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AI- AND EMPLOYEE-BASED CUSTOMER SERVICES IN RESTAURANTS: CUSTOMER ENGAGEMENT LEADING TO LOYALTY DURING THE COVID-19 PANDEMIC

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Abstract

This study aims to examine the extent to which customers' perceptions of AI and employee services evaluations, influence their engagement with restaurant service delivery, which in turn drives customer loyalty during the COVID-19 pandemic. Data were gathered from 527 respondents via an onsite survey from restaurants providing both AI and human staff services. A partial least squares structural equation modelling (PLS-SEM) technique was used to formulate hypotheses and develop the model. The results of this study contrast with previous research which states that customers tend to appreciate AI services rather than human staff. The AI-based service performance value and trust in the AI-based service and system had a strong effect on customer engagement, whereas employee-based service support significantly explained substantial variance in customer engagement. Interestingly, customer engagement with AI-based services had a negative impact on loyalty. While customer engagement with employee-based services had a positive impact, this impact was not significant with regard to loyalty. One possible explanation for this result is that restaurant businesses preferred to use AI-based services that replaced human-based services in order to provide contactless options during the COVID-19 outbreak. Additionally, restaurant image positively moderates the link between service evaluation and customer engagement with AI service and negatively moderates the effects of service evaluation on customer engagement with employee services.

Keywords Artificial intelligence (AI), Employee service, Service evaluation, Customer engagement, Customer loyalty, COVID-19

1. INTRODUCTION

In early 2020, the coronavirus pandemic significantly impacted several businesses, causing them to temporarily close or enact severe restrictions (Belso-Martínez et al., 2020). Food and beverage operations in particular were dramatically affected as a result of the outbreak. Restaurant retailers were challenged to adapt their services to handle this situation and respond to changes in customer preferences, such as providing an increase in take-away and delivery options (Yoopetch et al., 2022). A variety of technologies became important tools in assisting the hospitality and service industries during COVID-19 lockdowns. Businesses within the restaurant industry can use service robots as part of the distribution process. This minimizes human contact, thus creating safer and more secure services (Zeng et al., 2020).,

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which may create increased trust between consumers and retailers (Kim et al., 2021). Robotic services offer a number of benefits to the food service industry. Not only can they provide “novel, extraordinary and unique” experiences for customers who dine in restaurants, but they can also perform several tasks efficiently, such as serving, cooking, cleaning tables, hosting, and communicating with consumers (Seyitoğlu and Ivanov, 2020). Customers have been reported as being very satisfied with robot services (Lee et al., 2018). Thus, restaurant operators are increasingly considering the use of advanced technologies such as robots due to their utility, ease of use, cost savings, and ability to generate greater revenue and profit. While AI has brought benefits to the hospitality industry, the AI revolution is threatening the overall job market. However, Prentice et al. (2020) argued that robots and AI can only be used to replace low-skill tasks and assist employees, not replace them. In fact, AI tends to enhance employees’ performance rather than take their jobs.

Previous studies of AI have focused on providing an overview of AI (Bowen and Morosan, 2018); the types and roles of robots in the hospitality and tourism industry (Chiang and Trimi, 2020; Zeng et al., 2020); trust, interactivity, and quality (Lee et al., 2018); the robotic restaurant experience among travellers (Ivanov et al., 2020); the impact of service robots on customers and employees (Smith, 2019); and the future roles of service robots (Wirtz et al., 2018). However, a limited number of studies have explored the services provided by both AI and human staff (Kim et al., 2021; Prentice et al., 2020), while even fewer have examined customer engagement with AI and employees at restaurants (Prentice and Nguyen, 2020). In addition, the literature at this point has yet to explore how restaurant image influenced the effect of service evaluation on customer engagement during the COVID-19 pandemic. This type of study could extend the restaurant image literature in the context of AI and employee services in the restaurant industry. Therefore, the purpose of this study was to explore customers’ perceptions of AI and employee services via the factors of service evaluation, customer engagement, customer loyalty, and restaurant image. Restaurant image was used as a moderator in testing the effects of service evaluation on customer engagement.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 Artificial Intelligence (AI)-Based Service in Restaurants and Social Exchange Theory (SET)

AI can be defined as software that undertakes specific roles in a way that mimics human cognition with the aid of automation, big data, or machine learning (Prentice et al., 2020). Specifically within restaurants it is primarily used to aid customers in ordering, or paying for food, and enhancing their overall dining experience (Lu et al., 2019). Until recently, savvy restaurateurs have primarily chosen to use AI with the expectation that it can positively enhance customer satisfaction and purchase decisions (Prentice et al., 2020), through their perceptions of service quality and overall image (Ivanov and Webster, 2019). A recent impetus for AI use in restaurants has been the COVID-19 pandemic, which has had huge repercussions on the world’s economy and created considerable challenges for the hospitality industry. The introduction of such technological safeguards as service robots, contactless payment methods, digital menus viewable on personal mobile devices, and touchless elevators were studied by Gursoy and Chi (2020), who found that almost 65% of restaurant customers viewed them as necessary. For these reasons, the integration of AI into the hospitality industry is likely and warrants further study.

Central to a restaurant’s success is diners’ patronage and the products and services received in exchange. This can be evaluated by service quality, or the degree to which the services offered by an establishment meet the needs of customers. This is qualitatively assessed by the customers' own perception of those services (Priporas et al., 2017). These assessments are usually based on attributes, such as service performance (Jeaheng et al., 2020; Priporas et al., 2017) and trust (Jeaheng et al., 2020). Each of these qualities contributes to customer satisfaction and loyalty (Prentice, 2013; Jeaheng et al., 2020; Zeithaml et al., 1996) and to a customer's overall service evaluation (So et al., 2016). In considering these factors, the present study assessed AI-based service evaluation in relation to the three components of service performance, service support, and trust. Furthermore, service evaluation can be explained through social exchange theory (SET), which posits that customers' perceptions of service quality, as they relate to the success or failure of an experience, affect their emotional responses (Priporas et al., 2017). In the context of this research, SET was applied to the exchange between restaurant service providers and customers, including two forms of service types: robots and employees.

2.2 AI-Based Service Evaluation, Consumer Engagement with AI, and Customer Loyalty

Service evaluation is defined as how well a customer's expectations of the experience are met (Parasuraman et al., 1994). It follows that when using AI in service roles central to this experience, it is important to understand the degree to which it meets customer expectations. In this case, it has the potential to provide uniform, efficient, and excellent service. If AI can satisfy customer expectations, it is likely to have a positive effect on the customer experience, in turn increasing customers' interest in the products and setting (Luo et al., 2019). Such active interest in products and services refers to the concept of consumer engagement. While a number of studies have investigated the adoption of AI, no study has yet directly explored the relationship between AI-based service quality and customer engagement in the hospitality area. AI research projects have focused on the relationship between customer satisfaction and customer engagement (Prentice et al., 2020), innovativeness (Karnreungsiri, 2022), customer value co-creation behavior (Yen et al., 2020), and AI and employee engagement (Smith, 2019). The current research identifies a gap in the literature and aims to fill this gap by studying the relationship between AI-based service evaluation and customer engagement.

Engagement arises through customers' evaluations of both the material and emotional benefits of an exchange (Chen et al., 2020). When engagement is high, emotional and mental facilities are energized, and conversely, when engagement is low, there is little emotional or mental investment in the experience (Hallmann and Zehrer, 2017). In the hotel industry, for example, hotels that provide outstanding experiences will enhance their customers' engagement. When this experience is provided by AI-based services, customers are likely to be more engaged with the hotel (Prentice and Nguyen, 2020). Additionally, high consumer engagement tends to result in an increased interest in a business's services (Chen et al., 2020). This in turn, results in strong brand loyalty (Bergel et al., 2019) that drives desired consumer behaviors, such as brand evangelism (Van Doorn et al., 2010). In related research, So et al. (2016) studied the role of customer engagement in building consumer loyalty to tourism brands and found that brand loyalty can be increased through both the quality of the direct service experience and by further engaging consumers outside of that encounter. Based on the previous studies, the following hypotheses were proposed:

H1: AI-based service evaluation has a positive effect on consumer engagement with AI.

H2: Consumer engagement with AI has a positive effect on customer loyalty.

2.3 Employee Service Evaluation, Consumer Engagement with Employees, and Customer Loyalty

In restaurants, diners' positive interactions and communications with service staff results in increased dining pleasure and comfort (Zhang et al., 2020), and customer engagement (Pansari and Kumar, 2017). Past research has shown that employees are often able to gauge customer perceptions of service quality due to their direct involvement in the customer experience (Delcourt et al., 2013). By being in this position and ensuring that this experience is positive, employees are able to increase customer engagement, leading to higher levels of loyalty (Delcourt et al., 2013). Based on this discussion, we assume that the degree to which customers perceive quality in employee delivered services influences their engagement with the employees. For this study, employee-based service evaluation consists of three components: employee-based service performance, employee-based service support, and employee trust. Moreover, a number of studies considered loyalty to be the most important result of consumer engagement (Naumann et al., 2020; Brodie et al., 2011). True loyalty arises through emotionally engaging consumers with the business (Bowden-Everson et al., 2013; Naumann et al., 2020). While rational motivations provided to customers help increase the perceived value of the product (Hapsari et al., 2017; Brodie et al., 2013), without the emotional attachments formed and maintained through repeated interactions with service staff (Brodie et al., 2013; Naumann and Bowden, 2015), customer loyalty is easily swayed by logically compelling choices offered by the competition (Bowden-Everson et al., 2013). For this study, customer engagement with employees is defined as the degree to which customers feel comfortable communicating with employees, think that it is more convenient to receive services from employees, and feel that communication with human employees is better than that of an AI-based service. Hence, the following hypotheses were proposed:

H3: Employee-based service evaluation has a positive effect on consumer engagement with employees.

H4: Consumer engagement with employees has a positive effect on customer loyalty.

2.4 Restaurant Image as a Moderator

A final concept explored in this study was the effect of restaurant image on service evaluation and, by extension, customer engagement. A restaurant's image refers to consumers' assessments of its brand, products, services, and location (Ryu et al., 2008; Bloemer and de Ruyter, 1998), and is an important factor in customers' perceptions of quality due to the cognitive stimulation provided by engagement with those features (Han and Hyun, 2017). This moderating effect of image is displayed in its relationship with customers' evaluations of the quality of factors such as communication, location, outcome, management, and enjoyment (Choi and Kim, 2013; Wu et al., 2019). In the restaurant context, this relationship has been studied in a number of locations. Han and Hyun (2017) also found that it affected diners' perceptions of a restaurant's location, products, and services, and that contributed to their overall satisfaction with the experience. Additionally, Lo et al. (2018) investigated the moderating effect of brand image on relationship quality in the chain restaurant industry. The results of their study indicated that a favourable brand image strengthens the relationship between restaurant patrons and service providers; the better the brand image, the more favorable the relationship. These findings were further supported by Wu et al. (2019) who studied the factors that drive loyalty towards green restaurants, seeking to explore how the effect of image on different categories' quality moderates a customer's overall evaluation of the experiential quality. The results demonstrated that restaurant image moderates the effect of physical environment quality on experiential quality, as well as the effect of both outcome quality and experiential quality. Brand image moderates the relationship between relationship quality and the patrons' dining experience.

In the present research, overall restaurant image was indicated by the degree to which customers perceived a restaurant had a good image, and the degree to which customers perceived a restaurant had a good reputation. Though it has not been concluded that restaurant image directly moderates the effect of service evaluation on customer engagement, evidence toward that effect can be found (Sawaftah et al., 2020; Lo et al., 2018; Wu et al., 2019). Additionally, as mentioned earlier, customer satisfaction is an antecedent to creating customer engagement (Bergel et al., 2019), and service quality evaluation has a potential effect on how customers engage with AI or employees. From this discussion, we assume that restaurant image might be a moderator of the effect of service evaluation on customer engagement. Therefore, the following hypotheses were formulated:

H5: Restaurant image positively moderates the effect of AI-based service evaluation on consumer engagement with AI.

H6: Restaurant image positively moderates the effect of employee-based service evaluation on consumer engagement with employees.

Although customers prefer engaging with employees than robots (Wirtz et al., 2018), AI is a tool that service entrepreneurs are increasingly implementing in their operations for several reasons, such as cost savings; greater profitability; multi-functionality, convenience, and consistency; as well as due to the high turnover of employees (Seyitoğlu and Ivanov, 2020). The number of previous studies that focus on customer engagement with AI and employees is limited (Prentice and Nguyen, 2020). In addition, customer service preferences might have altered due to the COVID-19 pandemic. For this reason, customers' preferences and engagement with AI and employees which lead to their loyalty might also be affected. Thus, the following hypotheses are proposed:

H7: Customer engagement with AI accounts for greater variance in overall customer engagement than customer engagement with employees.

H8: Customer engagement with AI accounts for greater variance in customer loyalty than customer engagement with employees.

3. METHODOLOGY

3.1 Research Design and Measures

This study aims to study the drivers of customer loyalty in comparing the use of AI and employees in restaurant service operations during the COVID-19 outbreak. The current study was undertaken at restaurants in Thailand. These restaurants used various AI tools to support their service operations for customers including quick response (QR) codes for menu ordering, waiter robotics, and digital assistance. To gather the data, a survey was designed and administered to a sample of customers who had experienced dining at the selected restaurants and had just paid for a meal.

To ensure content validity, the survey instrument was constructed by adapting existing measures drawn from the literature. Eleven items measuring AI-based service evaluation were drawn from de Kervenoael et al. (2020), Han and Hyun (2015), Hu et al. (2021), and Ivanov and Webster (2019). This measure is reflective of service performance value, service support, and trust in AI-based service. Eight items measuring the employee-based service evaluation construct were adapted from Han and Hyun (2015), O'Cass and Sok (2015), and Sok et al. (2018). The customer engagement scale was adapted from the work of Pagani and Mirabello (2011); four items were adopted from Vesal et al. (2021) to measure restaurant image. Finally, customer loyalty was measured with four items from the work of Zeithaml et al. (1996). A seven-point Likert scale (with 1 = "completely disagree" and 7 = "completely agree") was used to measure all items. An exploratory factor analysis with all the manifest factors was undertaken using Harman's single-factor test. The amount of variance in the largest factor did not exceed 50%, suggesting that the data collected did not present a common method bias.

3.2 Sample Profile

Survey responses were collected onsite from February through May 2021. A non-probability purposive sampling method was employed. To qualify to participate, the respondents had to have interactions with the AI-based service (QR menu offering and robotic waiter service) and the staff operation service to ensure that they had engaged with both service providers. Additionally, the respondents were over 20 years of age. This was done by asking potential respondents to answer three questions: (1) Did you use the AI service at the restaurant? (2) What kinds of AI service did you use? (3) Have you interacted with the service staff at the restaurant? After this initial screening, the surveys were distributed to 600 respondents. After removing incomplete responses, 527 completed surveys were deemed usable for further analyses. Hence, the effective response rate was 87.83%.

Of the 527 survey participants, 76.9% reported that this was their first time visiting and interacting with the AI tools, while 23.1% were repeat customers. Approximately 56.9% of the participants were female, and the average age was 31.22 years old. Regarding the level of education, about 64.1% of the participants reported that they had completed an undergraduate degree, 20.9% indicated that they were postgraduate degree holders, and 4.6% reported that they were doctoral degree holders (or currently enrolled in a doctoral programme). In terms of their income level, approximately 22.8% indicated that their monthly income was between THB15,001 and THB25,000, followed by under THB15,000 (19.5%), and between THB25,001 and THB35,000 (17.3%).

4. RESULTS

4.1. Measurement Model

Partial least squares structural equation modelling (PLS-SEM) (variance-based path analysis) was used to analyse the data and test the proposed conceptual model as a Type 1 second-order factor model; a conventional method to measure the validity and reliability of the scales composed of reflective indicators was employed (Diamantopoulos and Winklhofer, 2001: 269-277). The examination of individual-item reliability was assessed through convergent and discriminant validity. As presented in Table 1, all indicator loadings were greater than the recommended 0.7 (Kumar et al., 2017).

Table 1 Preliminary Analysis Results

Dimensions and Manifest Variables	Sample (n = 527)	
	Factor loadings	t-value
AI service performance value		
AI works more effectively than humans	0.83	40.19*
AI helps shorten waiting time for services	0.71	27.55*
AI in a restaurant looks better than some human employees	0.77	31.06*
The chance of human staff delivering bad services to customers in the restaurant is higher than that for AI machines	0.70	20.60*
AI service support		
Easy use and entertainment for customers	0.73	26.70*
Thai language graphic user interface and simple sentences for	0.74	27.76*

Table 1 (Continued)

Dimensions and Manifest Variables	Sample (n = 527)	
	Factor loadings	t-value
communication of greeting		
AI in a service environment is programmed to cater to specific customers' needs	0.82	36.52*
AI in a service environment is available whenever it is convenient for customers	0.82	35.10*
It is getting easier to understand how to use AI in a restaurant	0.78	33.37*
Trust in AI		
I feel I can trust the AI at this restaurant	0.96	194.08*
I have confidence that the AI at this restaurant is very competent	0.96	216.17*
Employee service performance value		
The staff of this restaurant are friendly and helpful to customers	0.90	56.27*
The staff of this restaurant provide me with a more reliable service	0.95	130.03*
The staff of this restaurant provide me with a service level that meets the industry quality standard better	0.92	98.94*
Employee service support		
The staff of this restaurant are more available when I need information	0.93	95.58*
The staff of this restaurant explain item features and benefits to overcome customer objections	0.94	116.57*
The staff of this restaurant respond faster when I need information	0.95	146.91*
Trust in employee		
I feel I can trust the staff at this restaurant	0.97	202.38*
I have confidence that the employees at this restaurant are very competent	0.97	201.77*
Customer engagement with AI		
I feel comfortable interacting with AI in a service environment	0.87	53.22*
I feel more comfortable interacting with AI in a service environment	0.90	58.60*
It is easier to interact with AI in a service environment	0.87	69.47*
Customer engagement with service employee		
I feel comfortable interacting with restaurant staff in a service environment	0.88	99.25*
I feel more comfortable interacting with restaurant staff in a service environment	0.76	24.04*
It is easier to interact with restaurant staff in a service environment	0.81	34.40*
Restaurant image		
This restaurant has a good image	0.94	83.12*
This restaurant has a good reputation.	0.96	117.00*
Customer loyalty		
I consider this restaurant as my first choice when choosing to eat shabu compared to other restaurants	0.85	37.00*
I have a strong intention to visit this restaurant again	0.94	146.56*
I would say positive things about this restaurant to other people	0.89	42.90*
I would recommend this restaurant to others	0.88	26.19*

Note1. * Significance at .001 level

The composite reliabilities of the six constructs were above the 0.70 benchmark suggested by Fornell and Larcker (1981), as shown in Table 2. The average variance extracted (AVE) for each construct exceeded the recommended level of 0.50, representing adequate reliability and convergent validity. Discriminant validity was assessed using the Fornell and Larcker (1981) criteria. The results found that the square root of the AVE values ranged from 0.67 to 0.95 and were consistently greater than the individual correlations (ranging from 0.15 to 0.76), therefore presenting evidence of discriminant validity, as shown in Table 3.

Table 2 Internal Consistency Criteria of Reflective Latent Variable Constructs

Latent Variable	AVE	CR	α
AI service performance value	0.57	0.84	0.75
AI service support	0.61	0.88	0.84
Trust in AI	0.93	0.96	0.92
Employee service performance value	0.85	0.95	0.91
Employee service support	0.88	0.96	0.93
Trust in employees	0.93	0.97	0.93
Customer engagement with AI	0.78	0.91	0.86
Customer engagement with service employees	0.66	0.86	0.76
Restaurant image	0.90	0.95	0.89
Customer loyalty	0.80	0.94	0.92

Note: AVE = Average Variance Extracted, CR = Composite Reliability, α = Cronbach α.

Table 3 Correlations and Square Root of AVE (diagonal)

Variable	Mean	SD	CR	AVE	Correlation matrix					
					AISE	CEAI	ESE	CEE	RM	CL
AISE	4.50	1.02	0.90	0.50	***0.67***					
CEAI	4.27	1.35	0.91	0.78	0.64	***0.88***				
ESE	5.95	1.00	0.96	0.75	0.46	0.16	***0.87***			
CEE	5.60	1.09	0.86	0.66	0.31	0.15	0.70	***0.82***		
RM	5.44	1.15	0.95	0.90	0.44	0.21	0.67	0.52	***0.95***	
CL	4.50	1.02	0.94	0.80	0.46	0.22	0.58	0.46	0.76	***0.89***

AISE = AI service evaluation, CEAI = Customer engagement with AI, ESE = Employee service evaluation, CEE = Consumer engagement with employees, RM = Restaurant Image, CL = Customer loyalty

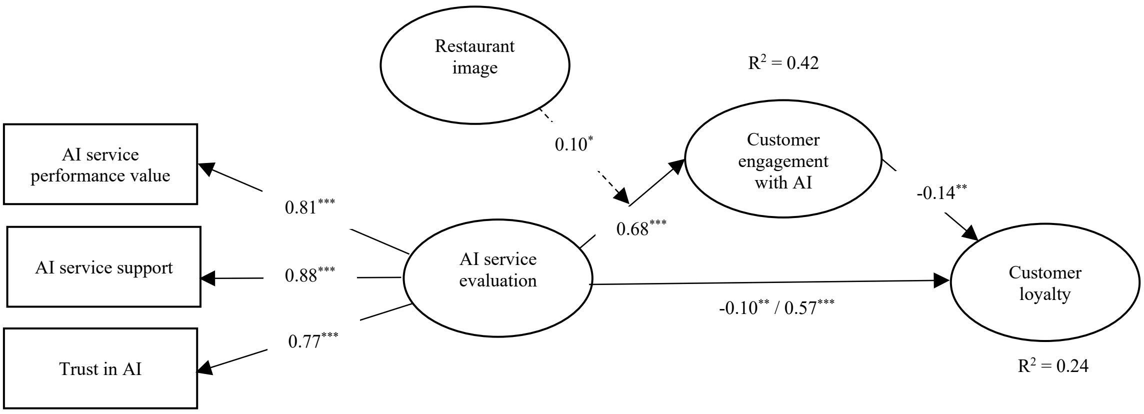
4.2 Main and Moderation Effects

Based on Brown and Chin (2004), a bootstrapping approach was used to test the proposed hypotheses. The path coefficients were re-estimated with each random sample and the mean parameter estimates. In addition, the standard errors were formulated across the total number of samples. Therefore, a bootstrapping approach with 500 runs was used to compute the statistical significance of the parameter estimates. To test the direct and moderated effects, the R^2 value for the endogenous latent components was calculated as a measure of model fit for the structural model. Moreover, as presented in Fig. 1 and 2, the analysis of all R^2 values indicated the predictive capability of the model, with all values being satisfactory within the recommendations of Escobar-Rodríguez and Carvajal-Trujillo (2014). According to Tenenhaus et al. (2005), the global fit measure goodness-of-fit (GoF) was developed for PLS.

GoF is the geometric mean of the average communality and the average R^2. However, as this study used formative second-order indicators, GoF was not a suitable measure of fit (Wynstra et al., 2010).

The estimated path coefficients (significant paths indicated with an asterisk) and associated t-values of the paths are shown in Fig. 1 and 2. The model of this study is focused on the inner model findings in which the hypothesised relationships between the latent variables are represented as H1 to H4. Defined as the ratio between the estimated and standard errors, critical values greater than 1.64 and 1.96 indicated statistical significance at the 90% and 95% levels, respectively. The results show that the AI-based service evaluation was found to have a significant effect on consumer engagement with an AI path coefficient of 0.68 (t-value = 21.97, $p < 0.001$). This variable accounted for 42% of the variance in consumer engagement with AI, thus supporting H1. However, the results show that consumer engagement with AI had a significant negative relationship with customer loyalty, with a path coefficient of -0.14 (t-value = 2.71, $p < 0.01$), and is thus, at odds with our expectations (H2). AI-based service evaluation also had a direct effect with a path coefficient of 0.57 (t-value = 12.10, $p < 0.001$, CI95% = [0.47, 0.66]) and an indirect effect with a path coefficient of -0.10 (t-value = 2.50, $p < 0.01$, CI95% = [-0.18, -0.03]) on customer loyalty (see Figure 1).

Figure 1 The Relationships Between AI Service Evaluation, Consumer Engagement with AI and Customer Loyalty



The results of testing H3 showed that that employee-based service evaluation was found to have a significant effect on consumer engagement for employee-based service with a path coefficient of 0.63 (t-value = 10.37, $p < 0.001$). This variable accounted for 50% of the variance in consumer engagement with employee-based service, thus supporting H3. We tested H4, which proposed that consumer engagement with employee-based service positively affected customer loyalty. The results failed to support this hypothesis (path coefficient = 0.08, t-value = 1.36, $p > 0.01$). Employee-based service evaluation also had a direct effect with a path coefficient of 0.54 (t-value = 10.03, $p < 0.001$, CI95% = [-0.04, 0.18]) but did not have an indirect effect on customer loyalty (see Figure 2), with a path coefficient of 0.05 (t-value = 1.43, $p > 0.01$, CI95% = [-0.03, 0.12]).

Further analyses were conducted to assess how each service evaluation component contributed to customer engagement and loyalty. The findings indicate that AI-based service performance value and trust in AI significantly affected customer engagement, but only AI-based service support and trust in AI significantly affected customer loyalty (Table 4). In the case of employee-based service evaluation components, employee-based service performance value and service support significantly affected customer engagement. However, only trust in employees significantly affected customer loyalty.

Figure 2 The Relationships Between Employee Service Evaluation, Consumer Engagement with Employees, and Customer Loyalty.

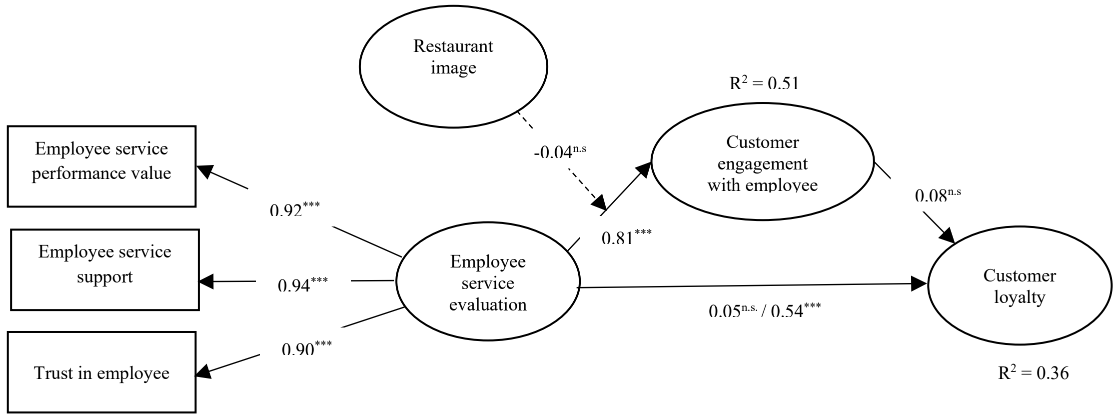


Table 4 The Respective Impact of AI and Employee Service Evaluation Dimensions on Customer Related Outcomes

AI Service evaluation	**CEAI**	**CL**	**Employee service evaluation**	**CEE**	**CL**
AI service performance value	0.45***	-0.03	Employee service performance value	0.27**	0.18*
AI service support	0.11*	0.22***	Employee service support	0.32***	-0.00
Trust in AI	0.23***	0.40***	Trust in employees	0.16**	0.49***
R^2	0.43	0.30	R^2	0.49	0.39

Note 1. * p < .05; ** p < .01; *** p < .001
Note 2. CEAI = Customer engagement with AI, ESE = Employee service evaluation, CEE = Consumer engagement with employees, RM = Restaurant Image, CL = Customer loyalty

The moderation effect of restaurant image on the two service modes was also tested (H5 and H6). Restaurant image was found to significantly moderate the relationship between the AI-based service evaluation and customer engagement with AI, which was found to have a coefficient of 0.06 (t-value = 2.22, $p < 0.05$). However, restaurant image did not significantly moderate the relationship between the employee-based service evaluation and customer engagement with the employees, which was found to have a coefficient of -0.04 (t-value = 1.21, $p > 0.05$). Also, there were no significant interaction effects for the relationship between the employee-based service evaluation and customer engagement with employees. Thus, given the non-significant effects, it was not logical to examine this relationship further.

In examining the moderation effects when employing PLS, a hierarchical process was used to compare the R^2 value for the interaction model with that of the main effects model, which excluded the interaction construct. Following Cohen (1988), the difference in the R^2 values was used to evaluate the overall effect size f^2 for the interaction, where 0.02, 0.15, and 0.35 have been suggested as small, moderate, and large effects, respectively. As shown in Table 5, the model in which restaurant image was proposed to moderate the effect between the AI-based service evaluation and customer engagement with AI—and was found to be statistically significant with a path coefficient of 0.06 (t-value = 2.22, $p < 0.05$) —possessed a significantly higher explanatory power than the main effects model, although the effect size for the interaction was only 0.03 (small). As suggested by Limayem and Cheung (2008), a small f^2 does not necessarily imply an unimportant impact.

Table 5 Hierarchical Test

	R^2
Main effect model (H1)	0.40
Interaction effect model (H5)	0.42
F^2	0.03
Main effect model (H3)	0.50
Interaction effect model (H6)	0.51
F^2	0.02

Note. $f^2[R^2$(interaction effect model) - R^2 (main effect model)] / [1 - R^2 (main effect model)]

Moreover, the findings show that the effect of the employee-based service evaluation reduced the path coefficient in the overall engagement with the restaurant service, whereas the effect of the AI-based service evaluation was significant. Only trust in employees was significantly related to customer loyalty, as shown in Table 6. These findings reject H7 and H8.

Table 6 The Effects of AI and Employee Service Evaluation on Overall Engagement with the Restaurant Service and Customer Loyalty

Service evaluation components	Engagement	Customer loyalty
AI service evaluation		
AI service performance value	0.33^{***}	$0.06^{n.s}$
AI service support	0.13^{*}	$0.09^{n.s}$
Trust in AI	0.20^{**}	0.14^{*}
Employee service evaluation		
Employee service performance value	$0.08^{n.s}$	$0.11^{n.s}$
Employee service support	0.19^{*}	$0.01^{n.s}$
Trust in employees	$0.02^{n.s}$	0.38^{***}
R^2	0.49	0.42

5 CONCLUSIONS AND IMPLICATIONS

5.1 Conclusions

This study examined how AI- and employee-based service evaluations contribute to customer engagement and loyalty. When considering the three dimensions of AI- and employee-based service evaluations and regressing them into one equation, the results revealed that the AI-based service performance value and trust in the AI-based service and system had a strong effect on customer engagement, while employee-based service support was found to significantly explain substantial variance in customer engagement. Furthermore, the results showed that trust in employee service significantly affected customer loyalty to the restaurant. One possible explanation for this result is that, although the use of AI-based service can reduce human interaction in the service process, customers may return to prefer employee-based service over AI-based service after the COVID-19 outbreak as employee service is characterised as involving emotion, guarantees, and communicability.

Interestingly, this study showed a significant negative impact of customer engagement with AI-based service on loyalty. The nature of AI-based service is computer oriented and can be thought of as a one-way communication which might be unable to understand customers' questions. In contrast, customer engagement with employee-based service had a positive impact, although this impact was not significant with regard to loyalty. One possible explanation for this result is that restaurant businesses preferred to use AI-based services that replaced human-based services in order to provide contactless options during the COVID-19 outbreak. A customer may feel uncomfortable about the lack of service promptness due to limited human staffing. Turning to the moderation impact of restaurant image, the results present additional insight into how outcomes of the relationship between service evaluation and customer engagement can be increased through the possession of a positive restaurant image. The findings suggest that customers will have a good impression of restaurants where AI-based services were used in order to maintain social distancing during the COVID-19 pandemic, resulting in greater trust in the restaurant, which may induce customer engagement with the AI-based service. These findings are important given the state of the current literature, which has to date not theorised and tested the role of restaurant image in enhancing such a relationship. The findings lead to straightforward suggestions for hospitality businesses with regard to successfully managing their communications and promotions strategies to ensure customers continue to use AI-based services.

5.2 Theoretical and Practical Implications

Although prior studies have examined the effect of AI- and employee-based services on satisfaction and customer loyalty, they did not consider the role of customer engagement with AI- and employee-based services (Prentice et al., 2020). The extant literature demonstrates that both AI- and employee-based service influence customer satisfaction and that they both have a direct impact on customer loyalty (Prentice et al., 2020). The current study contributes to a more comprehensive understanding by investigating the role of customer engagement with AI- and employee-based services. Furthermore, this study examined how AI- and employee-based service evaluation leads to increased customer engagement. According to the results of the study, the main reason for the positive effect of both types of service evaluation on customer engagement was that customer engagement was associated with a restaurant's service interaction with the AI- and employee-based service, and customers may feel more comfortable interacting with the restaurant AI for service during the COVID-19 pandemic. Moreover, both AI- and employee-based services were easy to interact with in the service environment, leading to increased customer engagement.

In testing the direct effect of both AI- and employee-based service evaluation on customer loyalty, this study contributes to the knowledge of service business by empirically representing that AI- and employee-based service evaluations had a strong influence on customer loyalty to the restaurant. These results, as well as the incremental explanatory power of AI- and employee-based service evaluation in predicting customer loyalty, generate strong support for the important role of service evaluation experiences in loyalty formation. However, this study also demonstrates that customers still prefer employee-based services. The findings suggest that researchers and practitioners should take caution, seeking to provide more empirical evidence before making any general claims that state otherwise. Therefore, this research offers a meaningful synthesis of the customer loyalty literature, as well as the emerging service experience literature, yielding a framework that encapsulates customer–service experiences within service encounters during the COVID-19 pandemic.

The results of this study provide useful implications for restaurants and service-related businesses. Managers can use AI-based services to promote their services while encountering a new normal. The results of the study suggest that it is necessary to present clear instructions and guidelines for first-time customers using AI-based services in order to successfully implement and commercialise them. Plus, managers may benefit more from highlighting the novelty and entertainment components of AI-based services than from indicating the efficacy of these devices in order to increase positive customer experiences in interacting with them. Although AI-based services are currently employed in particular areas, their functions are limited. Additionally, customers also prefer to interact with human service staff who may be able to spend more time providing personalised services to them. The implementation of robots at restaurants should be managed from a relational point of view, complementing, personalising, and developing both AI- and human-based service interactions and customer service. This interaction should be enhanced and performed by people, not just technological devices, to implement a unique customer experience. Therefore, although AI-based services may perform some functions in restaurants, this does not mean that they should replace all human service tasks in restaurant service operations.

6. LIMITATIONS

Firstly, the use of AI-based service in restaurants in Thailand was not yet widespread at the time the researchers were collecting data. In order to add to the generalizability of these findings, the researchers will continue to collect data from additional restaurants with AI support in additional research. Secondly, the sample target was only Thai consumers. Additional data should be collected from other Asian consumers to minimize the bias of the study. Thirdly, this study focused on comparing consumers' preferences for using AI and having services provided by employees in general. Therefore, future study should be more specific by investigating the preferences of using AI- and employee-based services in restaurants, comparing, for example, Generation X and Generation Z. Consumers in different age groups might prefer different types of services. The results would allow restaurant owners to offer services that better match the desires of their target consumers.

REFERENCES

Belso-Martínez, J. A., A. Mas-Tur, and M. Sánchez, M. J. López-Sánchez. (2020). The COVID-19 response system and collective social service provision. Strategic network dimensions and proximity considerations. *Service Business,* 14(3), 387-411.

Bergel, M., P. Frank, and C. Brock. (2019). The role of customer engagement facets on the formation of attitude, loyalty and price perception. *Journal of Services Marketing*, 33(7), 890-903.

Bloemer, J., and K. de Ruyter. (1998). On the relationship between store image, store satisfaction and store loyalty. *European Journal of Marketing,* 32(5/6), 499-513.

Bowden-Everson, J. L.-H., T. S. Dagger, and G. Elliott. (2013). Engaging customers for loyalty in the restaurant industry: The role of satisfaction, trust, and delight. *Journal of Foodservice Business Research*, 16(1), 52-75.

Bowen, J., and C. Morosan. (2018). Beware hospitality industry: the robots are coming. *Worldwide Hospitality and Tourism Themes,* 10(6), 726-733.

Brodie, R. J., L. D. Hollebeek, and B. Jurić, A. Ilić. (2011). Customer engagement: Conceptual domain, fundamental propositions, and implications for research. *Journal of Service Research*, 14(3), 252-271.

Brodie, R. J., A. Ilic, B. Juric, and L. Hollebeek. (2013). Consumer engagement in a virtual brand community: An exploratory analysis. *Journal of Business Research,* 66(1), 105-114.

Brown, S. P., and W. W. Chin. (2004). Satisfying and retaining customers through independent service representatives. *Decision Sciences*, 35(3), 527-550.

Chen, J.-S., H.-T. Tsou, C. Y. Chou, and C.-H. Ciou. (2020). Effect of multichannel service delivery quality on customers' continued engagement intention. *Asia Pacific Journal of Marketing and Logistics*, 32(2), 473-494.

Chiang, A.-H., and S. Trimi. (2020). Impacts of service robots on service quality. *Service Business*, 14(3), 439-459.

Choi, J. B., and S. H. Kim. (2013). The impact of outcome quality, interaction quality, and peer-to-peer quality on customer satisfaction with a hospital service. *Managing Service Quality: An International Journal,* 23(3), 188-204.

Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences. Routledge, New York.

de Kervenoael, R., R. Hasan, A. and Schwob, E. Goh. (2020). Leveraging human-robot interaction in hospitality services: Incorporating the role of perceived value, empathy, and information sharing into visitors' intentions to use social robots. *Tourism Management,* 78, 104042.

Delcourt, C., D. D. Gremler, A. C. R. van Riel, and M. van Birgelen. (2013). Effects of perceived employee emotional competence on customer satisfaction and loyalty. *Journal of Service Management,* 24(1), 5-24.

Diamantopoulos, A., and H. M. Winklhofer. (2001). Index construction with formative indicators: An alternative to scale development. *Journal of Marketing Research*, 38(2), 269-277.

Escobar-Rodríguez, T., and E. Carvajal-Trujillo. (2014). Online purchasing tickets for low cost carriers: An application of the unified theory of acceptance and use of technology (UTAUT) model. *Tourism Management,* 43, 70-88.

Fornell, C., and D. F. Larcker. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50.

Gursoy, D., and C. G. Chi. (2020). Effects of COVID-19 pandemic on hospitality industry: review of the current situations and a research agenda. *Journal of Hospitality Marketing and Management*, 29(5), 527-529.

Hallmann, K., and A. Zehrer. (2017). Event and community involvement of sport event volunteers. *International Journal of Event and Festival Management,* 8(3), 308-323.

Han, H., and S. S. Hyun. (2015). Customer retention in the medical tourism industry: Impact of quality, satisfaction, trust, and price reasonableness. *Tourism Management*, 46, 20-29.

Han, H.,and S. S. Hyun. (2017). Impact of hotel-restaurant image and quality of physical-environment, service, and food on satisfaction and intention. *International Journal of Hospitality Management*, 63, 82-92.

Hapsari, R., M. D. Clemes, and D. Dean. (2017). The impact of service quality, customer engagement and selected marketing constructs on airline passenger loyalty. *International Journal of Quality and Service Sciences,* 9(1), 21-40.

Hu, X., H. Yan, T. Casey, and C.-H. Wu. (2021). Creating a safe haven during the crisis: How organizations can achieve deep compliance with COVID-19 safety measures in the hospitality industry. *International Journal of Hospitality Management*, 92, 102662.

Ivanov, S., F. Seyitoğlu, and M. Markova. (2020). Hotel managers' perceptions towards the use of robots: a mixed-methods approach. *Information Technology and Tourism,* 22(4), 505-535.

Ivanov, S., and C. Webster. (2019). Perceived appropriateness and intention to use service robots in tourism. In *Information and communication technologies in tourism 2019*, 237-248.

Jeaheng, Y., A. Al-Ansi, and H. Han. (2020). Impacts of Halal-friendly services, facilities, and food and Beverages on Muslim travelers' perceptions of service quality attributes, perceived price, satisfaction, trust, and loyalty. *Journal of Hospitality Marketing and*

Management, 29(7), 787-811.

Karnreungsiri, I. (2022). Applying Importance-Performance Analysis for Developing a Model of Quick Service Restaurant Innovation Strategies in Downtown Bangkok. *ABAC Journal*, 42(2), 27-51.

Kim, S., J. Kim, F. Badu-Baiden, M. Giroux, and Y. Choi. (2021). Preference for robot service or human service in hotels? Impacts of the COVID-19 pandemic. *International Journal of Hospitality Management*, 93, 1-12.

Kumar, B., A. K. Manrai, and L. A. Manrai. (2017). Purchasing behaviour for environmentally sustainable products: A conceptual framework and empirical study. *Journal of Retailing and Consumer Services,* 34, 1-9.

Lee, W.-H., C.-W. Lin, and K.-H. Shih. (2018). A technology acceptance model for the perception of restaurant service robots for trust, interactivity, and output quality. *International Journal of Mobile Communications,* 16(4), 361-376.

Limayem, M., and C. M. Cheung. (2008). Understanding information systems continuance: The case of Internet-based learning technologies. *Information and Management*, 45(4), 227-232.

Lo, Y. T., A. Jusoh, A. Mardani, and D. Streimikiene. (2018). Restaurant branding matters: A quantitative report on how brand image can moderate relationship. *Journal of International Studies,* 11(4), 270-281.

Lu, L., R. Cai, and D. Gursoy. (2019). Developing and validating a service robot integration willingness scale. *International Journal of Hospitality Management,* 80, 36-51.

Luo, J., I. A. Wong, B. King, M. T. Liu, and G. Huang. (2019). Co-creation and co-destruction of service quality through customer-to-customer interactions. *International Journal of Contemporary Hospitality Management,* 31(3), 1309-1329.

Naumann, K., and J. Bowden. (2015). Exploring the process of customer engagement, self-brand connections and loyalty. Problems and Perspectives in Management, 13(1), 1-11.

Naumann, K., J. Bowden, and M. Gabbott. (2020). Expanding customer engagement: the role of negative engagement, dual valences and contexts. *European Journal of Marketing*, 54(7), 1469-1499.

O'Cass, A., and P. Sok. (2015). An exploratory study into managing value creation in tourism service firms: Understanding value creation phases at the intersection of the tourism service firm and their customers. *Tourism Management,* 51, 186-200.

Pagani, M., and A. Mirabello. (2011). The influence of personal and social-interactive engagement in social TV web sites. *International Journal of Electronic Commerce,* 16(2), 41-68.

Pansari, A., and V. Kumar. (2017). Customer engagement: the construct, antecedents, and consequences. *Journal of the Academy of Marketing Science,* 45(3), 294-311.

Parasuraman, A., V. A. Zeithaml, and L. L. Berry. (1994). Reassessment of expectations as a comparison standard in measuring service quality: implications for further research. *Journal of Marketing,* 58(1), 111-124.

Prentice, C. (2013) Service quality perceptions and customer loyalty in casinos. *International Journal of Contemporary Hospitality Management,* 25(1), 49-64.

Prentice, C., S. Dominique Lopes, and X. Wang. (2020). The impact of artificial intelligence and employee service quality on customer satisfaction and loyalty. *Journal of Hospitality Marketing and Management*, 29(7), 739-756.

Prentice, C., and M. Nguyen. (2020). Engaging and retaining customers with AI and employee service. *Journal of Retailing and Consumer Services*, 56, 1-13.

Prentice, C., S. Weaven, and I. A. Wong. (2020). Linking AI quality performance and customer engagement: The moderating effect of AI preference. *International Journal of Hospitality Management*, 90, pp. 1-10.

Priporas, C.-V., N. Stylos, R. Rahimi, and L. N. Vedanthachari. (2017). Unraveling the diverse nature of service quality in a sharing economy. *International Journal of Contemporary Hospitality Management*, 29(9), 2279-2301.

Ryu, K., H. Han, and T.-H. Kim. (2008). The relationships among overall quick-casual restaurant image, perceived value, customer satisfaction, and behavioral intentions. *International Journal of Hospitality Management,* 27(3), 459-469.

Sawaftah, D., C. Calıcıoglu, and R. Awadallah. (2020). The relationship between viral marketing and consumer purchase intention, the moderator role of brand image and age: Evidence from smartphone users in North Cyprus. *Management Science Letters*, 10(6), 1307-1320.

Seyitoğlu, F., and S. Ivanov. (2020). Understanding the robotic restaurant experience: a multiple case study. *Journal of Tourism Futures,* 7(3), 303-309.

Smith, C. (2019). An employee's best friend? How AI can boost employee engagement and performance. *Strategic HR Review,* 18(1), 17-20.

So, K. K. F., C. King, B. A. Sparks, and Y. Wang. (2016). The role of customer engagement in building consumer loyalty to tourism brands. *Journal of Travel Research,* 55(1), 64-78.

Sok, K. M., P. Sok, L. Snell, and P. Qiu. (2018). Does transformational leadership always matter in frontline service roles. *Journal of Service Theory and Practice*, 28(6), 733-751.

Tenenhaus, M., V. E. Vinzi, Y.-M. Chatelin, and C. Lauro. (2005). PLS path modeling. *Computational Statistics and Data Analysis*, Vol. 48 No. 1, pp. 159-205.

Van Doorn, J., K. N. Lemon, V. Mittal, S. Nass, D. Pick, P. Pirner, and P. C. Verhoef. (2010). Customer engagement behavior: Theoretical foundations and research directions. *Journal of service research,* 13(3), 253-266.

Vesal, M., V. Siahtiri, and A. O'Cass. (2021). Strengthening B2B brands by signalling environmental sustainability and managing customer relationships. *Industrial Marketing Management*, 92, 321-331.

Wirtz, J., P. G. Patterson, W. H. Kunz, T. Gruber, V. N. Lu, S. Paluch, and A. Martins. (2018). Brave new world: service robots in the frontline. *Journal of Service Management*, 29(5), pp. 907-931.

Wu, H.-C., C.-C. Cheng, and C.-H. Ai. (2019). What drives green experiential loyalty towards green restaurants. *Tourism Review*, 76(5), 1084-1103.

Wynstra, F., F. Von Corswant, and M. Wetzels. (2010). In chains? An empirical study of antecedents of supplier product development activity in the automotive industry. *Journal of Product Innovation Management*, 27(5), 625-639.

Yen, C., H. Teng, and J. Tzeng. (2020). Innovativeness and customer value co-creation

behaviors: Mediating role of customer engagement. *International Journal of Hospitality Management,* 88, 1-11.

Yoopetch, C., Siriphan, P., & Chirapanda, S. (2022). Determinants of Customer Satisfaction Via

Online Food Delivery Applications. *ABAC Journal*, 42(2), 70-88.

Zeithaml, V. A., L. L. Berry, and A. Parasuraman. (1996). The behavioural consequences of service quality. *Journal of Marketing,* 60(2), 31-46.

Zeng, Z., P.-J. Chen, and A. A. Lew. (2020). From high-touch to high-tech: COVID-19 drives robotics adoption. *Tourism Geographies,* 22(3), 724-734.

Zhang, T., P. Zhang, and L. Lu. (2020). Service encounter value and online engagement behaviors. *International Journal of Hospitality Management*, 85, 1-13.