

Understanding Restaurant Service Robot Adoption: The Moderating Effect of Age Generations

Nur Amerah Nabihah Mohd Nazri, *Noradzhar Baba, Norhidayah Abdullah
Faculty of Hotel and Tourism Management, Universiti Teknologi MARA, Malaysia
Email: *noradzhar@uitm.edu.my
Corresponding Author: Noradzhar Baba

Abstract: As Malaysia transitions into the endemic phase, ensuring customer satisfaction and public approval is critical for the successful implementation of robotic services in restaurants. This research investigates the critical factors influencing customer attitudes, emphasizing the reliability and efficiency of robots, as well as their capacity to deliver a personalized, human-like dining experience. As the restaurant industry navigates post-pandemic challenges, robot services are poised to revolutionize operations by enhancing safety and addressing public health concerns. Using the Unified Theory of Acceptance and Use of Technology (UTAUT2) as its framework, this study employed a quantitative research methodology, gathering data through survey questionnaires from 225 respondents. Descriptive statistics and Partial Least Squares Structural Equation Modelling (PLS-SEM) were utilized to test the hypotheses and evaluate the proposed model. Multivariate analysis revealed no significant generational divide in the adoption of service robots, with both younger and older generations displaying comparable levels of acceptance and usage. The findings underscore customer habit as the most significant predictor of robot service adoption, highlighting the UTAUT2 model's applicability in the Malaysian context. The study also reinforces the importance of considering age-related factors in understanding technology acceptance during the endemic period. Given the positive reception of robot services, the restaurant industry should focus on refining these technologies, ensuring that they meet the diverse needs of different age groups.

Keywords: *Customer acceptance and Usage, Trust, Robot Service Technology, Restaurant*

1. Introduction

The emergence of innovative technologies frequently elicits concerns regarding the displacement of traditional media forms. Historically, similar apprehensions were expressed when radio was thought to threaten the relevance of books, and later when television was anticipated to render radio obsolete (Ivanov et al., 2017). In contemporary times, rapid developments in robotics have reignited such fears, particularly surrounding the replacement of human labor in diverse industries (Decker et al., 2017). According to Zemke et al. (2020), service robots are self-operating systems engineered to execute useful tasks with minimal human involvement, except in specific industrial applications. Although many of these robotic technologies were originally intended for manufacturing environments, they have since been adapted for use in tourism and hospitality contexts, performing tasks such as baggage handling, cleaning services, and operating as automated baristas (Zemke et al., 2020).

In Malaysia, the restaurant industry has experienced significant growth over the past decade, encompassing a diverse range of establishments including high-end, fast-food, themed, ethnic, and casual dining venues. This expansion has not only fueled economic development but also created numerous job opportunities (Shahzadi et al., 2018). Concurrently, the robotics industry has made rapid strides, with continuous innovations leading to robots capable of interpreting human thoughts and gestures (Asif et al., 2015). The COVID-19 pandemic further accelerated the adoption of robotic service providers in restaurants as health concerns and dining restrictions shifted customer preferences toward low-contact and takeaway services (UNWTO, 2020; Bartik et al., 2020). The integration of robots in roles such as order taking and food delivery has enhanced service efficiency and minimized infection risks, as noted by Hwang et al. (2021) and Garcia-Haro et al. (2021).

Despite these advancements, there remains a lack of empirical research on customer satisfaction and acceptance of robotic services, particularly in the post-pandemic context (Lee et al., 2018; Hwang et al., 2019; Seo & Lee, 2021). This study aims to address this gap by examining Malaysian customers' perceptions of robot waitstaff and their intentions to use these services, with a focus on generational differences in acceptance and adoption (Kim et al., 2021; Kautonen et al., 2015). By integrating customer intentions into the UTAUT2 model, the research seeks to enhance the understanding of technology acceptance and provide actionable insights for

restaurants considering the adoption of robotic systems (Venkatesh et al., 2012; Zemke et al., 2020). The findings are expected to reveal how age influences customer attitudes and behaviors toward service robots, thereby assisting restaurants in improving the dining experience, operational efficiency, and competitiveness in an increasingly technology-driven market (Kim et al., 2021; Zemke et al., 2020). This study aims to develop and test a theoretical model to answer the following research questions:

RQ1: Do customer acceptance and usage of robot service positively influence customer behavior and customer usage intention?

RQ2: Does age generation moderate the relationship between customer behavior and usage intention?

This study enhances the existing literature on technology adoption and application usage in the post-pandemic setting of restaurant business transactions by examining the impact of trust and age generation. In addition, this study aims to explore the awareness of the possible advantages of comprehending customer usage intention in relation to the utilization of customized robot service technologies.

2. Literature Review

Restaurant Industry and Technology

The competitive nature of the restaurant industry compels business owners to continually develop new strategies aimed at increasing revenue and enhancing customer satisfaction (Huber et al., 2010). The growing tendency of consumers to dine out—largely influenced by hectic work routines and reduced time for home cooking—has contributed to significant expansion in the sector. In response to these evolving consumer habits, restaurateurs have been motivated to adopt more creative marketing approaches to differentiate their businesses and attract a broader clientele (Barrish, 2012).

In Malaysia, the food service industry faces increasing challenges, including the influx of diverse international cuisines (Harrington & Schaefer, 2014). The abundance of food options has made it difficult for restaurants to stay competitive. Globally, the food service industry is a major economic sector with producers and customers spread across various regions (Lee & Ha, 2012). As Malaysia's economy continues to grow, especially in the food service sector, businesses must adopt aggressive marketing strategies to attract and retain customers (Kimes, 2008). One such strategy involves integrating technology into restaurant operations, such as displaying visual representations and nutritional information on menus (Buchanan, 2011; Huber et al., 2010; Hsu & Wu, 2013).

Robot Service in the Food Service Industry

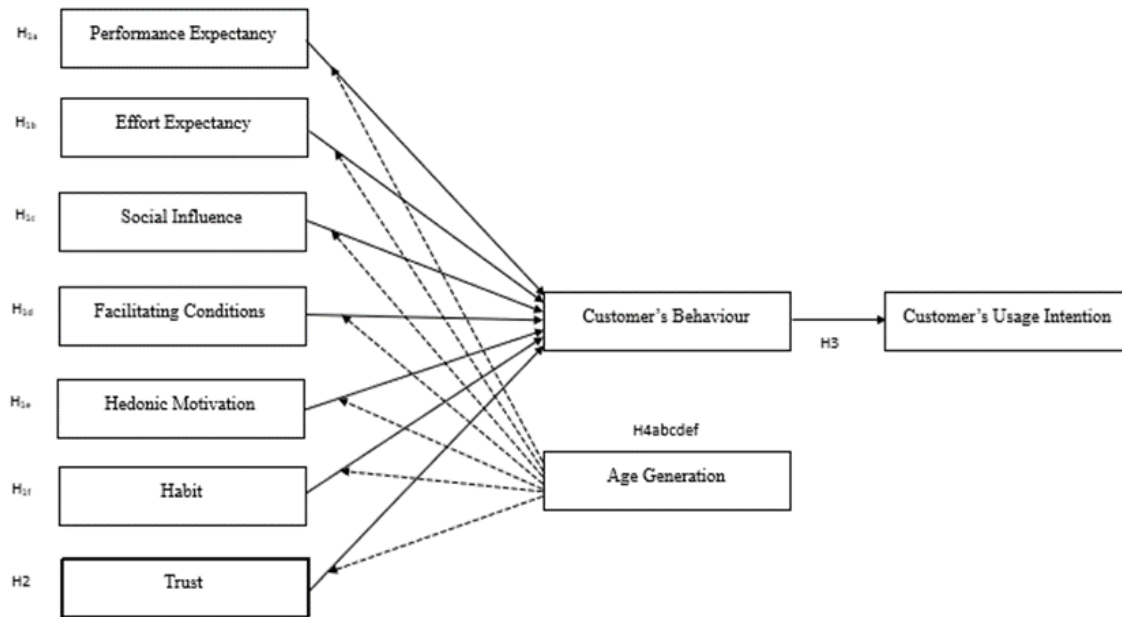
Robots are defined by the International Organization for Standardization (ISO) as actuated mechanisms that are programmable across multiple axes with a certain degree of autonomy. Robots fall into two main categories: industrial robots and service robots. According to the International Federation of Robotics (2016), service robots are autonomous entities that perform useful tasks for humans or equipment in non-industrial settings without needing human interaction. Service robots can be further divided into personal service robots, used in non-commercial settings like automated wheelchairs, and professional service robots, used for tasks like deliveries or cleaning in commercial environments. The operation of professional service robots often requires a human operator to initiate, monitor, and terminate activities (Zemke et al., 2020).

Service robots are designed to enhance human productivity and engage in social interactions through sensing, cognition, and action (Chan & Tung, 2019). Before service robots became widespread, industrial robots were used in manufacturing as early as the 1960s to reduce production costs and protect workers from hazardous tasks (Bard, 1986; Chan & Tung, 2019). These robots were mainly employed in tasks like welding, polishing, and assembly to replace manual labor (Chan & Tung, 2019). As robotic technology advanced, service organizations began integrating robots into customer interactions to support employees and provide services (Chan & Tung, 2019).

The adoption of robotic technology in restaurants offers several potential benefits. Robotic restaurants may attract technology enthusiasts who are eager to experience the latest innovations (Ivanov et al., 2017). According to Eksiri and Kimura (2015), younger generations of tech-savvy individuals are more likely to have

a positive attitude toward the use of robots in restaurants, which can help differentiate robotic restaurants from their competitors. Moreover, robots offer practical advantages over human employees, as they are not prone to illness, do not require vacations, and do not complain, making them a reliable option for consistent service (Berezina et al., 2019).

Figure 1: Depicts the interrelationships between customer acceptance and usage of robot service and their usage intention in a restaurant setting.



Hypotheses development

To understand customers' technology usage patterns, it is important to explore their expectations regarding its functionality (Ariaeinejad & Archer, 2014; Escobar-Rodriguez & Carvajal-Trujillo, 2014; Raman & Don, 2013; Venkatesh et al., 2012). "Customers are likely to adopt a technology if they believe it will help them accomplish tasks more efficiently (Venkatesh et al., 2012). In this context, performance expectancy relates to customers expecting quicker and more accurate service from robots. In using technology, customers are somewhat influenced by external factors, driven by the utilitarian aspects of technology, such as its perceived usefulness and expected outcomes (Venkatesh et al., 2003). "Perceived utility" (Phonthanukitithaworn et al., 2016) involves customers' expectations of how the service will enhance their ability to complete a transaction successfully. It is generally believed that using technology to save time and effort is beneficial. Therefore, this study suggests that individuals' perceptions of the usefulness of AI-powered food service establishments significantly shape their views, as supported by previous research (Liébana-Cabanillas et al., 2017; Upadhyay & Jahanyan, 2016).

H1a: Performance expectancy positively affects customers' behaviour.

According to Venkatesh et al. (2012), effort expectancy refers to an individual's perception of how simple and straightforward a particular technology is to use. As technological innovation progresses, users encounter increasingly advanced features, with user-friendliness often exemplified through tools such as touchscreens, graphical user interfaces, and diverse input devices (Mroz, 2013). Within the context of this study, effort expectancy pertains to customers' perception of the ease with which they can operate robot services—a factor that significantly shapes both initial acceptance and ongoing engagement. Prior studies have established a strong connection between perceived effort and users' behavioral responses toward technological systems (Ariaeinejad & Archer, 2014; Escobar-Rodriguez & Carvajal-Trujillo, 2013; Raman & Don, 2013; Venkatesh et al., 2012). Alalwan et al. (2017) observed that individuals tend to perceive new technologies as accessible and efficient. Additional research has reinforced the importance of perceived ease of use, often referred to as effort

prediction, in influencing adoption behavior (Davis et al., 1989; Alagoz & Hekimoglu, 2012; Alalwan et al., 2016; Okumus & Bilgihan, 2014). Ivanov et al. (2017) highlighted the role of computer-based services in enhancing operational productivity and alleviating workload, while Kwak and Park (2012) indicated that such technologies contribute to improved service standards and cost efficiency. Furthermore, Wirtz et al. (2018) stressed that customer receptiveness to service robots is contingent on how effectively these machines fulfill users' functional, interpersonal, and emotional expectations.

H1b: Effort expectancy positively affects customer behavior.

Social influence refers to the extent to which a person perceives that important others believe they should adopt a new technology system (Venkatesh et al., 2003). Research by Ouattara (2017) and Venkatesh & Davis (2000) has demonstrated that social influence significantly impacts behaviour. This influence is rooted in the internalization of the social system's culture, often referred to as "social impact" (Huang & Kao, 2015). Studies have also shown that age moderates the relationship between social influence and purchasing power (Okumus, 2018; Venkatesh, 2013). Social interaction plays a crucial role in spreading innovative technologies, with Hwang et al. (2019) finding that customers use drone food delivery services to stand out. Similarly, Chuah et al. (2021) examined how different types of value functional, emotional, social, epistemic, co-creative, and conditional influence customer behaviour towards robot waiters, including their willingness to use and pay more for these services. Since effort is a finite resource, customers are more inclined to adopt technologies that are easier to use (Yang, 2017). Factors such as the diversity of the restaurant's clientele, customer engagement, and the establishment's reputation and perceived legitimacy can all influence social impact.

H1c: Social Influence positively affects customer behavior.

Facilitating conditions, as defined by Venkatesh et al. (2012), pertain to customers' perceptions of the resources and support available to them for performing a specific behaviour. This concept is a well-established predictor of user acceptance and behaviour across various fields, including healthcare (Ariaeinejad & Archer, 2014; Zhou et al., 2010), mobile tour guides (Lai, 2013), and internet banking (Foon & Fah, 2011). Customers are more likely to use automated services, have positive experiences, and make recommendations if they believe that supportive conditions are in place. For instance, providing clear instructions and support for using robot services in restaurants such as user-friendly interfaces and responsive staff can enhance customer satisfaction. When customers receive thorough guidance and support, they are more likely to view the restaurant positively due to their successful interaction with the robot service.

H1d: Facilitating Conditions positively affect customer behavior.

Hedonic motivation, one of the additional components introduced into the original Unified Theory of Acceptance and Use of Technology (UTAUT), is defined as the pleasure or satisfaction derived from using technology (Venkatesh et al., 2012). This component enhances the model by integrating intrinsic motivation alongside the existing focus on extrinsic motivation related to performance expectancy (Venkatesh et al., 2012). The importance of hedonic motivation in technology acceptance has been supported by various studies on customer technology use (Wang et al., 2013; Venkatesh et al., 2012; Magni et al., 2010; To et al., 2007). Scholars argue that hedonic motivation significantly influences technology adoption and use due to the enjoyment and pleasure it provides (Arenas Gaitán et al., 2015; Baptista & Oliveira, 2015; Huang & Kao, 2015). From a hedonistic perspective, customers are inclined to seek pleasure and satisfaction in their interactions with products or services, including robotic systems for food delivery or customer engagement, which can result in positive experiences and increased customer satisfaction.

H1e: Hedonic motivation positively affects customer behavior.

Venkatesh et al. (2012) incorporated the concept of habit into the Unified Theory of Acceptance and Use of Technology (UTAUT), defining it as the predictable patterns in technology usage behaviour (Escobar-Rodriguez & Carvajal-Trujillo, 2014). Habit influences technology use through two main perspectives: the "habit/automaticity perspective" (HAP), which views technology use as an automatic response to habitual actions (Kim et al., 2005; Limayem et al., 2007; Venkatesh et al., 2012), and the "instant activation perspective" (IAP), which emphasizes the role of cognitive processes in forming habits through continuous use (Kim et al., 2005; Venkatesh et al., 2012). Venkatesh et al. (2012) found that individuals' desire to engage in activities is closely linked to their actual behaviour. Research by Morosan and DeFranco (2016) and Singh and Matsui (2017) shows that habitual behaviour and technological proficiency significantly affect system use, while

Palau-Saumell et al. (2019) highlight that technology usage patterns in restaurant settings are a key determinant of actual use.

H1f: Habit positively affects customer behavior.

Trust refers to the confidence placed in another party whether a person or a system to carry out responsibilities reliably and fulfill expected obligations, thereby promoting loyalty and effective interaction. It plays a vital role in sustaining assurance and interpersonal or institutional relationships, especially under uncertain conditions. In the context of technology acceptance, trust profoundly influences users' perceptions of security, ambiguity, and perceived risk. Liébana-Cabanillas et al. (2016) emphasized that trust contributes to enhanced user satisfaction in mobile banking environments. Although much of the existing literature on trust is based on self-reported evaluations, advancements in artificial intelligence and machine learning have enabled the development of algorithmic models that offer more objective and predictive insights into trust formation (Kaushik et al., 2015).

H2: Trust positively affects customer behavior.

Usage intention, which includes intent to use and willingness to pay more (Oliver, 2014), is shaped by positive evaluations of a product or service (Davis, 1989; Fishbein & Ajzen, 1977). In the context of robotic restaurants, this intention depends on the user's understanding of the technology and can be influenced by service issues (Lee & Lee, 2009; Go et al., 2020). Factors such as perceived value, ease of use, and social influence affect the likelihood of using robots (de Kervenoael et al., 2020; Gursoy et al., 2019). Overall, usage intention strongly predicts actual technology adoption (Taylor & Todd, 1995; Ajzen, 2002; Raman & Don, 2013).

H3: Customer behavior influences customer usage intention.

3. Research Methodology

This study investigates customers' behavioural intention towards the usage of robot services by analysing the causal relationship between constructs and variables, following the positivist method. The study data were acquired using a cross-sectional approach. The focus of this study is on persons who utilised robot service technology at eateries during the COVID-19 pandemic's movement control order (MCO). The MCO, or Movement Control Order, is a set of nationwide quarantine measures enforced by the Malaysian government in response to the COVID-19 pandemic. These restrictions were initiated on 18 March 2020. During the Movement Control Order (MCO), businesses were permitted to operate with limited human interaction, leading to an increased utilization of robot service by foodservice operators.

The survey items utilized in this inquiry (refer to Appendix 1) were adapted from previous studies (Parasuraman and Colby, 2015; Lien et al., 2011; Parasuraman et al., 2005) with minor modifications in language and substance to correspond with the research objectives. To align the questionnaire with the study's goals, modifications were applied to selected items while retaining their original meanings. The researchers employed a five-point Likert scale. The questions were developed in English and Malay. A pilot study was conducted to enhance the reliability and precision of the questionnaire. Based on the GPower minimum sample size calculation, a minimum of 163 respondents is required. The poll link was mostly disseminated on Facebook and WhatsApp through the snowball method. The participants were screened based on whether they had encountered any robot service at the restaurant. This is an important aspect to consider. At the beginning of the survey, each participant received a consent form. Then, they were assessed using a set of questions to determine if they met the precise requirements for participation.

The participants are Malaysian persons with prior proficiency in utilizing robot service technologies. Information was collected over three months. The surveys were collected via online questionnaires administered using Google Forms. The survey URLs were shared via social media platforms and actual QR codes were distributed at certain locations to guarantee broad distribution and engagement of participants. The research was performed utilizing a substantial dataset of 240 responses. The descriptive analysis was performed with SPSS version 24. Before performing hypothesis testing, the data were analyzed for any potential common method bias using Harman's single-factor test (Koh et al., 2003). Before conducting the structural equation modelling investigation, the data were tested for common method bias. Because the research data did not match the normality condition, this study used the variance-based technique known as

partial least squares-structural equation modelling. Partial least squares-structural equation modelling is suitable for this study environment when using a predictive strategy, addressing a complex structural model, and when the data distribution deviates from normality. The SmartPLS3.1.1 software is utilized for the validation of measurement and structural models.

Demographic profile

Of the 225 total respondents, 41.8% (n= 131) were men, while the female respondents were fewer than the male respondents by a noticeable slight margin. Meanwhile, 24.4% (n= 55) of the respondents were 18–24 years old, 51.6% (n= 116) respondents were 25–34 years old and 8.90% (n= 20) respondents were 35–44 years old. On the other hand, 66.70% (n= 150) of the respondents were single, while 33.30% (n= 75) were married. Most of them have a bachelor's degree (34.7%; n= 78), while 25.30% (n= 57) of the respondents have a master's degree. Respondents with diploma certificates were the third-largest group, reflecting 7.4% (n=59). Next, the data set comprises responses from 225 individuals, delineating various occupational categories as follows: 18.2% (n=41) identified as holding executive positions, while 20.9% (n=47) described their roles as non-executive. Further, 8.9% (n=20) reported involvement in their business endeavors, and 3.6% (n=8) indicated senior management positions. The largest cohort among respondents was students, constituting 41.8% (n=94), followed by retirees at 2.2% (n=5), and individuals not currently employed at 4.4% (n=10). Correspondingly, recent literature suggests that younger customers simultaneously affect their technology acceptance behaviour (Kim et al., 2013a, 2013b; Wang and Lin, 2017; Wang et al., 2009). Besides, the importance of education level on technology acceptance behaviour is well-researched and discussed. It can be said that most respondents are highly educated and are open to using the robot service. Notably, most researchers suggest that education level is positively related to the acceptance and adoption of technology (Schepers and Wetzels, 2007; Sinha et al., 2021), which aligns with the respondents' profile characteristics.

4. Findings

Measurement model assessment

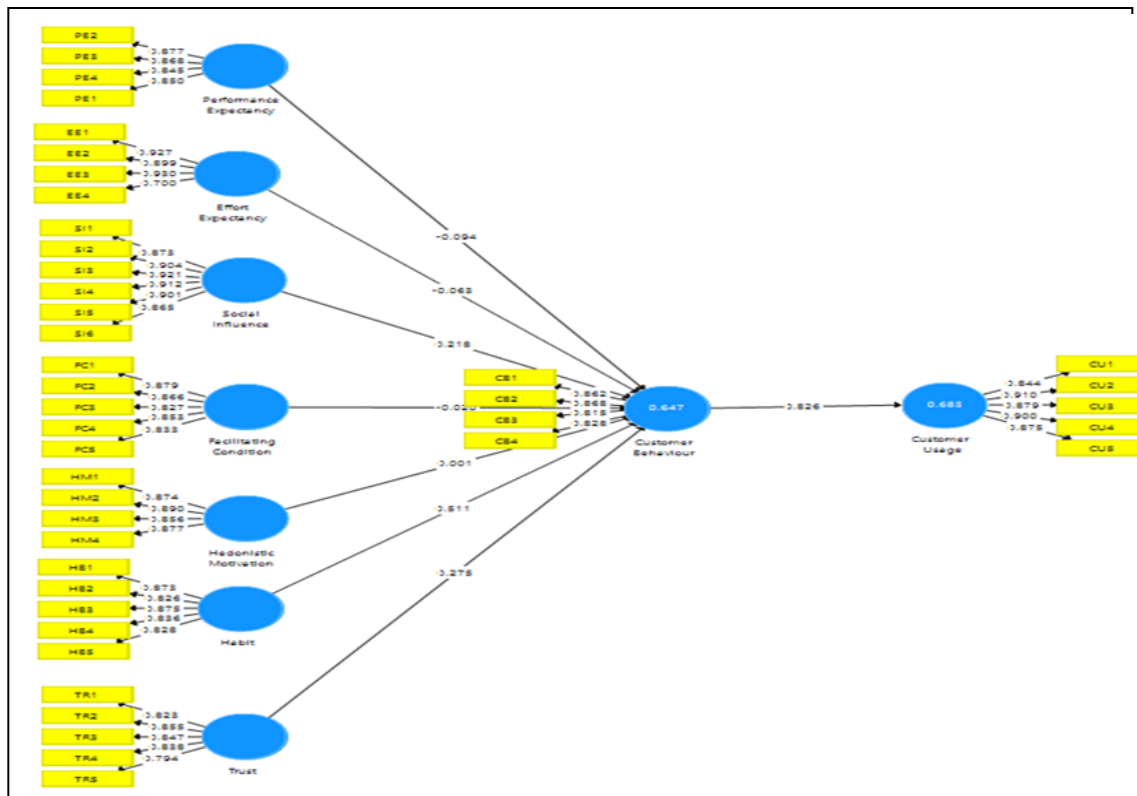
To test the proposed hypotheses, SmartPLS 3.1.1 was employed in a two-stage process: evaluating the measurement model and then analyzing the structural model. The evaluation of the measurement model (outer model) and the analysis of the structural model (inner model). As per the findings of Hair et al. (2016), the purpose of the measurement model's assessment is to determine the validity and reliability of the items that represent the constructs. During this phase, the study performed a reflective measurement assessment that encompassed internal consistency reliability, reliability of individual indicators, convergent validity of the measured construct, and discriminant validity as suggested by Sarstedt et al. (2014) and Hanafiah (2020). Figure 1 and Table 1 display the output of the assessment of the reflective measurement model, as shown in Figure 2. The model assessment process commenced by examining the loadings of each indicator. Table 1 shows that the indicator loadings scores range from 0.700 to 0.930, which indicates that the reliability is excellent.

The composite dependability value for the nine constructions ranged from 0.908 to 0.946, surpassing the acceptable threshold of 0.7. The Cronbach's alpha coefficient for all constructs ranged from 0.833 to 0.928, surpassing the acceptable threshold of 0.7. Therefore, the internal consistency of the items utilized in this investigation was sufficient and verified (Bagozzi and Yi, 1988). The average variance extracted scores, ranging from 0.661 to 0.863, are above the minimum allowed value of 0.50, demonstrating a satisfactory level of convergent validity (Hanafiah, 2020).

Table 1: Reflective measurement model assessment

Latent Variable	Code	Outer Loading	Cronbach alpha	Composite Reliability	Average Variance Extracted (AVE)
Performance Expectancy	PE1	0.850	0.833	0.919	0.740
	PE2	0.877			
	PE3	0.868			
	PE4	0.845			
Effort Expectancy (EE 5 Removed)	EE1	0.927	0.887	0.924	0.756
	EE2	0.899			
	EE3	0.930			
	EE4	0.700			
Social Influence	SI1	0.873	0.951	0.961	0.803
	SI2	0.904			
	SI3	0.921			
	SI4	0.912			
	SI5	0.901			
	SI6	0.865			
Facilitating Condition	FC1	0.879	0.905	0.930	0.725
	FC2	0.866			
	FC3	0.827			
	FC4	0.853			
	FC5	0.833			
Hedonic Motivation (HM 5 Removed)	HM1	0.874	0.898	0.928	0.764
	HM2	0.890			
	HM3	0.856			
	HM4	0.877			
Habit	HB1	0.873	0.902	0.927	0.719
	HB2	0.826			
	HB3	0.875			
	HB4	0.836			
	HB5	0.828			
Trust	TR1	0.823	0.889	0.918	0.692
	TR2	0.855			
	TR3	0.847			
	TR4	0.838			
	TR5	0.794			
Customer Behaviour	CB1	0.862	0.865	0.908	0.712
	CB2	0.868			
	CB3	0.815			
	CB4	0.828			
Customer Usage Intention	CUI1	0.844	0.928	0.946	0.777
	CUI2	0.910			
	CUI3	0.879			
	CUI4	0.900			
	CUI5	0.875			
Note: N 225					

Figure 2: Measurement model assessment



Structural model assessment

Structural model analysis was conducted by evaluating key statistical parameters, including path coefficients (β), the coefficient of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2) (Chin, 2010; Hair et al., 2016). The analysis revealed that the explanatory variables accounted for 64% of the variance in customer behaviour and 68% in customer usage intention. To determine the significance of individual exogenous variables on the endogenous constructs, effect size (f^2) calculations were employed. Based on Cohen's (1988) guidelines, f^2 values above 0.02, 0.15, and 0.35 correspond to small, medium, and large effects, respectively. The results showed that effort expectancy, performance expectancy, and social influence exerted only a minor influence on customer behavioural responses.

Meanwhile, the study found that changes in trust have a large effect on customer behaviour. Besides this, the changes in customer behaviour greatly affect customer usage intention. The rest of the construct reports a limited effect on customer behaviour. The path model's predictive accuracy (Q^2) on customer behaviour is 0.447, while the Q^2 value for the customer usage intention is 0.525. To conclude, customer behaviour has moderate prediction power, while customer usage intention has large prediction power. Next, the study hypotheses were tested by looking at the path coefficient (b) and the significance level (p -value). Table 2 presents the structural model's statistics and p -value.

Table 2: Path Coefficient (β), T-Value and Significance Level

	β	T-Value	p-values	Hypothesis
Performance Expectancy -> Customer Behavior	-0.094	0.799	0.424	Not Significant
Effort Expectancy -> Customer Behavior	-0.063	0.948	0.343	Not Significant
Social Influence -> Customer Behavior	0.218	1.457	0.146	Not Significant
Facilitating Conditions-> Customer Behavior	-0.020	0.185	0.853	Not Significant
Hedonic Motivation -> Customer Behavior	0.001	0.009	0.993	Not Significant

Habit -> Customer Behavior	0.511***	4.040	0.000	Significant
Trust -> Customer Behavior	0.218**	1.870	0.062	Not Significant
Customer Behavior -> Customer Usage Intention	0.826***	29.477	0.000	Significant

Notes: 99% confidence interval: $p\text{-value} < 0.00***$; 95% confidence interval: $p\text{-value} < 0.05**$

The initial hypothesis (H1a) suggests that Performance Expectancy does not have a positive impact on customer behaviour. The results suggest that Performance Expectancy does not significantly influence customer behaviour ($\beta = -0.094$, $t = 0.799$). Thus, the hypothesis H1a is not corroborated. The second hypothesis (H1b) posits that Effort Expectancy has a negligible effect on customer behaviour. The results indicate a negative relationship between the variables, with a beta coefficient of -0.063 and a t -value of 0.948 . Therefore, there is a lack of empirical data substantiating the claim of H1b. The findings do not support the third hypothesis (H1c) that suggests there is no significant and positive relationship between Social Influence and customer behaviour ($\beta = 0.218$, $t = 1.457$). Hypothesis H1d posits that the Facilitating Condition positively influences customer behaviour. The results suggest that the Facilitating Condition does not exert a substantial influence on customer behaviour. Therefore, there is no evidence to support H1d. The fifth hypothesis (H1e) asserts that there is no association between Hedonic Motivation and conduct. The results suggest that Hedonic Motivation does not have a statistically significant effect on customer behaviour ($\beta = 0.001$, $t = 0.009$). Thus, the proposed hypothesis H1e is not substantiated.

However, H1f has a favourable impact on customer behaviour. The findings indicate that the Habit has a substantial and beneficial impact on customer behaviour ($\beta = 0.511***$, $t = 0.762$). Therefore, the stated hypothesis H1f is confirmed. Additionally, the variable H1g has a detrimental impact on customer behaviour, with a coefficient of $0.218**$ and a t -value of 1.870 . Nevertheless, it is crucial to acknowledge that these effects lack statistical significance. Conversely, the third hypothesis (H3) proposes that customer behaviour has a favourable influence on customer usage intention, supported by a statistically significant p -value of 0.000 and a substantial β coefficient of $0.826***$. The β coefficient measures the extent to which each independent variable (IV) affects the dependent variable (DV). As the β coefficient grows, the influence of the independent variable (IV) on the dependent variable (DV) becomes more significant.

Moderating effects

According to the direct effect model (refer to Table 3), the findings indicate that Age Generation has a negative moderating effect on the link between Customer Behaviour and Customer Usage Intention ($\beta = -0.831$; $t = 0.579$; $p\text{-value} = 0.563$), and this association is not statistically significant. The negative beta value indicates that Age Generation has a detrimental impact on the correlation between Customer Behaviour and Customer Usage Intention. Thus, H4 was deemed invalid.

Table 3: Moderating Effect of the Age Generation

	Beta (β)	T Statistics	P Values	Result
H4: Customer Behavior + Age Generation -> Customer Usage Intention	0.831	0.579	0.563	Not significant

Notes: 99% confidence interval: $p\text{-value} < 0.00***$; 95% confidence interval: $p\text{-value} < 0.05**$

5. Conclusion

This study offers a comprehensive understanding of the primary determinants shaping the adoption of robotic services in restaurant settings, as well as their influence on customer behaviour and usage intentions. Robot-based service solutions have emerged as an innovative trend in the foodservice sector, offering a dynamic and efficient operational model tailored for restaurants. Survey results indicate that customers generally perceive these services as enjoyable, user-friendly, time-saving, and engaging. Additionally, the findings suggest that fostering customer trust plays a crucial role in enhancing behavioural engagement with robot services. The study also highlights the importance of investigating the factors that drive the acceptance of robotic technologies within the Malaysian restaurant context. By integrating and analysing the empirical data, this research contributes valuable theoretical insights and practical recommendations for the implementation of service robots.

Theoretical Implications

Restaurateurs need to comprehend customers' technological preferences to offer superior and contemporary services. This study significantly adds to the generation of fresh knowledge regarding the emergence of robot service technology in Malaysia's restaurant business. The analysis confirmed that only habit and customer behaviour significantly influenced customer usage intention, while the other variables did not have a significant impact. Significantly, due to the novelty of the robot service technology and its lack of financial incentives, it deterred additional adoption. Including trust in the analysis was a logical decision, as it was the most significant predictor of purchasing behaviour. Interestingly, the study found that trust did not significantly impact the adoption of robot service technology. This could be attributed to the widespread acceptance and use of technology across all age groups, which suggests that trust may not be a critical factor in influencing customer behaviour in this context. Instead, the familiarity and general comfort with using technology, regardless of age, appear to diminish the role of trust in the decision-making process.

Practical Implications

To ensure the successful integration of robot services in the food service industry, it's crucial to ignite customer enthusiasm and continuously gather their feedback for ongoing improvements. Building trust with customers is key, as businesses must demonstrate how these technologies can simplify decision-making, reduce effort, lower costs, and mitigate risks in a landscape filled with options. To further drive this evolution, additional research is needed to uncover what motivates or hinders the adoption of service robots in real-world scenarios. This understanding will enable more targeted marketing and communication strategies, effectively addressing the unique needs and concerns of diverse customer segments.

This study has profound implications for the food service industry. With the anticipated rise of robot services, food service businesses must embrace these innovations to maintain a competitive edge. However, understanding customer preferences, especially those influenced by age and cultural background is essential. The research highlights that younger customers may be more inclined to adopt robot services than their older counterparts. The current endemic environment provides a unique opportunity for the adoption of service robots, and further exploration of tailored marketing strategies is recommended to meet the distinct needs of different customer groups.

Additionally, effective promotional strategies for robotic restaurants should focus on reassuring customers about the capabilities of robot services, demonstrating that they can perform tasks just as efficiently as human staff. Aligning customer expectations with what robot services can deliver will likely boost acceptance and advocacy, benefiting restaurant owners and managers across various market segments.

This study also aims to raise awareness of robot services in restaurants among customers. Those who are innovation-minded are more likely to embrace new technological services, especially in an era that emphasizes contactless interactions. The findings provide valuable insights for businesses to develop strategies that cater to both their own needs and those of their customers, including leveraging social media to reach a wider audience and foster engagement. By aligning robot service adoption with customer expectations, the food service industry can ensure a positive experience for both businesses and their patrons.

Limitations and future studies

Data collection was completed immediately before the COVID-19 pandemic, which limits this study. The global epidemic may have altered popular attitudes about F&B service robots. Future studies must review attitudes to see if they have changed. Since industrialised countries will have a labour shortfall, food and beverage automation research should expand (Webster, 2021). Future research may examine the desire to pay for robot-delivered F&B services and how robots create memorable F&B experiences.

Overall, this study report shows that food and beverage automation will be built on a populace that understands the pros and cons of automation. The findings show the usefulness of dividing operations into automatable tasks in theory and methodology. This method shows that the public prefers robots for certain tasks. This recommends that future research should focus on activities rather than scenarios using robots, as the public seems to evaluate robot use differently based on tasks rather than grand scenarios like being given meals. The findings are intriguing because the public seems to recognise the drawbacks of robots in such procedures but

does not seem to question their suitability. The research suggests that fostering a positive attitude towards service robots will assist food and beverage operations in integrating robots. However, there is also evidence that the public will be willing to accept greater automation of food and beverage services, depending on the task, making some tasks easier to automate and less resistant to robots.

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Appendix 1

Table A1: Survey Instruments

Code	Items
PE1	Robot services have the features required to serve me.
PE2	Robot services will provide me with the help I need.
PE3	Robot services provide more accurate information than human beings
PE4	Robot services provide me with more consistent service than human beings.
EE1	Robot services provide me with more consistent service than human beings.
EE2	Robot services will be intimidating to me
EE3	Interactions with robot services will take too much of my time
EE4	My interaction with robot services is clear and understandable.
SI1	People who are important to me would encourage me to interact with the robot services
SI2	People whose opinions are valued would prefer that I interact with robot services.
SI3	People who influence my behaviour would want me to utilize robot services
SI4	People in my social networks who would interact with robot services in services have a high profile.
SI5	Interacting with robot services reflects a status symbol in my social networks.
SI6	People in my social networks who would be interacting with robot services have more prestige than those who don't.
FC1	In service encounters, guidance is available to me in the use of robot services.
FC2	In service encounters, specialized instruction concerning robot services is available to me.
FC3	In service encounters, a specific employee (or group) is available for assistance with robot services' difficulties
FC4	I have the knowledge necessary to use the robot service
FC5	Using the robot service is entirely within my control.
HM1	Using a robot service is fun.
HM2	Using the robot service is enjoyable.
HM3	Using a robot service is entertaining.
HM4	Using the robot service gives me pleasure.
HB1	The use of robot services has become a habit for me.
HB2	I am addicted to using robot services.
HB3	I must use a robot service.
HB4	Using the robot service has become natural to me.
HB5	A robot service is something I use without having any second thoughts when I go to a robot service restaurant.
TR1	I believe that robot service in a restaurant is trustworthy.
TR2	I feel assured that the robot service technology structures would prevent me from miscoding problems.
TR3	I usually trust a technology until it gives me a reason not to trust it.
TR4	My typical approach is to trust new technologies until they prove to me that I shouldn't
TR5	I generally give technology the benefit of the doubt when I first use it.
CB1	I usually use a robot service in a restaurant.
CB2	I use the robot service regularly.
CB3	I am content with my experience in using robot services.
CB4	I am delighted with my experience in using robot services.
CUI1	I intend to continue using the robot service in the future
CUI2	I plan to continue to use the robot service frequently.
CUI3	I will always use the robot service when possible
CUI4	I will often use robot services in the future.
CUI5	I will recommend others to use the robot service.