis, 2017). Therefore, supporting and opposing factors may co-exist and interact to influence users' acceptance behavior. Thus, given the multifaceted nature of incorporating AI devices into consumers' service transactions, it is necessary to outline decision stages that lead to positive (e.g., acceptance) and negative (e.g., objection) outcomes in the same conceptual framework. Findings of this study will provide critical insights to researchers and managers on the determinants of consumers' willingness to accept or reject the use of AI devices during service delivery. These findings can assist companies to develop advanced AI device investment and adoption strategies.

The remaining part of the article is structured as follows. In the literature review section, studies on consumer behavior with respect with AI devices are reviewed and the Lazarus's cognition-motivation-emotion framework (1991a) that informs the theoretical model of the study is discussed. The next section delves into the research methodology and the modeling process used to test the theoretical model. We then present that results of the study and discuss those in the light of the existing theoretical and empirical evidences. The theoretical and managerial implications and the limitations of the study are discussed.

2. Literature review

2.1. Willingness to accept the use of AI devices during service delivery process

Studies suggest that intentions and willingness generally determine individuals' actual behaviors (e.g., Cronan, Mullins, & Douglas, 2018). As suggested by the Theory of Reasoned Action (Fishbein & Ajzen, 1975), intention/willingness to use is the main determinant of customers' actual behavior. However, understanding the factors that influence customer willingness is a complex process. Previous studies that examined customers' willingness to adapt AI devices in service transactions reported a number of factors. For example, Niemelä, Arvola, and Aaltonen (2017) found that hedonic motivation is the primary factor influencing customers' behavior-intention of using AI devices in retail stores. Song (2017) found that perceived usefulness, social capability, and device appearance are the determinants of service robot adoption. Meanwhile, Stock and Merkle (2017) found that customers' intention to use AI device is influenced by their expectations of AI devices, frontline employees, and service quality in a general service setting. However, those studies that examined customers' willingness to adapt AI devices in service transactions were either descriptive or utilized the premises of technology acceptance models, which is argued to be inadequate for examining the AI device use adaption (Lu et al., 2019; Song, 2017).

Previous studies have developed a number of conceptual models to determine the factors that can influence customer willingness to adopt a new technology, such as perceived usefulness and ease-to-use (Davis et al., 1989; Hsiao & Yang, 2011; Ozturk, Bilgihan, Nusair, & Okumus, 2016; Wang, Wang, & Lin, 2018), social influence and cognitive process (Venkatesh & Davis, 2000a; Venkatesh & Davis, 2000b), previous experiences (Morgan-Thomas & Veloutsou, 2013), and hedonic motivations (Venkatesh et al., 2012). However, those technology acceptance models have mainly focused on adoption of functional technologies, technology-enabled services and self-service technologies (Lu et al., 2019; Mortenson & Vidgen, 2016) such as mobile check-in, self-service kiosks, or Apple Pay.

While many of the factors that are included in the technology

acceptance models can also explain customers' intention to use AI devices, Lu et al. (2019) argue that some of the core constructs of technology acceptance models such as perceived usefulness and ease of use may not be applicable to the AI device use intention context because such factors focus on customer learning of new technologies. In the context of AI device use, consumers are likely to focus on whether an AI device can deliver the same level of or better service as human employees are likely to deliver. Thus, Lu et al. (2019) developed a scale to measure customer's willingness to use AI service robots after conducting a comprehensive review that covered technology acceptance theories, related literature, and a number of focus groups. Through a number of qualitative and quantitative studies, Lu et al. (2019) identified six major predictors of consumers' willingness to integrate AI service robots into service delivery: performance efficacy, hedonic motivation, anthropomorphism, social influence, facilitating condition, and emotion (please see Lu et al., 2019 for more details).

Even though these factors were argued to have considerable predictability, interactions among them and their influence on customer's willingness to accept the use of AI devices during service encounters has not been investigated. As suggested by the Cognitive Appraisal Theory, individuals' response to a stimulus is ultimately determined by their emotions generated through a multi-level cognitive appraisal of the stimulus (Lazarus, 1991a; Lazarus, 1991b; Breitsohl & Garrod, 2016). Cognitive appraisal theory has been increasingly used to explain coping behaviors for complex events (Breitsohl & Garrod, 2016; Cai, Lu, and Gursoy, 2018). Thus, customers' final decision to accept the use of or refusal of AI devices during service encounters is also likely to be determined by their emotions, which are generated through a complex multi-stage appraisal process (Kuo & Wu, 2012).

2.2. Three-staged process of adoption/rejection

The current study utilizes Lazarus's cognition-motivation-emotion framework (1991a) and the major predictors of consumers' willingness to integrate AI service robots into service delivery identified by Lu et al. (2019) to examine customer's willingness to accept the use of AI devices during service encounters. Facilitating conditions was excluded in the current research because this variable can vary significantly across application vendors and service environments and is more relevant to predict actual behavior on-site rather than understanding the decision-making path-way (Venkatesh et al., 2012). Lazarus's framework suggests that during a decision making process, individuals go through several stages of appraisals, including evaluating importance (primary appraisal), analyzing behavioral options (secondary appraisal), and creating emotions toward the stimulus that leads to behavioral intentions.

Adopting Lazarus's framework, the current study proposes that the customer's willingness to accept the use of AI devices can be determined through a three-stage process: primary appraisal, secondary appraisal, and outcome stage as presented in Fig. 1. In the primary appraisal stage, customers assess the relevance and importance of using AI devices during service interactions based on three factors: social influence, hedonic motivation, and anthropomorphism. As suggested by the cognitive appraisal theory, individuals will first evaluate the relevance and importance of using AI devices during service delivery. Based on their primary appraisal, consumers who view utilization of AI devices during service delivery as relevant and important will perform a deliberate appraisal of benefits and costs of using AI devices based on performance expectancy and effort expectancy of AI devices, which will result in generation of emotions toward AI devices (Lazarus, 1991a). Customers' emotions toward using AI devices will then determine their willingness and objection levels for accepting the use of AI devices during service delivery process.

2.2.1. Primary appraisal

Before considering the adoption of AI devices into their service

delivery process, consumers will first evaluate the relevance and the congruence of AI devices to themselves (Lazarus, 1991b). Relevance is the extent to which the stimulus is related to the individual. An irrelevant stimulus will not cause further assessment and emotion. Congruence reflects to extent to which the stimulus pose threats or benefits to an individual's values or beliefs related to goal attainment. If the stimulus is not likely to result in any outcomes for a person, no emotions will be generated. In the proposed AIDUA model, based on Lu et al.'s (2019) study, three factors are identified as critical constructs that can influence consumers' primary evaluation of AI devices. They are social influence (Chou, Wang, & Tang, 2015; Ifinedo, 2016; Kim & Kim, 2018; Venkatesh et al., 2012), hedonic motivation (Allam, Blielme, Spiteri, Blustein, & Ali-Hassan, 2019; Koivisto & Hamari, 2019; Venkatesh et al., 2012), and anthropomorphism (van Doorn et al., 2017; Lu et al., 2019). During the primary evaluation process, consumers' evaluation of AI device use in service delivery is based on their social group norms, hedonic motivation and the level of anthropomorphism. If their initial evaluation indicates that the use of AI devices in service delivery is relevant and congruent with their social networks and their own norms, they are likely to move to the second stage of evaluation where they will conduct a deliberate appraisal of costs and benefits of using AI devices (Lazarus, 1991a).

Social influence refers to the degree that a customer's social group (e.g. family, friends, etc.) believes that using AI devices in service delivery is relevant and congruent with group norms. Social Impact Theory (Latané, 1981) suggests that people are more likely to conform to group norms if the group is important to them. Previous studies found that customers' social network's norms and attitudes are critical determinants of individuals' behavioral intentions (Rather, 2018). This is particularly true when individuals do not have sufficient knowledge to make an informed decision (Althuisen, 2018; Venkatesh & Davis, 2000a; Venkatesh & Davis, 2000b). For example, Gursoy, Del Chiappa, & Zhang (2017) report that family and friend are one of most important sources of information during a consumer's decision making process. Likewise, Jeon, Lee and Jeong (2018)'s findings indicate that customers tend to adopt their social groups' culture, values and norms as their own and make behavioral decision accordingly. Furthermore, as suggested by the Social Identity Theory (Tajfel & Turner, 1979), adopting a group's behavioral norms will strengthen individuals' attachment level of belongingness to that group. Thus, if a customer's social network (e.g. friends, co-workers, family members) holds favorable opinions and attitudes toward AI device use in service delivery and recommends the customer to use AI devices, using AI devices will benefit the customer's social identity. One component of attitude relates to the performance expectancy of the AI devices that refers to the perceived benefits that a customer can gain from using such devices. As a result of this benefit, the customer is likely to conform to his/her group's norms by forming an initial positive attitude toward AI devices. Based on the preceding theoretical and empirical discussions, the following hypothesis is developed:

H1. Social influence is positively related to performance expectancy of AI devices.

Another dimension of customer attitudes is the *effort expectancy* that refers to the perceived difficulty of using AI devices. Based on the Lazarus's framework, social norms is proposed to influence effort expectancy. The constructs of social norms (sometimes referred to as subjective norms) and perceived difficulty have been the focus of some empirical studies carried out across a range of contexts (Hall & Henningsen, 2008; Hsu & Lin, 2008). If the customer's social groups hold positive opinions about the AI device by believing that it is easy to use, then the customer is less likely to perceive the device as difficult to use. Accordingly, based on the preceding theoretical and empirical discussions from the literature, the following hypothesis is proposed:

H2. Social influence is negatively related to effort expectancy of AI

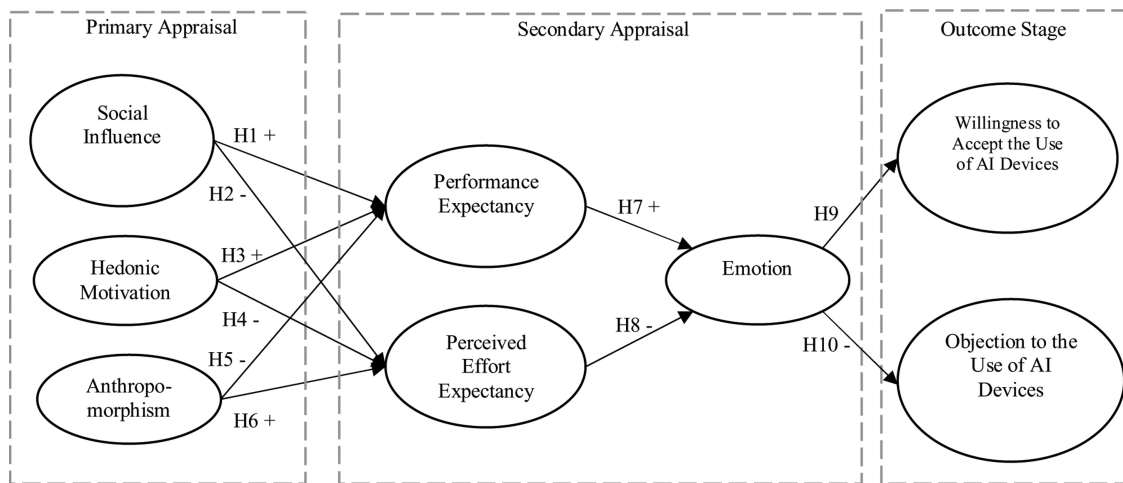


Fig. 1. Proposed AIDUA model.

devices.

Hedonic motivation refers to the perceived fun or pleasure an individual expect to receive from using AI devices in service delivery. Previous literature argues that hedonic motivation is the main predictor of technology adoption behavior (Allam et al., 2019; Law, Chan, & Wang, 2018; Venkatesh et al., 2012). When a customer has a hedonic motivation toward AI devices, using AI devices will benefit the customer by satisfying his/her personal interest or need for seeking novelty and entertainment (Fryer, Ainley, Thompson, Gibson, & Sherlock, 2017). As a result, customers who have hedonic motivations for using AI devices is likely to have positive attitudes toward using them. Accordingly, the following hypothesis is proposed:

H3. Hedonic motivation is positively related to perceived performance expectancy of AI devices.

Consumers' motivation represents a compensatory strategy to protect performance in the presence of increased task difficulty (Hockey, 1997). Early studies in psychology suggest that motivation interacts with task difficulty to influence the perceived mental effort required to perform a task (Humphreys & Revelle, 1984). Studies have validated a relationship between motivation and the level of perceived difficulty/effort expectancy in relation to a task (Capa, Audiffren, & Ragot, 2008; Eccles & Wigfield, 1995; Gendolla & Wright, 2005; Wright & Kirby, 2001). Based on the preceding discussion, we extrapolate to propose that highly motivated consumers are less likely to perceive that performing tasks in relation to AI devices is difficult. Thus, the following hypothesis is proposed:

H4. Hedonic motivation is negatively related to perceived effort expectancy of AI devices.

Anthropomorphism refers to the level of an object's humanlike characteristics such as human appearance, self-consciousness, and emotion (Kim & McGill, 2018). The physical and intellectual resemblance of AI devices instantaneously trigger consumers' initial evaluation on self-relevance; and whether such design is aligned to their existing beliefs of technologies used for service interactions. Studies argue that anthropomorphism is an important determinant of customers' AI device use behaviors (Lu et al., 2019; van Doorn et al., 2017). In general, people who have a high level of perceived anthropomorphism of AI devices believe that AI devices with humanlike features threaten human's distinctiveness and self-identity (Rosenthal-von der Pütten & Krämer, 2014; Ackerman, 2016). For example, in a study that examined the adoption of robotic teachers in pre-schools and elementary schools, most kids perceived a threat from the robotic teacher (Fernández-

Llamas, Conde, Rodríguez-Lera, Rodríguez-Sedano, and García, 2018). Research on social robots also suggests that consumers respond more favorably to a partially anthropomorphic appearance than a complete human appearance (Goudey & Bonnin, 2016). Since human-like features of AI devices can pose a threat to customers' human identity (Ackerman, 2016; Gursoy, 2019), consumers may attempt to justify their objection by assuming that these AI devices are not likely to perform as promised.

H5. Anthropomorphism is negatively related to perceived performance expectancy of AI devices.

Consumers may further justify their objection to the use of AI devices in service delivery by assuming that interacting with an AI device is likely to require more effort than interacting with a human employee due to the fact that they will be required to treat the AI device as an intelligent being based on their own social beliefs and norms (Kim & McGill, 2018). The identity of being a humanoid suggests effort coming from two sources: effort required to interact with a real human and effort needed to learn a technological device. Thus, anthropomorphic features may increase consumers' perception of the effort required when using AI devices (e.g., effort related to interacting with human and machines).

H6. Anthropomorphism is positively related to customer perceived effort expectancy of AI devices.

2.2.2. Secondary appraisal

During the secondary appraisal stage, individuals mainly consider the decision options and results of each decision in terms of emotions. In the willingness to accept the use of AI device context, customers will evaluate the costs and benefits of AI device use in service delivery based on perceived performance and effort expectancy (Venkatesh et al., 2012) of AI devices, and then form their emotions toward AI device use in service delivery. The current study proposes that these two factors are the main constructs that are likely to be used by customers to appraise the costs and benefits of using of AI devices. These constructs serve as critical determinants of customers' emotions toward AI devices as suggested by Lu et al. (2019).

As discussed earlier, these expectations are likely to be influenced by a customer's existing attitudes toward using AI devices. Customers' negative evaluation of AI devices generated during the primary appraisal process will be enhanced by higher level of effort expectancy and weakened by higher level of performance expectancy. This is because effort expectancy perpetuates their existing negative perceptions, whereas performance expectancy mitigates their existing negative

attitudes. On the other hand, customers' positive evaluation generated during the primary appraisal will be weakened by higher level of effort expectancy and enhanced by higher level of performance expectancy. However, as suggested by the Cognitive Dissonance Theory (Festinger, 1962), a person's assessment of an object that is inconsistent with their existing beliefs causes cognitive dissonance, which leads to discomfort.

In these situations, individuals tend to minimize the dissonance by conforming to the previous evaluation rather than to challenge it. As a result, customers who generate positive attitudes toward AI devices during the primary appraisal stage tend to agree with the existing evaluations during the secondary appraisal process, and vice versa. Deliberate evaluation of the costs and benefits of using AI devices during the secondary appraisal process will result in generation of emotions toward AI device use in the service delivery. If customers believe that using AI devices will benefit them by providing fast, reliable, accurate and consistent services (Lu et al., 2019; West et al., 2018), and thus results in improved service quality (e.g. high-performance expectancy), positive emotions will be generated.

H7. Performance expectancy has a positive impact on generation of positive emotions toward the use of AI devices.

However, the use of AI devices in service delivery may also lead to significant communication barriers between customers and AI devices (Lu et al., 2019) or require more cognition to understand the confusing and complex design of AI devices (Thompson, Higgins, & Howell, 1991), which may increase the amount of effort required. Thus, if customers believe that using AI devices will require too much effort, negative emotions will be generated (Lazarus, 1991b).

H8. Effort expectancy has a negative impact on generation of positive emotions toward the use of AI devices.

2.2.3. Outcome stage

After the complex appraisal process, emotions toward AI device use will be generated, which will consequently determine customer's willingness to accept the use of AI devices and/or objection to the use of AI devices during service encounters. Willingness to accept the use of AI devices refers to customer's willingness to use AI devices in the future service encounters. Positive emotions such as anticipation, content, happy, pleased, joy, and surprise have been found to influence consumption-related behaviors (Watson & Spence, 2007). As suggested by the Cognitive Appraisal Theory, customers with such positive emotions toward AI devices will have higher willingness to accept the use of AI devices during service delivery process. Accordingly, the following hypothesis is proposed:

H9. Emotion is positively related to customer's willingness to accept the use of AI devices during service delivery.

Objection to the use of AI devices refers to consumers' unwillingness to use AI devices due to their need for the human social interaction during service encounters. Emotions during the decision-making process with respect to AI devices may not only involve positive ones, but may also relate to frustration, fear, feelings of uncertainty and anxiousness, and worry (Raghunathan & Pham, 1999; Rucker & Petty, 2004). As postulated by the Cognitive Appraisal Theory, such emotions are likely to lead to a rejection of certain products or services. For example, Chen and Granitz (2012) found that certain forms of emotion led consumers to reject a tech-enabled change. Based on the preceding theoretical and empirical evidences, the following hypothesis is proposed:

H10. Emotion is negatively related to customer's objection to accept the use of AI devices during service delivery.

3. Method

3.1. Sample and data collection

The proposed AIDUA model was tested utilizing consumer data that were collected through an online consumer panel provided by the Amazon Mechanical-Turk (www.mturk.com). This web-based platform has been argued to provide access to more representative sample of U.S. population with comparable or even better data quality compared to traditional approaches (Buhrmester, Kwang, & Gosling, 2011). Furthermore, data gathered from the Amazon Mechanical-Turk platform have been frequently used by previous technology acceptance studies (e.g., Chen, Xu, & Arpan, 2017; Lunney, Cunningham, & Eastin, 2016; Perry, 2016). In the current study, participants were asked to complete an online survey in return for a small monetary incentive. To ensure the validity and reliability of responses, a number of validation and attention check questions were inserted into the online survey in order to identify completed surveys that were randomly responded to. Responses that failed any of the validation and/or attention check questions were deleted, which resulted in a sample size of 439 which was considered to be adequate for a covariance based structural equation modeling (CB-SEM) analysis (Nunkoo, Ramkissoon, & Gursoy, 2013; Nunkoo & Ramkissoon, 2012; Sarstedt, Hair, Ringle, Thiele, & Gudergan, 2016).

3.2. Survey instruments

The survey instrument used in this study consisted of two sections: demographic information and main questions. The demographic information section asked questions related to gender, age, marital status, occupation, education, and income. The main questions consisted of the items to measure eight latent constructs included in the proposed model. Most of the items were adopted from previous scales. More specifically, items for social influence (6 items), hedonic motivation (5 items), anthropomorphism (4 items), performance expectancy (4 items), effort expectancy (3 items), emotion (5 items), and willingness to accept the use of AI devices (3 items) were adopted from the UTAUT scale (Venkatesh et al., 2012) and SRIW scale (Lu et al., 2019). Items for objection to using AI devices (4 items) were generated based on Wirtz et al.'s (2018) qualitative study. Items that were used to assess emotions were measured using a 5-point bipolar scale (e.g. bored/relaxed or unsatisfied/satisfied). Items that were used to assess other constructs included in the proposed model were measured by a 5-point disagree-agree Likert scale (1 – strongly disagree; 5 – strongly agree).

3.3. Data analysis

The proposed conceptual model was tested utilizing Mplus 7.11 through a two-step process. First, a confirmatory factor analysis (CFA) was conducted to test the adequacy of the measurement model. Afterwards, a structural model was tested to assess the magnitude and direction of the proposed relationships. In the first step, the measurement model was evaluated in terms of normality, reliability, convergent validity and discriminant validity. In the second step, the structural model was assessed by using maximum likelihood estimation based CB-SEM. Compared to PLS-SEM, CB-SEM provides smaller bias and more accurate results when the goal of the study is to test a theoretical model (Hair, Hult, Ringle, & Sarstedt, 2014) and when the constructs' measurement model is conceptualized as reflective and measured by a common factor model (Sarstedt et al., 2016).

4. Results

4.1. Demographic profile of respondents

As presented in Table 1, 57.5% of the participants were female and

Table 1
Demographic profile of respondents.

Items	Category	Distribution (%)
Gender	Male	42.5
	Female	57.5
Age	18–25	12.0
	26–34	38.2
	35–54	35.9
	55–64	10.5
	65 or over	3.4
Marital status	Single	31.6
	Married	46.4
	Live together	9.8
	Widowed	1.6
	Divorced	10.7
Occupation	Student	6.8
	Professional	44.8
	Managerial	14.1
	Sales	7.3
	Homemaker	11.8
Education	Other	15.2
	Less than high school	0.50
	High school graduate/G.E.D.	20.70
	Associate degree/Certificate	14.50
	Bachelor's degree	41.40
	Master's degree	15.7
	Doctorate degree	4.3
Annual Income	Others	3.0
	Under \$15,000	11.1
	\$15,000–\$29,999	17.5
	\$30,000–\$44,999	17.5
	\$45,000–\$59,999	19.1
	\$60,000–\$74,999	13.0
	\$75,000–\$89,999	7.0
	\$90,000–\$104,999	6.6
	\$105,000–\$119,999	3.0
	\$120,000–\$134,999	1.8
	\$135,000 and above	3.4

43.5% of them were male. A large portion of the participants were between 26 and 34 years old (38.2%), were married (46.4%), had professional occupations (44.8%), earned bachelor's degrees (41.4%), and had an annual family income in the range of \$45,000 to \$59,999 (19.1%). The demographic profile of respondents reported in this study is similar to the demographic profiles reported in previous technology acceptance studies that utilize a variety of data collection methods such as MTurk (Perry, 2016), convenience sampling in retail stores (Foroudi, Gupta, Sivarajah, & Broderick, 2018), or random sampling approach in market research studies (McLean, Al-Nabhani, & Wilson, 2018). This suggests that the sample is appropriate for this study in terms of demographic distribution.

4.2. Measurement model assessment

To ensure the quality of the data analysis, the study assessed the measurement model through a CFA. First, the normality of the measurement items for each construct was checked (Thompson, 2004). Based on the rule that the skewness and kurtosis should be less than 2 (Hair, Anderson, Tatham, & William, 1998), the result revealed no issues in the current dataset. Next, the internal consistency reliability, convergent validity, and discriminant validity of the items and constructs were assessed. Results indicated that all Cronbach's Alphas (Table 2) for the constructs were greater than the suggested cut-off value of 0.70 (Hair, Ringle, & Sarstedt, 2011) and the factor loadings (Table 2) for all items were substantial and significant, providing evidence for strong internal consistency. The average variance extracted (AVE) values (Table 2) for all constructs were above 0.50, indicating desired convergent validity (Fornell & Larcker, 1981). As presented in Table 3, all constructs' squared roots of AVEs were greater than the correlation between themselves and the other constructs (Table 3),

Table 2
Measurement scale properties.

Constructs/items	Item loadings	Cronbach's alphas	AVE
Social influence (SI)		0.93	0.69
SI1	0.823		
SI2	0.833		
SI3	0.856		
SI4	0.826		
SI5	0.809		
SI6	0.826		
Hedonic motivation (HM)		0.96	0.84
HM1	0.940		
HM2	0.949		
HM3	0.885		
HM4	0.926		
HM5	0.881		
Anthropomorphism (A)		0.92	0.75
A1	0.788		
A2	0.888		
A3	0.880		
A4	0.903		
Performance expectancy (PE)		0.64	
PE1	0.827		
PE2	0.786		
PE3	0.821		
PE4	0.765		
Effort expectancy (EE)		0.90	0.74
EE1	0.882		
EE2	0.878		
EE3	0.825		
Emotion (E)		0.95	0.77
E1	0.828		
E2	0.858		
E3	0.836		
E4	0.931		
E5	0.928		
Intention to use (I)		0.93	0.81
W1	0.865		
W2	0.934		
W3	0.900		
Objection to using AI(O)		0.91	0.73
O1	0.848		
O2	0.896		
O3	0.775		
O4	0.892		

Notes: SI = social influence; HM = hedonic motivation; A = anthropomorphism; PE = performance expectancy; EE = effort expectancy; E = emotion; W = willingness to accept the use of AI devices; O = objection to the use of AI devices.

suggesting desired discriminant validity (Hair et al., 2014).

Lastly, the overall measurement model's global fit was assessed. Result revealed that the measurement model had a good model fit. The CFI and TLI were 0.97 and 0.97 respectively, exceeding the recommended cut-off value of 0.95 for a good model fit (Hu & Bentler, 1999). The Root Mean Square Error of Approximation (RMSEA) was 0.04, and the standardized root-mean-square residual (SRMR) was 0.04, indicating a good fitted model as well (Hu & Bentler, 1999). The Chi-square value of the measurement model was 909.19, with 492 degrees of freedom. The ratio of Chi-square to degrees of freedom was less than 3, suggesting an adequate model fit (Kline, 2005).

4.3. Structural model assessment

The CFA results provided strong evidence that the measurement model was valid and reliable. Next, the AIDUA model was examined utilizing a CB-SEM. First, the model fit of the structural model was assessed. The Chi-square value of the structural model was 1258.41, and the degrees of freedom was 506 (yielding a ratio of Chi-square to degrees of freedom 2.59), suggesting that the model fit was good (Kline, 2005). The CFI and TLI were 0.95 and 0.94 respectively, indicating a good fitted model (Hu & Bentler, 1999). The RMSEA and SRMR of the

Table 3
Discriminant validity (correlation between construct and square roots of AVE).

Construct	SI	HM	A	PE	EE	E	W	O
Social influence (SI)	(0.831)							
Hedonic motivation (HM)	0.521	(0.917)						
Anthropomorphism (A)	0.416	0.238	(0.866)					
Performance expectancy (PE)	0.366	0.511	0.090	(0.800)				
Effort expectancy (EE)	−0.043	−0.306	0.294	−0.344	(0.860)			
Emotion (E)	0.572	0.795	0.206	0.609	−0.422	(0.877)		
Willingness to accept the use of AI devices (W)	0.507	0.758	0.155	0.656	−0.415	0.854	(0.900)	
Objection to the use of AI devices (O)	−0.261	−0.480	0.008	−0.415	0.541	−0.594	−0.613	(0.854)

Notes: Numbers in parentheses are square roots of AVE.

SI = social influence; HM = hedonic motivation; A = anthropomorphism; PE = performance expectancy; EE = effort expectancy; E = emotion; W = willingness to accept the use of AI devices; O = objection to the use of AI devices.

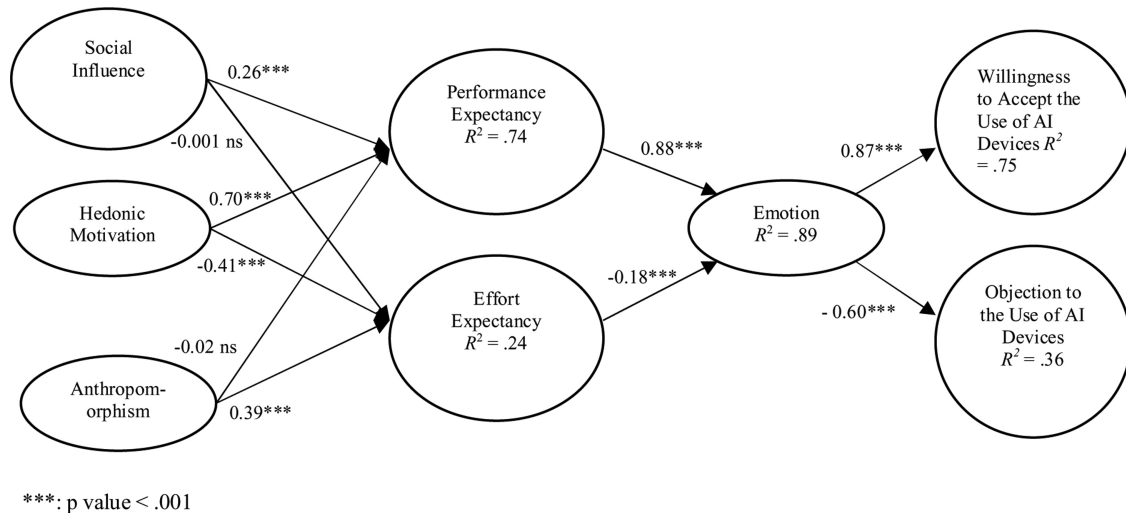


Fig. 2. Results of structural equation modeling. $***$ p value $< .001$.

model were 0.06 and 0.06 respectively, providing more evidence for the adequacy of the structural model (Hu & Bentler, 1999).

As shown in Fig. 2, results of the SEM indicated that all of the proposed hypotheses were supported, except for the H2 and H5. More specifically, this study found that social influence was positively related to performance expectancy ($\beta = .26$, $p < .001$), therefore, H1 was supported. Hedonic motivation was positively related to performance expectancy ($\beta = .70$, $p < .001$) and negatively related to effort expectancy ($\beta = -.41$, $p < .001$), providing support for H3 and H4. Anthropomorphism was positively related to effort expectancy ($\beta = .39$, $p < .001$), supporting H6. Performance expectancy was positively related to emotion ($\beta = .88$, $p < .001$) and the effort expectancy was negatively related to emotion ($\beta = -.18$, $p < .001$), thus, H7 and H8 were supported. In addition, emotion was positively associated with willingness to accept the use of AI devices ($\beta = .87$, $p < .001$) and negatively associated with objection to using AI devices ($\beta = -.60$, $p < .001$), supporting H9 and H10. However, findings indicated a non-significant negative relationship between social influence and effort expectancy ($\beta = -.001$, $p = .98$) and a non-significant negative relationship between anthropomorphism and performance expectancy ($\beta = -.02$, $p = .55$), thus, H2 and H5 were rejected.

The proposed structural model explained a significant portion of variances in each construct. More specifically, the model explained 74% ($p < .001$) of the variance in performance expectancy, 24% ($p < .001$) of the variance in effort expectancy, 89% ($p < .001$) of the variance in emotion toward using AI devices, 75% ($p < .001$) of the variance in intention to use, and 36% ($p < .001$) of variance in objection to using AI devices.

To provide more insight from the proposed model, indirect effects of

social influence, hedonic motivation, and anthropomorphism on emotion, and indirect effects of performance expectancy and effort expectancy on willingness and objection to accept the use of AI devices were estimated. Results revealed a significant positive indirect effect of social influence on emotion ($p < .001$) through significant effect of performance expectancy ($p < .001$) and non-significant effect of effort expectancy ($p = .98$), controlling for the effect of other variables included in the model. The indirect positive effect of hedonic motivation on emotion ($p < .001$) through significant effect of performance expectancy ($p < .001$) and significant effect of effort expectancy ($p < .001$) was also found to be significant, controlling for the effect of other variables included in the model. The indirect negative effect of anthropomorphism on emotion ($p = .01$) through non-significant effect of performance expectancy ($p = .55$) and significant effect of effort expectancy ($p < .001$) was found to be significant, controlling for the effect of other variables included in the model. In addition, higher levels of performance expectancy significantly predicted higher levels of willingness to accept the use of AI devices ($p < .001$) and lower levels of objection through the effect of emotion ($p < .001$), controlling for the effect of effort expectancy. Furthermore, higher levels of effort expectancy significantly suppressed willingness to accept the use of AI devices ($p < .001$) and higher levels of objection through the effect of emotion ($p < .001$), controlling for the effect of performance expectancy. A summary of the indirect effects is presented in Table 4.

5. Discussion

Findings of the current study support the proposed three-stage AIDUA model. More specifically, customers' evaluation of the

Table 4
Indirect effects among constructs.

Path	Estimated coefficient	p-value	
SI to E via PE	0.233	< .001	s
SI to E via EE	0.000	.983	ns
HM to E via PE	0.621	< .001	s
HM to E via EE	0.072	< .001	s
A to E via PE	−0.021	.553	ns
A to E via EE	−0.069	< .001	s
PE to W via E	0.768	< .001	s
PE to O via E	−0.532	< .001	s
EE to W via E	−0.154	< .001	s
EE to O via E	0.106	< .001	s

Notes: SI = social influence; HM = hedonic motivation; A = anthropomorphism; PE = performance expectancy; EE = effort expectancy; E = emotion; W = willingness to accept the use of AI devices; O = objection to the use of AI devices.

importance and relevance of using AI devices is based their social networks and group norms, hedonic motivation, and anthropomorphism during the primary appraisal. The primary appraisal stage results in a prime effect toward using AI devices and significantly influences customers' deliberate evaluations in the secondary appraisal stage. Meanwhile, during the secondary appraisal, the evaluation of performance expectancy and effort expectancy strongly determine customers' emotions toward AI device use. In the outcome stage, customers' emotions play a crucial role in determining their behavioral intentions toward AI devices. Results clearly suggest that customers' willingness to accept AI device use in service encounters is determined through a complex multi-stage process. This resonates with Lazarus's cognition-motivation-emotion framework (1991a), which argues in favor of a multi-steps belief/intention generation mechanism.

Findings suggest that norms and attitudes of individuals' social networks and groups (e.g. encouragement of friends and relatives for using AI devices) have a significant impact on customers' assessment of the costs and benefits associated with AI device use; the stronger is the social influence, the higher is the benefit perceptions and the lower is the cost perceptions. When individuals have inadequate experience with new technologies (e.g., AI devices), referents' opinions not only help decide whether these devices are worth using (Althuizen, 2018; Venkatesh & Davis, 2000a; Venkatesh & Davis, 2000b), but also alters their subjective evaluations on the perceived benefits and sacrifices. This study has revealed new insights that articulate the hidden rationale accounting for significant role of social influence in developing positive behavioral intentions toward AI device uses, beyond merely confirming previous findings (Althuizen, 2018; Jeon, Lee, & Jeong, 2018).

This study suggests that the customer is likely to view the AI device use as being relevant to his/her lifestyle as soon as their social networks have endorsed this new technology. This suggests that even before deliberately evaluating the benefits of using AI devices, a customer's social norms can result in generation of a prime effect that significantly influences the customer's secondary appraisal and their behavioral intentions toward AI device usage. This prime effect can work in different ways. First, the customer may believe that other people are willing to accept the use of AI devices because AI devices bring essential benefits such as performance competency. As a result, this belief positively influences the customer's own assessment on the performance features. Second, based on the social identity theory, the customer may believe that using AI devices benefits his/her social identity since other people in his/her social group are willing to accept the use of AI devices in service delivery. As a result, a positive attitude toward AI device usage is created due to this external motivation factor. Furthermore, as suggested by the non-significant relationship between social influence and effort expectancy, customers may not worry about the amount of effort required to use AI devices as long as they believe that the AI use is congruent with their group norms.

Thus, as the findings indicate, when customers conform to their group norms, they are more likely to focus on the benefits rather than on the costs. In fact, social influence (or social norms) can affect consumers' decision making due to various reasons (e.g., compliance, internalizing reference beliefs) such that its effect on technology adoption is context-dependent (Venkatesh & Morris, 2000). Although prior research has confirmed the positive effect of social influence on user acceptance of technologies (e.g., Venkatesh & Morris, 2000; Venkatesh, Morris, Davis, and Davis, 2003), existing studies only test its direct effect without supporting evidence explaining the underlying mechanisms. Beyond conforming to group norms, this study indicates that social influence is an important criterion for the focal customer to assess the performance benefits of AI devices, which in turn prompts positive emotions and behavioral outcomes.

Moreover, findings indicate a positive effect of hedonic motivation on performance expectancy and a negative effect on effort expectancy. Findings further suggest that hedonic motivation is the strongest predictor among the three determinants of performance and effort expectancy ($\beta = .70$ and $\beta = -.41$). This resonates with van der Heijden (2004) and Wei, Torres, and Hua, (2016) argument that hedonic motivation, such as perceived enjoyment and entertainment, plays a major role in determining customers' technology acceptance behavior. This finding suggests that customers who believe that using AI devices is fun and interesting are likely to perceive a higher level of performance of AI devices and lower level of effort required. There are two possible explanations for this phenomenon. First, high levels of hedonic motivation may bias customers' perception of benefits and costs of using AI devices. Again, based on Cognitive Dissonance Theory (Festinger, 1962), customers who have a high level of hedonic motivation for using AI devices are more likely to perform a deliberate evaluation that favors using AI devices. Second, customers who have a high level of hedonic motivation for using AI devices may have more experience with using new technology (Froehle & Roth, 2004). Therefore, they may be more knowledgeable and less concerned about the performance of AI devices. The higher levels of technology readiness can mitigate the perceived effort required for using AI devices.

Findings of this study also reveal that the higher level of anthropomorphism increases customers' perception of the effort required to use humanlike AI devices. This finding somewhat contradicts the results of previous studies that anthropomorphic features of an AI device positively influence customers' behaviors by increasing their engagement (Schuetzler, Giboney, Grimes, & Nunamaker, 2018), social presence, trust, and enjoyment (Qiu & Benbasat, 2009). In the current context, AI device's anthropomorphic features increase customers' perception of the amount of effort required to use the device. As discussed earlier, when customers interact with a humanlike AI device, they may treat the AI device as an intelligent being using their own social beliefs and norms (Kim & McGill, 2018). This process is likely to increase the effort required because they will be expected to perform two different types of activities: effort required to interact with a real human, as well as effort might be needed to learn a technological device. Thus, the human resemblance increases consumers' apprehension of the effort required when using AI devices (e.g., effort related to interacting with human and machines). This social attitude extension can be viewed as a double-edged sword. While some studies argue that social attitude extension can have positive impact on customers' attitudes toward the humanlike object, especially for non-intelligent self-service technologies, others argue that humanlike features of devices that possess humanlike intelligence may challenge customers' perception of human distinctiveness and self-identity (Ackerman, 2016; Fernández-Llamas et al., 2018). As a result, negative attitudes toward anthropomorphic AI devices may create a need to justify their objection to the use of AI devices. As suggested by the cognitive dissonance theory, consumers may use the amount of effort required as a defense mechanism to justify their unwillingness to use AI devices.

Another interesting finding revealed by the result is that there is a

non-significant negative relationship between anthropomorphism and customer's performance expectancy. This finding seems to challenge the findings of previous studies, which suggest that the more the humanlike features of a new technology, better the technology; thus, better the product performance (Canning, Donahue, & Scheutz, 2014; Wan & Aggarwal, 2015). However, anthropomorphism as a positive feature is only found for non-intelligence devices where the human appearance increases perceived performance as it relates the device to human intelligence (Mimoun, Poncin, and Garnier, 2012; Garnier & Poncin, 2013). These previous findings do not hold in the context of AI device use during service encounters. In fact, based on the current study, it is reasonable to conclude that customers' perceived anthropomorphism of AI devices is likely to cause negative attitudes toward these devices due to the perceived threat of self-identity. The human-identity triggered by anthropomorphism may lead customers to relate AI devices to regular human staff, as opposed to other non-intelligence devices. Their performance expectancy cannot be assessed based on the magnitude of human-resemblance. This clearly indicates that humanlike features do not bring any benefits associated with task performance and expected service quality of an AI device.

Findings indicate that both perceived performance of AI devices and perceived effort required to use them are critical factors that are used by customers to appraise the costs and benefits of AI device use and serve as critical determinants of customers' emotions toward their willingness to accept the use of AI devices. This finding highlights the utilitarian nature of customer's purchase evaluation behavior. That is, when customers are making a pre-purchase/pre-use evaluation, they are likely to analyze the benefits and costs associated with each available option. However, many other factors such as perceived social influence, hedonic motivation, and anthropomorphism may cause prime effects on this cost-benefit analysis. Based on this analysis, customers then generate their emotions toward their willingness to accept the use of AI devices in the service context. Findings also indicate that the effect of performance expectancy on emotions is much stronger than the effect of effort expectancy on emotions. This finding indicates that customer's perceived AI device performance is a more powerful predictor of their emotions, suggesting that service performance is likely to be a more important motivation factor than the perceived effort required.

Lastly, the current study finds emotions to be an ultimate antecedent of customers' willingness to accept the use of AI devices in service delivery. This resonates with Lu et al.'s (2019) finding that emotion is the most prominent determinant of customer's willingness to accept the use of AI devices. Instead of an instantaneous response to AI devices use, emotions in this study are developed through multiple stages of cognitive appraisals. Findings also indicate that the effect of emotions on willingness to accept the use of AI devices is large while the effect of emotion on objection is moderate. Customers who have higher positive emotions yield higher willingness to accept the use of AI devices. However, a plethora of concerns have risen when replacing service personnel with AI devices such as moral debates over a rising unemployment rate, diminished human civilization, inequality, and erosion of traditional value in services (i.e., high-touch) (Bossman, 2016; Huang & Rust, 2018). Thus, factors that lead to opposition of using AI in service encounters may be too complicated to be fully explained by emotion.

5.1. Theoretical contribution

This study makes some important contributions to the literature. The research identifies the most critical antecedents of customers' AI device acceptance willingness and tests the interrelations among those antecedents. Findings of this study suggest that utilization of previous technology acceptance models such as Technology Acceptance Model, Customer Acceptance of Technology, and Unified Theory of Acceptance and Use of Technology may not be applicable to studying customers' willingness to accept the use of AI devices because those models mainly

focus on customers' adoption of unintelligent functional technologies (Chan, Okumus, & Chan, 2017). As evidenced in this study, some of the most important determinants of technology adoption identified in those models are not applicable to the AI device adoption context. Furthermore, those models do not include some of the critical factors customized for AI device adoption behavior as per the recent research that develops a scale to conceptualize consumers' willingness to integrate artificially intelligent robots in service interactions (Lu et al., 2019). Thus, previous frameworks cannot explain the complex and multi-staged decision making process involved in this specific context (Lai, 2017; Lu et al., 2019).

The proposed AUDUA model suggests that customers go through a multi-stage decision making process resonating from the Cognitive Appraisal Theory in determining their willingness to accept the use of AI devices during service interactions. This multi-stage approach has transcended existing technology acceptance literature by identifying the underlying psychological path-ways to explain the evolution of consumers' behavioral intentions with AI devices that assume the role of service personnel. Including a multi-stage appraisal is necessary to understanding the complexity of the event and the subsequent behavioral outcomes (Tracy & Robins, 2004). Instead of treating all antecedents as independent factors as did previous research (e.g., Venkatesh et al., 2012), this multi-stage framework has revealed a theoretical rationale that explains the inter-dependent nature of these decision drivers and their sequence of occurrence.

Drawing on the Cognitive Appraisal Theory, the generation of positive emotions ultimately determines customers' willingness to accept the use of AI devices. Furthermore, the current study finds that the perceived level of anthropomorphism of an AI device significantly enhances customers' effort expectancy of using this device. This provides further support for the multi-stage decision making process. Rather than having a direct negative impact on customers' willingness to accept the use of AI devices, the negative effect of anthropomorphism is mediated through effort expectancy, which suggests that customers justify their refusal of using AI devices because of their humanlike features by assuming that interactions with them will require too much effort. This finding has unveiled an alternative mechanism that accounts for the negative emotion/consumers' behavioral outcomes engendered by anthropomorphism, which goes beyond the previous argument on the identity-threat imposed by the human-appearance (Ackerman, 2016). From an appraisal theory perspective, the current framework has added new knowledge to the literature.

5.2. Managerial implications

As discussed earlier, an increasing number of service companies are investing in development of AI devices in order to increase operational efficiency and decrease costs. However, studies suggest that not all customers are willing to accept the use of AI devices during their service encounters (Lu et al., 2019). For this reason, blindly investing in the AI technology without understanding customers' willingness to accept the use of AI devices may lead to waste of resources and/or even loss of customers. This is especially true in the service industry where employee-customer interaction is considered as one of the most critical determinants of service quality. Having AI devices to fulfill functional, social and emotional roles assumed by human employees has fundamentally challenged the core beliefs of customer service. Thus, customers may not view interacting with an AI device during service encounters as appropriate and may demand interactions with human employees (Lu et al., 2019). Therefore, understanding the decision drivers that lead to acceptance or objection of the use of AI devices in service delivery, and how these antecedents occur/interact in customers' decision pathways is fundamental for service companies that plan to introduce and/or increase AI device presence during service delivery.

Findings suggest that customers' positive emotions toward AI devices can alleviate customers' objection to the use of AI devices during

service encounters. In this study, the objection to the use of AI device is measured by a number of items that are related to customers' needs for social interaction, such as "people need emotion exchange during service transactions" or "I prefer human contact in service transactions". The negative relationship between emotions toward the use of AI and objection clearly indicates that some customers need interactions with human employees during service encounters. However, this does not mean that companies should shun AI devices for frontline services. Rather, AI devices can be used as supportive services under the supervision of human staff, which may be perfectly acceptable by AI opponents. Findings also indicate that performance expectancy is an important determinant of positive emotions. Thus, managers should focus on ensuring and enhancing the performance of AI devices as a means of eliminating human errors and improving service competency (e.g., language assistance, task efficiency, and information storage). Highlighting the performance advantages such as accuracy, reliability, efficiency and consistency in communication and marketing materials may increase customers' willingness to at least try services provided by AI devices.

Findings also highlight the importance of social influence on AI devices' performance expectancy. Results indicate that as more and more in-group members are willing to accept the use of AI devices, the focal customer is likely to view the use of AI devices as an efficient and effective service delivery tool and, thus, be more willing to accept their use in service delivery. For this reason, marketers may want to focus on individuals who are open to the use of AI devices in service delivery and use their testimonials to attest to AI devices' superior performance through marketing communication materials. These active users/interested groups should also be incentivized to share their experiences through social media (e.g., Facebook, Instagram, twitter, and YouTube) to gain further traction from their internal social network. Service companies may also create on-site experiential events using AI devices to increase publicity and encourage customer participation from local communities. After gaining direct experience and knowledge of AI device use in service delivery, consumers are more likely to embrace their presence at service encounters (Virabhakul & Huang, 2018). Such actions may help marketers to develop strategies to turn AI use in service encounters into a social trend.

Findings also provide support for previous studies arguing that the humanlike features of AI devices do not necessarily lead to customer acceptance (Goudey & Bonnin, 2016; Lu et al., 2019). More specifically, this study found that the anthropomorphism of an AI device increases customers' perception of effort required to interact with an AI device during service delivery, which also lowers customers' perceptions of AI device performance. Humanlike appearances seem to threaten customers' human identity (Ackerman, 2016) because people may become uncomfortable with the thought that humans might be losing their distinctiveness to humanoids (Ackerman, 2016). Thus, AI devices should not possess humanlike appearances and body structures if they are to be used in the service delivery process. Thus, having partially anthropomorphic appearance or little human resemblance may work better than having a complete humanlike appearance.

6. Conclusion

This study developed and tested a theoretical model to explain the multi-stage decision-making of customers' willingness to accept AI device use in service encounters and the interrelationships among important predictors. Six predictors that significantly influence customers' AI adoption behavior were identified from previous studies, including

social influence, hedonic motivation, anthropomorphism, performance expectancy, effort expectancy, and emotion toward the use of AI devices in service encounters. Based on the premises of the cognitive appraisal theory, this study proposed a three-stage artificial intelligent (AI) device use acceptance (AIDUA) model. The primary appraisal stage involves customers' evaluation of the importance and relevance of AI device use; the secondary appraisal stage focuses on consumers' evaluation of the perceived benefits (performance expectancy) and the perceived costs (effort expectancy) of using AI devices, which results in generation of emotions toward the use of AI devices in service encounters. The outcome stage reflects the impact of emotions on customers' willingness to accept AI device use and their objection to the use of AI devices in service encounters.

As discussed earlier, even though several studies have already investigated different AI related topics, there is still not a comprehensive theoretical and conceptual framework that can be used to explain customers' attitude generation process toward the use of AI devices and the most critical determinants of AI acceptance. In other words, there is still a lack of understanding of how customers' AI device use acceptance willingness is generated or curbed by a battery of different antecedents in the service context. The AIDUA model proposed in this study can be used to explain customers' willingness to accept the use of AI devices or refuse to use AI devices during service encounters.

6.1. Limitations and future research directions

The current study is not free of limitations. First, the AIDUA model needs to receive additional testing to increase its generalizability. Data for this study were collected from U.S. residents through an online survey, so the generalizability of the model to populations from other countries is unknown. Future research should be conducted using the general public sample, preferably a cross-national sample to assess the generalizability of the AIDUA model proposed and tested in this study. In addition, future studies are needed to test this AIDUA in different service sectors such as hotel, restaurant, retail store, or airline. Since different service sectors may involve different type and amount of employee-customer interaction, testing AIDUA in a specific sector can provide more insight to understand customers' AI device adoption behavior.

The cross sectional design used in this study may have limited the ability of observing change patterns of subjects across time, which may have caused misidentification of the relationships between variables. Longitudinal study designs provide opportunities to validate the AIDUA model's stability over time and to investigate the relationships among the variables in more valid ways. Especially, if data on other criterion variables are collected using a longitudinal administration of the AIDUA model, the validity of the AIDUA model can be assessed more accurately.

This study examined only a small number of factors that can influence customers' willingness to accept the use of AI devices during service encounters. There might be other variables that may have significant impact on customers' willingness to accept the use of AI devices. Future studies should investigate if there are any other antecedents of willingness to accept the use of AI devices that can be added to the current framework in order to increase the model's predictive power. This might be especially useful if the future studies can identify other factors to predict the effort expectancy since the antecedents used in the current study (hedonic motivation and anthropomorphism) explained only 24% of the total variance for effort expectancy.

Appendix

Construct	Item NO.	Items	Means	SD	Skewness	Kurtosis	Supporting literature
Social influence	SI1	Using AI devices reflects status symbol in my social networks (e.g., friends, family and co-workers)	3.15	1.733	.486	−.786	Lu et al. (2019)
	SI2	People who influence my behavior would want me to utilize AI devices	3.46	1.652	.080	−.902	Venkatesh et al. (2012)
	SI3	People in my social networks who would utilize AI devices have more prestige than those who don't	3.24	1.700	.311	−.945	Lu et al. (2019)
	SI4	People whose opinions that I value would prefer that I utilize AI devices	3.45	1.597	.213	−.681	Venkatesh et al. (2012)
	SI5	People who are important to me would encourage me to utilize it	3.43	1.599	.210	−.747	Venkatesh et al. (2012)
	SI6	People in my social networks who would utilize artificially intelligent have a high profile	3.55	1.622	.065	−.758	Lu et al. (2019)
Hedonic motivation	HM1	I have fun interacting with AI	4.30	1.736	−.387	−.806	Lu et al. (2019)
	HM2	Interacting with AI devices is fun	4.22	1.673	−.341	−.732	Venkatesh et al. (2012)
	HM3	Interacting with AI devices is entertaining	4.46	1.675	−.573	−.561	Venkatesh et al. (2012)
	HM4	Interaction with AI is enjoyable	4.23	1.699	−.288	−.786	Venkatesh et al. (2012)
	HM5	The actual process of interacting would be pleasant	4.17	1.636	−.230	−.725	Lu et al. (2019)
Anthropomorphism	A1	AI devices have a mind of their own.	2.33	1.580	1.241	.694	Lu et al. (2019)
	A2	AI devices have consciousness.	2.08	1.426	1.545	1.960	Lu et al. (2019)
	A3	AI devices have their own free will.	2.17	1.478	1.435	1.454	Lu et al. (2019)
	A4	AI devices will experience emotions.	1.98	1.372	1.603	1.921	Lu et al. (2019)
Performance Expectancy	PE1	AI devices are more accurate than human beings	4.66	1.525	−.695	−.126	Lu et al. (2019)
	PE2	AI devices are more accurate with less human errors	4.86	1.467	−.760	.103	Lu et al. (2019)
	PE3	AI devices provide more consistent service than human beings	4.85	1.524	−.666	−.121	Lu et al. (2019)
	PE4	Information provided by AI devices are more consistent	4.95	1.429	−.823	.268	Lu et al. (2019)
Effort Expectancy	EE1	Using AI devices takes too much of my time.	3.13	1.620	.472	−.637	Lu et al. (2019)
	EE2	Working with AI devices is so difficult to understand and use in services	3.00	1.580	.544	−.685	Lu et al. (2019)
Emotion	EE3	It takes me too long to learn how to interact with AI devices	2.99	1.687	.608	−.709	Lu et al. (2019)
	E1	Bored-relaxed	4.62	1.557	−.277	−.323	Lu et al. (2019)
	E2	Malancholic-contented	4.55	1.560	−.315	−.363	Lu et al. (2019)
	E3	Despairing-hopeful	4.38	1.590	−.184	−.412	Lu et al. (2019)
	E4	Unsatisfied-satisfied	4.54	1.805	−.403	−.812	Lu et al. (2019)
Willingness to Accept the Use of AI Devices	E5	Annoyed-pleased	4.35	1.832	−.305	−.932	Lu et al. (2019)
	I1	I am willing to receive AI device services	4.88	1.654	−.946	.212	Venkatesh et al. (2012)
	I2	I will feel happy to interact with AI devices	4.46	1.796	−.430	−.824	Lu et al. (2019)
Objection to the Use of AI Devices	I3	I am likely to interact with AI devices	4.62	1.772	−.581	−.648	Lu et al. (2019)
	O1	The information is processed in a less humanized manner	4.33	1.879	−.308	−1.084	Wirtz et al.'s (2018)
	O2	I prefer human contact in service transactions	4.57	1.985	−.454	−1.083	Wirtz et al.'s (2018)
	O3	People need emotion exchange during service transactions	3.95	1.849	−.133	−1.146	Wirtz et al.'s (2018)
	O4	Interaction with AI devices lacks social contact	4.44	1.949	−.388	−1.121	Wirtz et al.'s (2018)

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