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Linking AI quality performance and customer engagement: The moderating effect of AI preference

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ABSTRACT

Drawing upon affordance theory, this study positions artificial intelligence (AI) as a commercial service in examining its influence on customer engagement in the hotel context. In particular, we seek to understand linkages between customer perceptions of AI service quality, AI customer satisfaction and engagement. Given the multiplicity of services offered by service organisations, customers' preference for AI service is modelled as a moderator of customer perceptions and attitudes towards AI. Data was collected from a sample of hotel customers in Australia who had previously used AI tools or services. Our results reveal a significant chain effect between AI service indicators, service quality perceptions, AI satisfaction and customer engagement. AI preference has a significant moderation effect on information quality and satisfaction. These findings provide new insights into the consumer services literature and have important implications for marketing practitioners.

1. Introduction

Artificial intelligence (AI) refers to computational agents that act, respond or behave intelligently (Poole and Mackworth, 2010). AI is manifested in humanoid and non-humanoid forms (e.g., automated services) that can mimic or perform human tasks and solve problems through learning, analysing and interpreting data (Mellit and Kalogirou, 2008). AI has evolved rapidly from performing simple tasks (e.g., Siri) to undertaking more sophisticated social functions such as recognising customers' emotions for subsequent intervention (Prentice et al., 2019a). AI can be effectively utilised in reasoning, explaining, modelling, predicting and forecasting.

AI as an information technology (IT) innovation has progressively infiltrated the commercial world to facilitate internal business operations for the organisation and external transactions with customers in both personal and impersonal service encounters (Prentice et al., 2019a,b,c). For instance, AI can be used in personnel recruitment by combining face recognition and natural language processing technologies during interviews; training and development using robots and visual scanning technologies; and salary evaluation through neural network functioning (Jia et al., 2018). Amazon and Netflix routinely utilise AI to analyse customer data and customise products for customers (Walch, 2019).

Despite its extensive application across organizations and industries, AI research has centred on technological development and advancement in IT-related disciplines (Prentice et al., 2019a,b,c). Given its technological focus, there has been a plethora of research investigating technological acceptance and user (e.g., IT technicians) satisfaction over the last decade (e.g., Dwivedi et al., 2019; King and He, 2006; Marangunić and Granić, 2015; Wixom and Todd, 2005; Wu and Chen, 2017). In practice, AI (e.g. robots) is extensively used in customer service to engage customers and enhance the service experience by providing convenience and flexibility (e.g., 24 -h automated services; concierge robots). Industry practitioners and IT consultants are the most prominent protagonists who promote and reinforce the role of AI in customer-centric businesses (e.g., Kannan and Bernoff, 2019; Walch, 2019; Walchuk, 2019). Research in this area is rather limited, which in part is due to disparate understanding and conceptualisation of AI. From an IT perspective, AI refers to intelligence exhibited by machines through machine learning and natural language processing (Russell and Norvig, 2016). From the business perspective, AI represents technologically powered systems or tools that facilitate business operations to achieve cost efficiencies and promote profit maximisation (Prentice et al., 2019a,b,c). From a user perspective, AI is a series of tools that improve task efficiency (e.g., for employees) and provide added convenience and flexibility to consumers (Wirtz et al., 2018). These firm-level perspectives view AI as a type of commercial service that is enabled by IT, provided by organizations, and utilised by customers to

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improve the customer service experience and engage customers.

This paper positions AI-powered tools (e.g., concierge robots in hotels, travel enhancers, chatbots) as computer/machine-enabled services that cater to customers in a fashion similar to other commercial services (e.g., employee service) and benefit all involved parties (e.g., the organisation, customers) (de Kervenoael et al., 2020). These tools hereafter are referred to as AI services, or (more simply) AI in this study. This view accords with affordance theory (Gibson and Nobel, 1986), which considers environmental objects around an organism (e.g., an animal, a human) as an opportunity for action (Gibson, 2000). We suggest that AI services can be such objects. In particular, customers or service providers represent organisms that perceive AI as an opportunity to attain added convenience (for customers) and can provide increased levels of customer engagement (for the provider). The affordance theoretical perspective suggests that AI tools have inherent meaning that users can understand and apply without necessarily understanding their sophisticated technological underpinning (Jones, 2003).

Although the theory originated in the ecological literature, the affordance concept has been widely applied to organisations to understand how technologies (e.g., AI) can be utilised to achieve organizational outcomes including operational efficiency, customer satisfaction and engagement (e.g., Cabiddu et al., 2014; Ganguli and Roy, 2011). In essence, AI-powered tools in service organisations are manifested as services provided to customers such as the humanoid robot "Connie" in Hilton hotels, and chatbots providing around-the-clock messaging services. These AI-powered tools facilitate business transactions and enhance customer experiences.

Viewed as a commercial service, AI must demonstrate its economic value in terms of how customers perceive, value, assess and respond to such service. Customer perceptions and assessments determine service quality outcomes. Customer responses are reflective of their attitudes (e.g., satisfaction) and behaviours (purchase and loyalty), as explained by Ajzen's (1985) theory of planned behaviour (TPB). This theory links beliefs, attitudes, behavioural intentions and behaviours and has been extensively applied in various fields including psychology, marketing and IT (De Groot, Steg, 2007; Liao et al., 2007; Prentice and Kedan, 2019). However, TPB has attracted some criticism. Numerous studies have shown that attitudes (e.g., satisfaction) can be a significant antecedent of behavioural intentions but an insignificant predictor of behaviours; nevertheless, objective beliefs such as perception of service quality often lead to purchase and loyalty behaviours (e.g., Prentice, 2013; Sniehotta et al., 2014a,b). Such inconsistency may be attributed to study contexts, research design, or choices of behavioural indicators (Sniehotta et al., 2014a,b). To understand how AI, as commercial services provided to customers by service organizations, relates to customer response, the current study adopts customer engagement as the outcome variable, as this construct captures multidimensional outcomes (affective, cognitive and behavioural) rather than behavioural consequences (Hollebeek, 2011; So et al., 2016).

In reality, AI has been used in customer services to engage customers. For instance, chatbots as the first point of contact could identify customer needs and problems and transfer customers to human agents when necessary. Chatbots sometimes engage customers by providing a positive and consistent level of interaction with customers and continuous service to promote seamless service experiences (Walch, 2019). Customer engagement is related to organizational consequences including financial and non-financial outcomes (Pansari and Kumar, 2017; Prentice et al., 2020; So et al., 2016). Understanding linkages between AI and customer engagement has implications for optimising organizational performance manifested in customer- and firm-related outcomes (Van Doorn et al., 2010; Prentice et al., 2019b).

Consistent with the preceding discussion, this study examines how AI services are related to AI service quality, customer satisfaction and customer engagement. Given that organisations provide multiple service components (e.g., servicescape, employee service), the study also investigates how customer preferences for AI service influence customer satisfaction with AI services and engagement in the hotel setting. The next section reviews relevant literature in relation to AI and customer engagement, and proposes relationships that link these two areas. Then, the research findings, implications and salient conclusions are presented.

2. Literature review

2.1. AI service quality

AI generally embodies machine simulations of human intelligence for performing human tasks operated through machine or deep learning (Russell and Norvig, 2009). Machine learning inlcudes the interpretation and understanding of imputed data which are used for predetermined goals and tasks (Russell and Norvig, 2009). AI can act humanly; and has the ability to learn, react and cooperate like humans (Russell and Norvig, 2009). AI has evolved from a narrow conceptualisation of intelligence centering on the performance of simple tasks (e.g., Siri being able to solve problems independently), to artificial super intelligence, which is yet to be invented but anticipated to be capable of incorporating more sophisticated social skills and creativity (Kaplan and Haenlein, 2019). This evolution accords with Wirth's (2018) weak AI that is designed to perform specific tasks, hybrid AI that can blend multiple solutions and undertake new tasks, and strong AI that can deal with a variety of more complex tasks. Based on its functionality, AI can be categorised into analytical AI, human-inspired AI, and (forthcoming) humanized AI (Kaplan and Haenlein, 2019). Analytical AI is manifested in cognitive intelligence and learning for forecasting and predicting. Human-inspired AI is designed to recognise and understand human emotions (facial recognition tools to understand customers' emotions) in decision-making. Humanised AI will possesses cognitive, emotional, and social intelligence that closely resembles that of humans. For clarity, these categories can be classified as informational and systematic AI.

AI has been incorporated into various types of technologies: for instance, 1) automation, such as robotic process automation, which differs from IT automation and can be programmed to perform high-volume, repeatable tasks like humans; 2) machine or deep learning, which enables computers to automate predictive analytics and act without programming, including supervised, unsupervised and reinforcement learning; 3) machine vision, which captures and analyses visual information using cameras and digital signal processes such as human eyesight, which can be used, for example, in signature identification and image analysis; 4) natural language processing (NLP), which is based on machine leaning and processes human language via a computer program including text translation, sentiment analysis and speech recognition (e.g., spam detection which determines a junk or spam mail based on the subject line and the text); 5) robotics that are used to perform mundane tasks requiring low-level social interactions (e.g., assembling lines in manufacturing); 6) self-driving cars, which automate safe driving using computer vision, image recognition and deep learning capabilities (Burns and Laskowski, 2018).

AI has been applied across various fields (Buhalis and Leung, 2018; Yu and Schwartz, 2006). For instance, in healthcare, AI is used to improve symptoms diagnoses to improve patient outcomes and reduce costs (Jiang et al., 2017). In education, AI is used to automate grading, track students' progress, and support tutors and students (McArthur et al., 2005). In finance, AI is used to collect biodata for the provision of financial advice for clients (Bahrammirzaee, 2010). In retailing, AI can support inventory management (e.g., Amazon's analytical AI) (Liu et al., 2018). And in tourism, AI-powered robots can serve as tour guides to improve tourist participation (Ivanov et al., 2017). In human resource management, AI assists in screening and selecting suitable candidates (Maduravoyal, 2018). AI in service organizations has functioned as part of service offerings provided to customers to facilitate

transactions and improve customer experience (Bolton et al., 2018; Chung et al., 2018). For instance, AI is used in customer relationship management by tracking customer information to customise services (Morosan and Bowen, 2018). Hotels use chatbots to answer customer inquiries, and auto-cars to pick up guests at the airport and assist check-in processes (Chung et al., 2018). "Connie" is a robot concierge used in Hilton hotels to interact with guests and provide requested information.

As in any commercial service, the value of AI services is revealed in customer perceptions and assessments of such services. In the service-marketing literature, service quality often reflects customers' perceptions and value-judgments of a service Yuan and Jang (2008). Service quality captures service excellence that is deemed to meet or exceed customer expectations (Parasuraman, 1995; Prentice, 2013; Shi et al., 2014). Equally, the quality of AI services is manifested in customers' perceptions and assessments. Unlike other services offered by organizations, AI is a technology-based service which involves information and system characteristics that influence information and system quality perceptions and, ultimately, user satisfaction (Wixom and Todd, 2005).

Information quality is pertinent to accuracy, currency, presentation and completeness of AI service provision (Wixom and Todd, 2005). The information provided by AI-powered applications such as Siri, chatbots and other automated messaging tools must be as accurate and timely as possible to effectively address users/customers' queries (Hong et al., 2001/2002). For example, AI-powered E-travel agents manage travel planning, sightseeing, car rentals and hotel bookings. The information relating to these activities must be reflective of customer requests and demands (Zanker et al., 2008). The activities recommended by AI-powered intermediaries must be consistent with tourists' preferences and requirements (Rodriguez-Garcia et al., 2011; Zanker et al., 2008). The accuracy of destination information by Smart Tourist Information Points is important for tourists' decision-making pertaining to destination choice (Garrido et al., 2017). System quality is predicated on the responsiveness of AI-powered tools and flexibility of the system adapted to a variety of user/customer demands (Wixom and Todd, 2005). For instance, restaurants use AI to assist customers in ordering food, which varies across customers. AI tools must respond to customers in a timely manner and provide sufficient flexibility in line with customer demands. These AI services are deemed as object indicators that influence object-based beliefs, while service quality is based on customers' perceptions and assessments; hence AI services regarded as object-based beliefs. This discussion informs the following hypotheses:

Hypothesis 1a. AI service is positively and significantly related to AI information quality.

Hypothesis 1b. AI service is positively and significantly related to AI system quality.

2.2. AI service quality and customer satisfaction

Service quality is related to an individual's object-based attitude, which is manifested in the level of satisfaction with service quality based on the theory of planned behaviour (Fishbein and Ajzen, 1980; Wixom and Todd, 2005). Customer satisfaction, deemed as a post-consumption response, is defined as an overall feeling of pleasure or disappointment emerging from comparisons of perceived performance of a service with pre-service expectations (Oliver, 1980). Customer satisfaction can be measured as transaction-specific with discrete elements or events (e.g., AI information quality, AI system quality), or as overall satisfaction reflecting a holistic assessment of all experience encounters (Cronin et al., 2000; Gustafsson et al., 2005; Veloutsou, 2015). Overall satisfaction with a service is relevant to the attributes of the provided service (Chow, 2014).

Service quality and customer satisfaction are generally regarded as discrete constructs and modelled separately (Cronin and Taylor, 1992; Jingxue & SooCheong, 2008; Hu and Huang, 2011; Yoon and Uysal, 2005). Service quality perceptions are cognitive reactions to the experience, whereas customer satisfaction represents an affective reaction to that experience (Tosun et al., 2015). Service quality is an antecedent to customer satisfaction (Cronin et al., 2000; Rust et al., 1995; Woodside et al., 1989; Zeithaml et al., 1996). Consistent with the aforementioned two-dimensional service quality, customer satisfaction can be operationalised into information and system dimensions. The services marketing literature confirms that service quality is widely recognised as an antecedent of satisfaction and behavioural intentions that leads to organisational profitability (Cronin et al., 2000; Kim et al., 2016; Zeithaml et al., 1996), and we believe that such a relationship would also be present in AI applications. Accordingly, we suggested:

Hypothesis 2a. AI information quality is positively and significantly related to customer satisfaction.

Hypothesis 2b. AI system quality is positively and significantly related to customer satisfaction.

2.3. Customer satisfaction and customer engagement

Customer engagement indicates the process of customers' "reaching out" to the organization, demonstrated in their cognitive, emotional, behavioural, sensorial, and social responses (Lemon and Verhoef, 2016). Customer engagement can also be referred to as state of mind or a psychological process that generates customer loyalty (Bowden, 2009; Kumar and Pansari, 2016). Customer engagement includes co-creation, social influence through word of mouth, customer referrals, purchasing behaviour, influencing, and knowledge behaviours (Verhoef et al., 2010)

Customer engagement reflects co-creation between the service providers and customers; and the level of engagement with the service organization and its associated businesses has financial implications for the organization as well as for customers (Brodie et al., 2011; Hoyer et al., 2010; Nambisan and Nambisan, 2008). Van Doorn et al. (2010) provided a comprehensive conceptual framework detailing the antecedents, components and consequences of customer engagement. Customer satisfaction is proposed as a customer-based predictor of customer engagement. Relevant marketing and management literature shows that customer satisfaction is a universal antecedent of behavioural intentions and behaviours (Bowen and Chen, 2001; Kandampully and Suhartanto, 2000; Yuksel et al., 2010). These studies show that a high level of satisfaction influences customer patronage and retention. However, many empirical studies also demonstrate that this relationship is not significant (e.g., Bitner and Hubbert, 1994; Kivela et al., 2000; Rust et al., 1995). Neal (1999) argued that satisfaction on its own cannot predict customers' purchase behaviour or loyalty, but could possibly improve customer involvement with the organization or the brand. For example, although a satisfied customer may not return to the business on account of financial constraints or other situational factors, this customer can still be engaged with the organization as a source of referrals. Similarly, an extremely dissatisfied passenger might engage with the organization in the sense of spreading negative word of mouth communication, or continue to be engaged in other ways that may be available.

Customer satisfaction with AI service quality should engage customers. For instance, a concierge robot can interact with hotel guests for an extended period of time (Rodriguez-Lizundia et al., 2015). Interactive experience is an important means to enhance customer engagement in the service organization (Hayes and MacLeod; Vivek et al., 2014). Customers tend to be more engaged when they receive pleasant and memorable experiences with AI services. Such experience motivates customers to have more physical, mental, social, and emotional engagement with the brand or the associated organisation (Carù and Cova, 2003; Hayes and MacLeod, 2007; Ullah et al., 2018). Based on the

preceding discussion, we proposed the following hypotheses:

Hypothesis 3. Customer satisfaction with AI (i.e., AI satisfaction) is positively and significantly related to customer engagement.

2.4. AI preference as a moderator

Service organisations offer tangible and intangible services. Tangible services generally include impersonal components such as facilities and other servicescape elements; whereas intangible services refer to services provided by employees. AI services can be tangible (e.g., concierge robots) or intangible (e.g., chatbots). Numerous studies have shown that employee service is pivotal in determining customers' attitudes and behaviours (e.g., Delcourt et al., 2013; Prentice, 2013). Customers prefer personal interactions with service employees who are reliable, responsive, professional, and empathetic as shown in SERVQUAL measures (Parasuraman et al., 1991; Prentice, 2013), AI does provide unprecedented convenience (24-h automated services) to customers. However, given that AI is operated through machines and computer programs, the level of AI service is dependent upon both imputed data and programming capability. Each individual customer has different requests and demands (Prentice, 2013), and AI may not equip to provide customised services (Prentice et al., 2019a, b, c). The choice of individualised services by employees and the convenience provided by machines may help satisfy individual preference.

In the social sciences, the notion of preferences is derived from rational choice theory, which refers to an optimal choice based on the decision-maker's best interest and the relative utility of given alternatives (Blume and Easley, 2016). The premise of the theory is that humans act as rational agents who consider the costs and benefits of a task carefully and behave consistently with self-determined choices (Tversky and Kahneman, 1986). Preference represents customers' disposition to favour services provided by an organization. Prior research shows that preference is related to customer-related outcomes such as purchase intention, willingness to buy and becoming a referral (Bagozzi, 1992). However, Tversky and Thaler (1990) indicate that preference is a context-dependent process by means of choice, and hence labile. We argue that customers who have a preference for AI services may hold more positive object-based attitudes (manifested in satisfaction with AI) and tend to be more engaged with object-related entities. This proposition accords with rational choice theory in that an individual would be able to better enjoy experience with AI services, and hence be more engaged with such "self-determined choice," when the quality of the AI service is superior and the consumer holds a high level of interest. Consequently, we hypothesized:

Hypothesis 4a. AI preference has a significant moderation effect on the relationship between AI information quality and AI satisfaction.

Hypothesis 4b. AI preference has a significant moderation effect on the relationship between AI system quality and AI satisfaction.

Hypothesis 5. AI preference has a significant moderation effect on the relationship between AI satisfaction and customer engagement.

The proposed research framework and relationships are shown in Fig. 1.

3. Methods

3.1. Sample

The study was undertaken at hotels in Australia. AI service is extensively used in hotels, where it includes robots like Connie in Hilton, chatbots and messaging, smart room controls, voice-controlled entertainment and etc. The data were collected from a sample of customers who had stayed in one of Australian hotels within last 12 months that used AI-powered tools to serve customers. The prospective respondents were those who understood and had used AI services in these hotels. The respondents were aged above 18 years. Screen questions were developed to ensure these criteria. Each AI service was explained in detail with examples and appropriate weblinks so that the prospective respondents had a better understanding of their AI service experience. The survey was conducted online through Qualtrics. Online surveys offer flexible, convenient and cost-efficient data collection (Burns and Bush, 2003). Virtual snowball sampling was employed to access hidden populations. This method has merits of recruiting more sample by respondents/participants distributing the online survey (the weblinks) to their networks on various social media platforms (e.g. Facebook, LinkedIn) (Baltar and Brunet, 2012). This sampling technique is respondent-driven and has advantage of generating more respondents with similar backgrounds since they are connected in their social networks as friends, relatives or colleagues (Heckathorn, 2011). Given AI service is manifested in various forms and some of which may not be perceived as AI, any relevant queries from respondents can be directed to their friends via social media for a speedy response rather than to the researchers.

3.2. Measures

The scale measurements of interest were adopted from the existing literature. Each scale item was evaluated using a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). AI-related variables including AI performance drivers, quality, and satisfaction were adopted from Wixom and Todd (2005). The *AI service performance drivers* scale contains 15 items pertaining to five aspects of AI performance, including *AI accuracy, currency, reliability, flexibility, and timeliness*. Each driver contains three items, and it demonstrates adequate scale consistency with Cronbach's alpha (α) $\geq$ .80. *AI information quality* and *AI system quality* both contain three items, and they demonstrate good scale consistency with $\alpha = .92$. Although *AI information satisfaction* and *AI system satisfaction* were assessed by two items, scale reliability remains adequate with $\alpha \geq .88$. AI preference was adopted based on the work of Cialdini et al. (1995). The scale contains three items, and it demonstrates good reliability with $\alpha = .93$.

A 25-item customer engagement measure was adopted from So et al's (2016) multidimensional scale. This measure was deemed to be suitable since it was developed in the tourism and hospitality context and reflects customers' affective, cognitive and psychological involvement with the brand or organisation. Five dimensions were included in this measure: 1) *identification*, representing customers' attachment to the brand; 2) *attention*, indicative of customers' attentiveness; 3) focus and connection with the brand, reflecting enthusiasm representing customers' excitement and interest; 4) *absorption*, indicating customers' pleasant state; and 5) *interaction*, indicating customers' participation. The scale is highly reliable, with $\alpha = .98$.

3.3. Procedure

A pilot study was conducted with PhD students who had experienced AI services in hotels, to ensure appropriate response time and clarity of wording. Consequently, some wording of the questionnaire items was modified. The information enclosed with the survey stated that participation in the survey was voluntary and anonymous, and could be terminated at any time at the respondents' discretion; although the survey was designed to prevent skipping questions should they decide to participate. Respondents were requested to respond as truthfully and accurately as possible. The survey was closed after 3 weeks, with nearly 400 valid responses generated. The demographic characteristics are shown in Table 1.

4. Analysis and results

Details for scale reliability and convergent validity (average

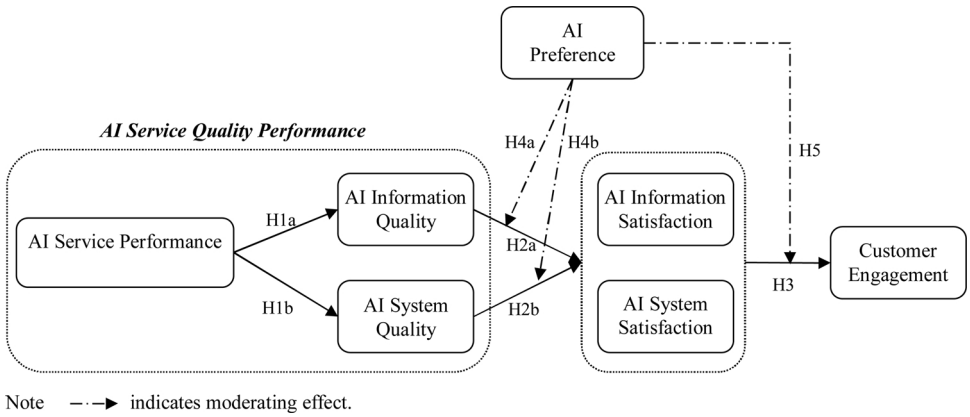

Fig. 1. Research Framework.

Table 1
Demographic profile (N = 380).

Characteristics		%
Gender	Male	49.2
	Female	50.8
Age	18 – 25	9.2
	26 – 35	28.2
	36 – 45	20.0
	46 – 55	17.1
	56 or more	25.5
Education	Below high school	1.3
	High school	17.4
	College	20.0
	Undergraduate	37.1
	Postgraduate	22.6
	Others	1.6
Reasons for stay	Business	25.3
	Leisure	43.9
	Visiting relatives	21.1
	Education	5.8
	Others	3.9

variance extracted [AVE]) are presented in Table 2. Discriminant validity was supported with AVEs for each factor greater than the squared correlation of each part of the factors. The measurement model as a whole demonstrates adequate fit with $\chi^2_{(1215)} = 2{,}719$ ($\chi^2/df = 2.30$), comparative fit index (CFI) = .99, root mean square error of approximation (RMSEA) = .06, and standardized root mean square residual (SRMR) = .06.

4.1. Data diagnostics

We diagnosed common method variance by using the marker variable method (Podsakoff et al., 2003). We selected a theoretically unrelated variable – employee empathy (five items) – adopted from Parasuraman et al. (1991). However, there is no significant change to the findings after partialing out its variance. Multicollinarity was assessed through variance inflation factor (VIFs) with values < 3.0 lower than the recommend threshold 10.

Descriptive statistics and zero-order correlation are presented in Table 2. To test the proposed relationships, we used multiple regression and presented the results in five models. Also, we controlled for hotel guests' demographic characteristics such as gender, age, education, and family income. Results from Model 1 reveal that the five AI performance drivers are all significant predictors of AI information quality ($b_{Accuracy} = .14$, $p < .05$; $b_{Currency} = .19$, $p < .01$; $b_{Reliability} = .12$, $p < .10$; $b_{Flexibility} = .18$, $p < .01$; and $b_{Timeliness} = .49$, $p < .001$) and IA system quality ($b_{Accuracy} = .11$, $p < .10$; $b_{Currency} = .15$, $p < .05$; $b_{Reliability} = .29$, $p < .001$; $b_{Flexibility} = .17$, $p < .01$; and $b_{Timeliness} = .39$, $p < .001$). Hence, Hypothesis 1 is supported. Model 2 assesses the relationships between AI quality and AI satisfaction. Results indicate that both AI information quality and AI system quality are significant predictors for AI information satisfaction ($b_{AI\ information\ quality} = .63$, $p < .001$; $b_{AI\ system\ quality} = .31$, $p < .001$) and AI system satisfaction ($b_{AI\ information\ quality} = .52$, $p < .001$; $b_{AI\ system\ quality} = .43$, $p < .001$), supporting Hypothesis 2. The results are present in Table 3.

Model 3 tests the moderating effect of AI preference on the quality–satisfaction relationship. Results show that the AI preference × information quality interaction ($b = -.10$, $p < .01$) and AI preference × system quality interaction are significant only on AI information satisfaction, partially supporting Hypothesis 4. Also, the direct effect of

Table 2
Descriptive Statistics, Correlations, AVE, and Reliabilities.

	Mean	SD	AVE	1	2	3	4	5	6	7	8	9	10
1. AI Preference	3.97	1.51	.82	*(.93/.93)*									
2. AI Accuracy	4.65	1.07	.59	.62	*(.80/.81)*								
3. AI Currency	4.81	1.13	.75	.56	.73	*(.90/.90)*							
4. AI Reliability	4.80	1.15	.79	.57	.76	.78	*(.92/.92)*						
5. AI Flexibility	4.57	1.08	.71	.53	.69	.74	.74	*(.88/.88)*					
6. AI Timeliness	4.57	.86	.73	.29	.39	.48	.48	.47	*(.92/.92)*				
7. AI Information Quality	4.79	1.22	.80	.56	.61	.66	.69	.65	.58	*(.92/.92)*			
8. AI System Quality	4.78	1.17	.79	.61	.60	.66	.65	.65	.63	.85	*(.91/.92)*		
9. AI Information Satisfaction	4.86	1.22	.85	.60	.60	.68	.69	.68	.57	.88	.83	*(.88/.88)*	
10. AI System Satisfaction	4.78	1.26	.79	.60	.57	.64	.64	.62	.57	.84	.82	.82	*(.98/.98)*
11. Customer Engagement	4.06	1.38	.86	.66	.53	.51	.52	.49	.25	.59	.61	.62	.62

Note: all correlations are significant at the .001 level.
SD = standard deviation, AVE = average variance extracted.
(Cronbach's alpha / composite reliability) are reported on the diagonals.

Table 3
Results of Parameter Estimation.

	Model 1		*Model 2*		*Model 3*		*Model 4*	*Model 5*
	AI Information Quality	AI System Quality	AI Information Satisfaction	AI System Satisfaction	AI Information Satisfaction	AI System Satisfaction	Customer Engagement	Customer Engagement
Main Effects								
AI Accuracy	.14*	.11†						
AI Currency	.19**	.15*						
AI Reliability	.12†	.29***						
AI Flexibility	.18**	.17**						
AI Timeliness	.49***	.39***						
AI Information Quality (AIIQ)			.63***	.52***	.60***	.49***		
AI System Quality (AISQ)			.31***	.43***	.26***	.35***		
AI Information Satisfaction (AIIS)							.38***	.28***
AI System Satisfaction (AISS)							.37***	.20**
Moderating Effect								
AI Preference					.09***	.12***		.02
AI Preference × AIIQ					−.10**	−.03		
AI Preference × AISQ					.08*	−.02		
AI Preference × AIIS								.11*
AI Preference × AISS								−.04
R^2	.61	.60	.79	.75	.81	.76	.42	.54
ΔR^2					.02	.01		.12

Note: † p < .10, * p < .05, ** p < .01, *** p < .001.

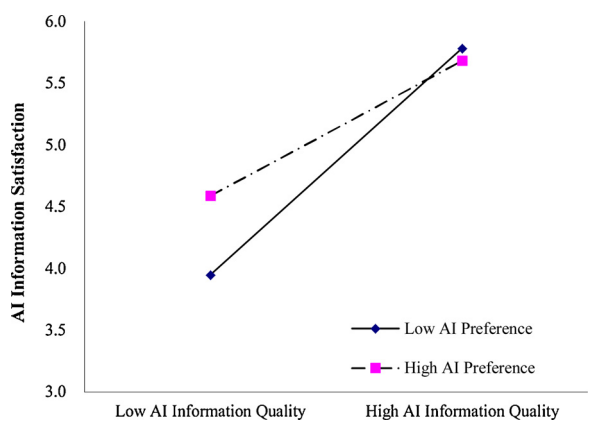

Fig. 2. AI Information Quality by AI Preference Interaction on AI Information Satisfaction.

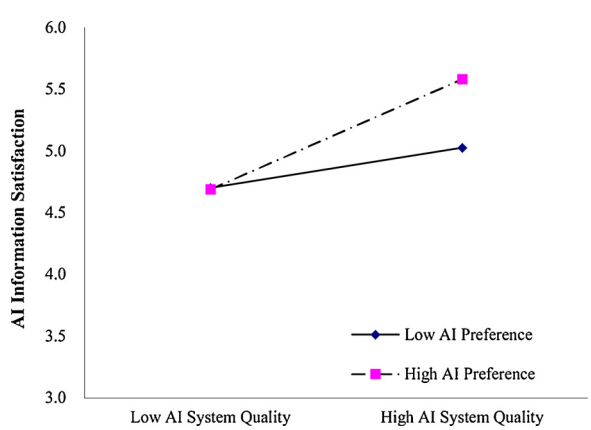

Fig. 3. AI System Quality by AI Preference Interaction on AI Information Satisfaction.

AI preference is also significant ($b \geq .09, p < .001$). We illustrated the moderation effect by following the simple slope approach and redefining the independent variables and moderator by plus and minus one standard deviation from the mean (Aiken and West, 1991). Fig. 2 depicts that the AI information quality – information satisfaction relationship is more salient for people who have a lower level of AI preference than for those who have higher preference; yet the effect of AI preference is only apparent for people who perceive a low AI information quality provided by a focal hotel. Fig. 3 illustrates that the AI system quality – information satisfaction relationship is more acute for people who have high AI preference, and the effect of AI preference is only apparent for those who perceive a high AI system quality offered by a focal hotel.

Model 4 examines the relationship between AI satisfaction and customer engagement. Results indicate that AI information satisfaction ($b_{AI\ information\ satisfaction} = .38, p < .001$; $b_{AI\ system\ satisfaction} = .20, p < .001$) and AI system satisfaction are both significant predictors of customer engagement, supporting Hypothesis 3. Model 5 tests the moderation of AI preference on the AI satisfaction – customer engagement relationship. Results show that only the AI preference × AI information satisfaction is significant ($b = .11, p < .05$), partially supporting Hypothesis 5. Following the simple slope procedure discussed above, we illustrated the interaction effect in Fig. 4. As the figure depicts, the AI information satisfaction – customer engagement relationship is more salient for high AI preference hotel guests.

We examined the mediation effect leading from AI performance to customer engagement through AI quality and AI satisfaction using the PROCESS macro with a bootstrapped sample of 5,000. Results show that AI information quality and AI system quality partially mediate the relationship between AI performance drivers (IA accuracy, currency, reliability, flexibility, and timeliness) and AI satisfaction (information satisfaction and system satisfaction) ($\beta \geq .08, t \geq 2.46, p < .05$ with a 95% confidence interview [CI] between ≥ .02 and ≥ .15). However, information satisfaction on one hand partially mediates the relationship between AI system quality and customer engagement ($\beta \geq .26, t \geq 2.89, p < .01$, 95% CI = .09 to .45.), and on the other hand fully mediates the relationship between AI information quality and customer engagement ($\beta = .05, t \geq .52, p = .60$, 95% CI = −.04 to .86), suggesting that the mediation of AI satisfaction is only salient for the AI information quality – customer engagement relationship.

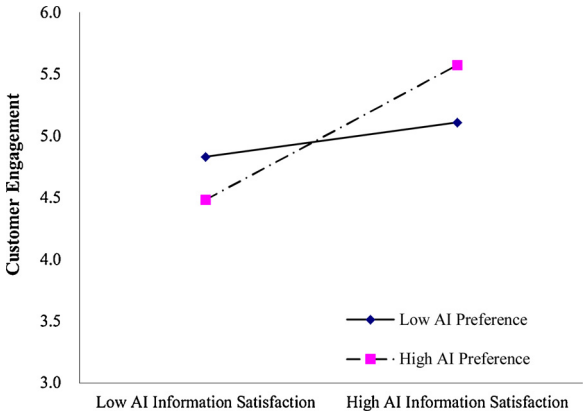

Fig. 4. AI Information Satisfaction by AI Preference Interaction on Customer Engagement.

Results also indicate that gender ($b = -.23, p < .05$), education ($b = -.13, p < .01$), income, ($b = .06, p < .05$), and age ($b = -.15, p < .001$) are all significant predictors of customer engagement. Controlling these factors helps guard against potential spurious relationships. In summary, each model presented in Table 3 demonstrates that the proposed relationships are able to explain 42%–81% of the variance of the dependent measures.

5. Discussion

The study drew upon affordance and rational choice theories to better understand how service organisations can utilise AI-powered tools as service indicators that specifically cater to customers to create opportunities for customer actions and behaviours. The theory of planned behaviours was utilized to reveal the relationship between object-related beliefs representing service quality, attitudes (e.g., customer satisfaction) and behaviours. Considering AI technology-based services, object-based service quality (beliefs) and customer satisfaction (attitudes) are operationalised into information and system components. Inconsistent relationships between attitudes and behaviours shown in the relevant literature prompted the study to propose customer engagement that is reflective of customers' affective, cognitive and behavioural involvement with the service organization as the outcome of object-related beliefs and attitudes. Given that AI service quality is an addition to traditional tangible and intangible service offerings, the study employed rational choice theory to propose preference as a moderator in the belief-attitude-engagement relationship chain. The results confirm significant relationships in this chain. However, preference for AI service mostly influences information-related beliefs and attitudes. Details of these findings are provided below.

5.1. The chain of AI service indicators and customer engagement

AI indicators in this study include information (i.e. completeness, accuracy, format, and currency) and system characteristics (i.e. reliability, flexibility, integration, accessibility, and timeliness). The results show that accuracy and currency indicators significantly influence customers' perceptions and assessments of AI information quality. Accuracy and currency indicate the information provided by AI is correct and up to date. Completeness represents all necessary information provided by AI; whereas format indicates presentation of the information. This finding shows that customers believe accurate and updated information is more important in their decision-making. Necessity of information is both subjective and context-dependent. Presentation of the information appears irrelevant to customers' quality perceptions. Customers understand that the information from AI is computer-generated. Accordingly, they are more tolerant of the level of thoroughness and formatting. At a minimum, customers should expect correctness and currency from their provider, as computer-operated AI can be more advanced than humans in collecting and disseminating information. The finding is consistent with that of previous service research. As correctness and currency are reflective of assurance and reliability, studies (Prentice, 2013; Shi et al., 2014) have shown that a firm's service that manifests assurance and reliability entices positive customer response.

In terms of AI system quality, the results show that reliability, flexibility and timeliness are significantly related to AI system quality. Reliability indicates the dependability of AI-powered systems. Flexibility represents adaptability and customisation that is provided for individual customers. Timeliness relates to the responsiveness of AI tools. These system indicators influence customer experience with AI, which affects their perceptions and assessments. Although these services are offered by AI-powered tools, from the customer's perspective, they are part of the firm's service offering and influence customers' overall quality perception. These AI-powered service dimensions are consistent with traditional service quality assessment (see Parasuraman et al., 1991). These findings of the study are consistent with those in Carlini and Wagner (2017). However, the system characteristics represent internal operations, which inevitably affect user experience. For instance, customers may not fully understand the internal operative system of the concierge robot in hotels. Customers would expect the robot concierge to be capable of making restaurants reservations, provide sightseeing recommendations, and book transportation. Customers judge the quality of the robot service, as shown in in Tussyadiah and Parks (2018), based on whether the recommended tours are as anticipated and whether time and location of the restaurant are consistent with their booking (i.e., reliability); whether they could alter their reservation (i.e., flexibility); and whether the robot responds to their requests in a timely manner (i.e., timeliness).

Both AI information and system quality significantly relate to information and system satisfaction, which subsequently influences customer engagement. These findings concur with those in Tung and Au (2018) showing how artificial intelligence in the hospitality context influences customer experience. The results show that information and system quality are equally important to customers, given that both simultaneously affect customer satisfaction, but that information quality has a larger effect. This result suggests that customers tend to perceive AI as a tool for information generation and are less concerned with the system of operation. As AI service quality represents object-based beliefs, and customer satisfaction refers to object-related attitudes, the finding of this significant chain relationship conforms Ajzen's (1985) theory of planned behaviour. Customer engagement in this study indicates affective, cognitive and behavioural involvement with the service organisation (the hotel in this study). The result confirms that customers' positive attitudes (satisfaction) towards AI service quality permits them to engage with the hotel to the extent that they feel they are affiliated and connected with the hotel emotionally, intellectually and behaviourally.

5.2. Preference as a moderator

Rational choice theory suggests that individuals have their own preferences among alternatives that are readily available and that enable optimal choice selection. Amongst available services provided by the organization, those who prefer AI services generally hold positive attitudes toward AI service quality. As shown in this study, AI preference has a significant direct effect on both information and system satisfaction. Such preferences enhance their beliefs about AI information quality and satisfaction, which leads to enhanced satisfaction and improved engagement with the organization, in line with the significant and positive moderation effect of AI preference. Notably, the moderation effect is consistently significant in relation to information quality and satisfaction, lending support to the contention that customers

perceive AI as information generation tools which provide convenience and flexibility.

6. Implications

6.1. Theoretical implications

The study proposes AI as commercial service and adopts the affordance theoretical perspective to build understanding of how such services can be regarded as opportunities to influence customer engagement. The theory of planned behaviour is utilized in examining the influence of AI service on customers' beliefs (service quality perception), attitudes (customer satisfaction) and engagement with the service organization. Rational choice theory is used to model customers' preferences for AI services as a moderator. In sum, this study contributes to AI research and extends the IT domain into marketing and customer relationship management research. In particular, the study extends current understanding in the IT literature by including commercial customers rather than IT technicians as AI users (see Wixom and Todd, 2005).

From a services marketing perspective, this study introduces a new measure of service quality by adding the service performed by computers or machines to quality assessments. Such AI-empowered services now permeate service delivery in these organizations. Customers' perceptions of these services influence customer attitudes and behaviours, and these findings present an opportunity for academics to look beyond traditional service quality measures. Furthermore, previous marketing research has tended to use TPB to explain the relationship between customer perceptions, attitudes and behaviours manifested in purchase and loyalty indicators. Given the weak relationship shown in a majority of empirical studies of attitudes and behaviours, this study models customer engagement as the outcome of customer perceptions and attitudes. As the engagement is reflected in affective, cognitive and behavioural connection with the service organization, our findings imply that customers' actual purchase and loyalty behaviours may be intervened by customer engagement. To better address customers' behavioural responses, it appears imperative to understand their involvement and connection with organizations. Our study responds to Sniehotta et al. (2014) call for "time to retire the theory of planned behaviour" – demonstrating that it may not necessarily be prudent to retire TPB, but it may be worthwhile to modify the theory by looking into mediators and moderators as well as the study context, since customers' preferences show a significant moderation effect.

The study also contributes to customer engagement research by incorporating AI as an antecedent to customer engagement. Researchers have attempted to identify customer, organisation and context-based predictors or motivators of customer engagement. AI service quality can bridge these domains and be viewed as a service offered by the organisation, perceived by customers, and operated in a technological context. Technology-based AI can be considered a new means to manage customer relationships and engage with customers.

6.2. Practical implications

The practical implications from the findings of this study are threefold. For IT practitioners or consultants, this study shows that AI is more than a package of technology-centric tools and advanced computer programming. AI should be designed to be a commercial service that can improve customer relationships with the service organisation and enhance customer experiences. As all dimensions of AI service performance contribute to overall quality perception, IT technicians or experts should look into these aspects and ensure optimal performance to enhance customer satisfaction. Customers may not be aware of the difference between AI system and information quality. AI tools must be designed to be user friendly since both quality dimensions influence customer satisfaction and engagement.

For marketers, this study provides a fresh perspective to attract customer satisfaction and loyalty. It appears timely to look beyond traditional marketing offerings such as promotions, complimentary services, and/or loyalty programs. Offering quality service has been the key approach to customer satisfaction. Service quality primarily consists of tangible (e.g. facilities, pleasant atmospherics) and intangible offerings (e.g. employee empathy, reliability) manifested in each service encounter. This study shows that services provided by machines or robots can contribute to service quality perception, customer satisfaction and engagement. Customers are now more technologically equipped, and their demands extend beyond tangible and intangible services.

For service organisations such as hotels, this study provides a new means to engage customers and enhance customer experiences. In particular, the study provides an additional service quality measure for hotels or service organizations to improve overall service quality and service experiences. Given that AI preference has a significant moderation effect, we recommend that organizations identify those technology/AI inclined customers and provide appropriate technology-based services – particularly AI tools that provide information, as AI preference is closely related to information quality and satisfaction. In other words, customers generally use AI tools for information and decision-making.

7. Limitations and future research

Whilst our approach aimed to enhance the rigor of this research, a few limitations should be acknowledged. First, the measurement of AI is adapted from the IT literature. The original scale was meant to assess IT users' beliefs and attitudes towards technology in general. Since there is no readily available scale to measure AI, the adapted scale may not be fully representative of all AI service indicators. Future research should endeavour to develop a scale that comprehensively and thoroughly embraces all AI services across industries. Second, the data was only collected in a single survey from hotel customers in Australia. This sample frame may limit the research findings. Validating the findings of this study in other industries and other geographic locations is recommended. A cross-sectional design was adopted in this study, and AI service quality is not necessarily representative of overall service quality of the service organization. Other service quality indicators should be regressed simultaneously to understand their respective influences on customer engagement. In addition, the questionnaire-based survey may not be reflective of customer perceptions and attitudes towards AI. Interviews and focus group studies should be utilised to provide more meaningful insights into the influence of AI on customer engagement.

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