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Shaping Customer Attitudes: The Role of AI-Driven Robotic Waiters in Restaurant Business

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Abstract *This study looks into how user impressions and opinions of robotic waiters in the hotel sector change depending on AI-enable service quality. Using the 'Technology Acceptance Model (TAM)' and the 'Information Systems (IS) Success Model' as theoretical frameworks, a survey of 267 patrons of Kuala Lumpur was conducted. The research showed that perceived usefulness and perceived ease of use are much influenced by artificial intelligence-enhanced service quality. Though perceived ease of use had no appreciable effect on attitudes, perceived usefulness was found as a mediator in the link between service quality and attitudes toward using. The study also looked at how trust and anthropomorphism can moderate the favorable effects of perceived usefulness and service quality on user attitudes. It found that both factors increased these effects. These results highlight the need of trust, humanistic traits, and service quality in fostering positive opinions about artificial intelligence-enabled products. The work ends with discussing theoretical and pragmatic implications, acknowledging constraints, and suggesting directions for next investigations.*

Keywords: *AI-Driven Service, Success Model, User Attitude, Anthropomorphism, Trust, Robotic Waiter*

INTRODUCTION

Driven by great changes across many industries, including hospitality (Griffy-Brown et al., 2018; Uzir et al., 2021), the fast growth of technology is altering both individual lives and more general society structures. Artificial intelligence (AI) and robotics form the foundation of this transformation; global companies are heavily investing in the development of sophisticated robotic systems. By extending the use of robotics across several sectors, these developments not only are reducing technical inequalities but also generating new market prospects (Fikry et al., 2023; Kumar et at., 2025; Lee et al., 2019). Robotic innovations in robotics have produced robots able to recognize and react to human actions, therefore greatly improving their value in the provision of services (Hsia et al., 2022; Blut et al., 2021).

Particularly in response to continuous Labor shortages, the use of robotic waiters is becoming more and more widespread in the restaurant sector, which is a clear application of robotics inside the hotel sector (Berezina et al., 2019). The COVID-19 outbreak has accelerated the deployment of robotic waiters (Abhari et al., 2022; Gu et al., 2023), hence aggravating the Labor shortage the food and beverage (F&B) sector is suffering in Malaysia. From ordering food to delivering orders, these robots can independently complete a range of duties and serve much more meals daily than human workers, so providing benefits like error-free service and low labour costs (Aydin, 2021; Tuomi et al., 2021; Ivanov & Webster, 2019).

Robotics' possible to offer competitive advantages, improve efficiency, and produce unique client experiences (Azeem et al., 2021) is well known when included into hotel services. Understanding their influence on consumer views and attitudes becomes critical as service robots are increasingly deployed in areas such housekeeping, hosting, and table service (Seyitowicz & Ivanov, 2022). Research on user

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attitudes toward robotic dining experiences is still scant despite this trend, especially in regards to how these attitudes affect the acceptance and use of robotic technologies in restaurants (Maruf et al., 2024; Liu et al., 2023; Rosete et al., 2020; Meidute et al., 2021; Tuomi et al., 2021).

Given the significance employee-customer interaction plays in the eating experience, this disparity is especially important. The change from human employees to robotic waiters brings a special context different from conventional eating settings and is still mostly unexplored. Though service robots are attracting interest, thorough understanding of consumer perceptions of robotic eating experiences is still absent. Studies on public opinion of artificial intelligence in urban areas have shown public perception gaps (Yigitcanlar et al., 2022). More research on this is therefore much needed. Furthermore, understudied is the effect of psychological features on attitudes toward robots, implying a discrepancy in knowledge of how these features affect technological acceptability (Koverola et al., 2018). Talks on how robots affect the labour market also underline the need of looking at public opinions (Lee, 2021). Finally, the lack of research on user perception elements influencing attitudes on service robots exposes a knowledge vacuum on the drivers of these opinions (Park & Pobil, 2013).

Examining consumer opinions of robotic dining facilities can help to close these gaps, with special focus on the effect of robotic technology on customer attitudes. Examining these points of view helps this study to improve academic debate and practical implementations in the hotel industry by providing important insights into the evolving dynamics of AI-enabled service settings.

LITERATURE REVIEW

This research uses the 'Technology Acceptance Model (TAM)' as its primary theoretical foundation. The TAM elucidates the mechanisms by which consumers embrace technology across various contexts (Davis, 1989; Venkatesh & Davis, 2000). It emphasizes two major factors: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). These elements shape consumers' impressions of a technology and determine their intention of application. Within the field of AI-driven services like robotic waiters, the TAM clarifies user impressions and acceptance of these systems. Directly affecting consumers' desire to use robotic waiters—including how well they accept orders, deliver food, and handle payments—are their usefulness (Jang & Lee, 2020). Comparably, customer attitudes and acceptability are shaped by the seeming simplicity and effortlessness of working with robotic systems (Ventre & Kolbe, 2020).

TAM has inherent restrictions even if its simplicity and resilience have made it a prevalent paradigm in studies of technology uptake. Critics contend that TAM frequently ignores the environmental, social, and emotional elements that also greatly influence user attitudes and actions, even if it is quite successful in capturing cognitive elements of technology adoption (Bagozzi, 2007; Venkatesh et al., 2012; Holden & Karsh, 2010). This study incorporates supplementary constructs from several theoretical frameworks to overcome these constraints and enhance the knowledge of technology adoption in service environments. It specifically integrates Service Quality from the Information Systems (IS) Success Model, Anthropomorphism from the AIDUA paradigm, and Trust as moderating variables.

Service Quality from the IS Success Model

In the year of 1992, DeLone and McLean developed IS Success Model, provides a theoretical framework for assessing the efficacy of information systems. The model recognizes the essential factors such as System Quality, Information Quality, and Service Quality contribute to the overall efficacy of an information system. Information Quality relates to the quality of the information given (e.g., accuracy, relevance), System Quality relates to the performance (e.g., dependability, speed), and Service Quality stresses the support offered by the system, generally through user interaction (DeLone & McLean, 2013).

In the domain of AI-driven services, Service Quality emerges as a fundamental feature. In contrast to conventional information systems that prioritize technical and informational elements, the assessment of AI-enabled services in the hotel sector focuses on the quality-of-service interactions they enable (Enholm et al., 2021). The way customers perceive service quality, especially how well and efficiently the robotic waiter performs its tasks, is likely to have the most immediate impact on their attitudes and future behavior (Kaartemo & Helkkula, 2018).

The emphasis on Service Quality over System Quality or Information Quality is informed by the distinctive characteristics of AI-enabled services within the hospitality context. Customer contacts with AI technologies in these environments are naturally direct and experiential. While both System Quality and Information Quality are still very important, they frequently play a more indirect role within the larger service experience and are less likely to dominate the conscious evaluation by consumers (Kaartemo & Helkkula, 2018; Parasuraman, Zeithaml & Berry, 1988). Service Quality becomes the most obvious factor for comprehending user attitude since, in AI-driven environments, service interactions form the core of the customer experience. Hence, the variable in this study was AI-enabled Service Quality.

Anthropomorphism Using the AIDUA Framework

Understanding human interactions with artificial intelligence and robotics depends on the fundamental idea of anthropomorphism—that is, the attribution of human-like traits to non-human entities—which shapes our perspective (McCartney & McCartney, 2020). Anthropomorphism is quite important within the AIDUA paradigm, which emphasizes on elucidating consumers' intention to accept AI devices in service delivery (Hengxuan et al., 2020). Studies have revealed that by influencing both cognitive and affective assessments, anthropomorphic traits of AI service robots can influence consumer acceptance (Zhang et al., 2021).

According to the motivating viewpoint on anthropomorphism, interacting with anthropomorphized objects may provide emotional benefits to consumers—especially those who are lonely or looking for social connection—Chen et al., 2018. In the field of robotic waiters, anthropomorphism could increase apparent value and usability by encouraging a more intuitive, human-like interaction (Lee et al., 2020). Research has underscored the influence of robot anthropomorphism on consumer behavior, notably enhancing revisit intentions following a service failure (Cui & Jian-an, 2023). This study incorporates anthropomorphism into the TAM and investigates its potential moderating effect on PU and PEOU in customer encounters with robots.

Trust

Adoption of technology depends on trust since users rely on it to perform activities with dependability and accuracy (Gefen et al., 2003; McKnight et al., 2002). Trust is the belief that technology will operate as expected and is safe for use, which can significantly affect both apparent simplicity of use and perceived usefulness (Lee & See, 2004). Regarding robotic waiters, trust might affect the relationship between these points of view and user impressions. More trust could improve the supposed advantages of utilizing the technology, thereby influencing more favorable views and higher adoption intentions (Lankton et al., 2014; Verhagen et al., 2015). This work tackles the emotional and cognitive dynamics not entirely captured by PU and PEOU by including Trust into TAM.

Combining artificial intelligence (AI) with anthropomorphism, trust, and service quality improves TAM's capacity to take into account more general elements of technology acceptance in service settings. Thus, providing a more complete understanding of what shapes customer attitudes and intentions toward AI services in hospitality.

HYPOTHESIS DEVELOPMENT

AI-Enabled Service Quality

Service quality is characterized as the disparity between client expectations and actual service performance (Pakurár et al., 2019). AI-enabled service quality includes the efficiency, reliability, and efficacy of cognitive technology in providing customer service (Kaartemo & Helkkula, 2018; Papadakis, 2022). The concept of AI-enabled service quality is particularly relevant in settings where the interaction between customers and AI-driven systems, such as robotic waiters, is direct and experiential.

According to the literature, consumers' impressions of the value of the technology may be much influenced by their impressions of AI-enabled service quality. In a retail environment, for example, robotic assistants who accurately suggest products, quickly answer consumer questions, or easily handle transactions are probably seen as quite valuable by consumers (Guan et al., 2022). In hospitality, too, where robotic waiters handle meal delivery and order-taking, the apparent value of these robots is intimately related to their capacity to effectively satisfy consumer expectations (Enholm et al., 2021).

Furthermore, crucial for clients' whole impression of service quality is their simple interaction with these robotic technologies. Consumers who find it simple to engage with robots for chores like traversing store layouts or locating specific products usually have a better perceived ease of use, which improves their whole experience and pleasure (Chuah et al., 2022). Therefore, robotic waiters who let consumers order, pay, and customize their dining experience easily are probably going to be more appreciated, thereby highlighting the need of apparent simplicity of use in technological acceptability (Kaartemo & Helkkula, 2018). As so, we propose the following hypotheses:

- H1: Service quality driven by artificial intelligence increases perceived value in using AI-Driven Robotic Waiters.
- H2: AI-enabled service quality positively influences perceived ease of use in AI-Driven Robotic Waiters.

Perceived Usefulness

Perceived usefulness denotes the individual believes that utilizes a specific system helps to improve their job performance or facilitate task completion (Davis, 1989). In the realm of AI-driven services such as robotic waiters, perceived utility is essential in influencing client sentiments about the technology (Go et al., 2020; Grewal et al., 2020). Often seen as highly valuable, robotic sales assistants who can precisely answer consumer inquiries, make tailored recommendations, and provide a speedier shopping experience help to raise customer happiness and enhance adoption chances (Jang & Lee, 2020). Likewise, robotic waiters that simplify the dining experience by lowering wait times, guaranteeing order accuracy, and improving general service efficiency are seen as helpful, therefore influencing consumers' opinions of utilizing these technologies (Ventre & Kolbe, 2020). Given the strong link between perceived usefulness and positive attitudes towards technology adoption, we hypothesize:

H3: Perceived usefulness has a favourable influence on attitudes toward use AI-Driven Robotic Waters.

Perceived Ease of Use

Perceived ease of use, another fundamental TAM construct, represents a person's belief to utilize a system will be effortless (Davis, 1989). This construct is especially important since it can reduce cognitive and physical barriers to the acceptance and use of technology, therefore increasing the chance that users would do so (Ventre & Kolbe, 2020). For example, if we are to embrace robots that assist consumers in navigating companies or finding products, they must be easily comprehended and operated upon. Those who find these robots easy to use are more likely to have positive impressions of them and to use them once more (Lu et al., 2020). The same is true of robotic waiters in the hotel sector; if consumers find these robots simple to operate—whether ordering, making payments, or customizing their meals—they are more likely to acquire a pleasant attitude about using them (Pitafi et al., 2020). Researchers suggest the following hypothesis:

H4: Perceived ease of use positively influences attitudes towards using AI-Driven Robotic Waiters.

Attitudes Towards Use

Attitudes towards using a service or system are characterized as the extent to which an individual has a positive or negative assessment of the action in question (Venkatesh & Davis, 2000). Regarding AI-driven services like robotic waiters, these impressions are shaped by both apparent simplicity of use and perceived benefit (Al-Rahmi et al., 2019; Taufik et al., 2019). In retail settings, their ability to enhance the shopping experience often shapes positive impressions of robotic assistants. Consumers who view robotic sales assistants as both helpful and user-friendly are more likely to form a good attitude about their use, therefore influencing their intents to adopt these technologies (Blanche et al., 2021). Similar ideas apply to robotic waiters; as customers view these AI-driven services as both useful and user-friendly, their impressions of using them change, hence increasing the acceptance rates (Molinillo et al., 2022).

Moreover, research show that the association between service quality and customer opinions is often tempered by perceived usefulness and simplicity of use. Good service quality can help to build impressions of usefulness and user-friendliness, thereby enhancing positive opinions on the use of technology (Hwang et al., 2021; Choe et al., 2022). Given this understanding, we suggest:

- H5: User perceptions are favourably changed by AI-enable service quality of Robotic Waiters.
- H6: Perceived usefulness mediates the association between views of robotic waiters and AI-improved service excellence.
- H7: Perceived ease of usage moderates the relationship between sentiments toward robotic waiters and AI-enabled service quality.

The Moderating Influence of Anthropomorphism

Consumers' impressions and interactions with artificial intelligence systems are much shaped by anthropomorphism. Anthropomorphism can help to make these technologies seem more relevant and understandable in-service environments (Gursoy et al., 2019). Robots who seem more human-like could improve the perceived value and quality of the services they offer (Lin et al., 2020; Gursoy et al., 2020). Blut et al., (2021) underline the need of integrating anthropomorphism in combination with traditional traits as perceived usefulness and convenience of use to understand technology acceptance. According to their studies, human acceptance and assessment of artificial intelligence systems might be quite influenced by anthropomorphic traits. Zhang et al., (2021) found similar findings about robots that resemble humans producing higher performance expectations whereas those that resemble machines are connected to higher effort expectations. The results show that anthropomorphism affects not just first impressions but also greatly affects long-term acceptance and use behavior.

Making robots more human-like in the case of robotic waiters could help to raise customer view of their utility. A robotic waiter that seems more human may help customers trust and grasp easier. This might cause more pleasure with the service given. Akdim et al. (2023) also showed that anthropomorphism is critical for the successful acceptance of service robots. Lin et al. (2024) further suggest that human-like features help build stronger emotional connections between users and technology, facilitating ongoing acceptance. These insights suggest that anthropomorphism enhances the connection between AI-enabled service quality and perceived utility. The projected beneficial influence of service quality on perceived utility is expected to be larger the more human-like robotic waiters are observed. This produces the following theory:

- H8: Anthropomorphism moderates the relationship between perceived usefulness and AI-enabled service quality; so, the correlation is strengthened when the robotic waiter is considered as more human-like.

The Moderating Role of Trust

Trust is essential for the acceptance of AI-enabled services, as users rely on technology to execute tasks with precision and dependability (Gefen et al., 2003). The incorporation of trust into the TAM has been thoroughly examined, with research emphasizing its impact on the correlations among perceived usefulness, perceived ease of use, and technology acceptance. For instance, Brasier and Wan (2010) looked at how including technology trust into TAM improves its capacity to explain technology adoption. Within the TAM model, trust also plays a major moderating role. To better grasp technological acceptance, Goundar et al. (2021) underline the need of customizing TAM by adding trust and risk considerations. In line with this, Linzenich and Ziefle (2018) investigated how acceptability of energy technology was influenced by trust and perceived fairness, therefore underlining the general relevance of trust in many technical environments.

In domains such as e-commerce, mobile banking, and smart cities, trust has consistently been shown to exert a positive influence on the acceptance of technology. Trust particularly mediates the perceived ease of use on the acceptability of users, as Toqeer et al. (2021) have deliberated. Trust has the potential to substantially influence both perceived utility and perceived ease of use (Lee & See, 2004). This is most relevant in the case of service robots, as exemplified in their application in restaurants and hospitality businesses. Gupta and Pande (2023) pointed out that trust, along with perceived usefulness and ease of use, had a significant influence on consumer intentions towards the acceptance of robot-based services in restaurants. Huang (2022) also found that trust indirectly moderates usage intentions via PEOU and PU, particularly for the acceptance of service robots by older customers in hotels.

In the case of robotic waiters, higher levels of trust can enhance the perceived benefits of the technology, thereby strengthening the positive relationship between perceived usefulness and attitudes towards use. When clients have confidence in a robotic waiter's ability to do its jobs reliably and efficiently, they are more inclined to view the technology as beneficial, hence cultivating more positive attitudes towards its adoption. This results in the subsequent hypothesis:

- H9: Trust moderates the association between perceived usefulness and attitudes towards use, indicating that the relationship is more robust when the robotic waiter is regarded as more trustworthy.

Based on the above discussion, Fig. 1 presents conceptual framework.

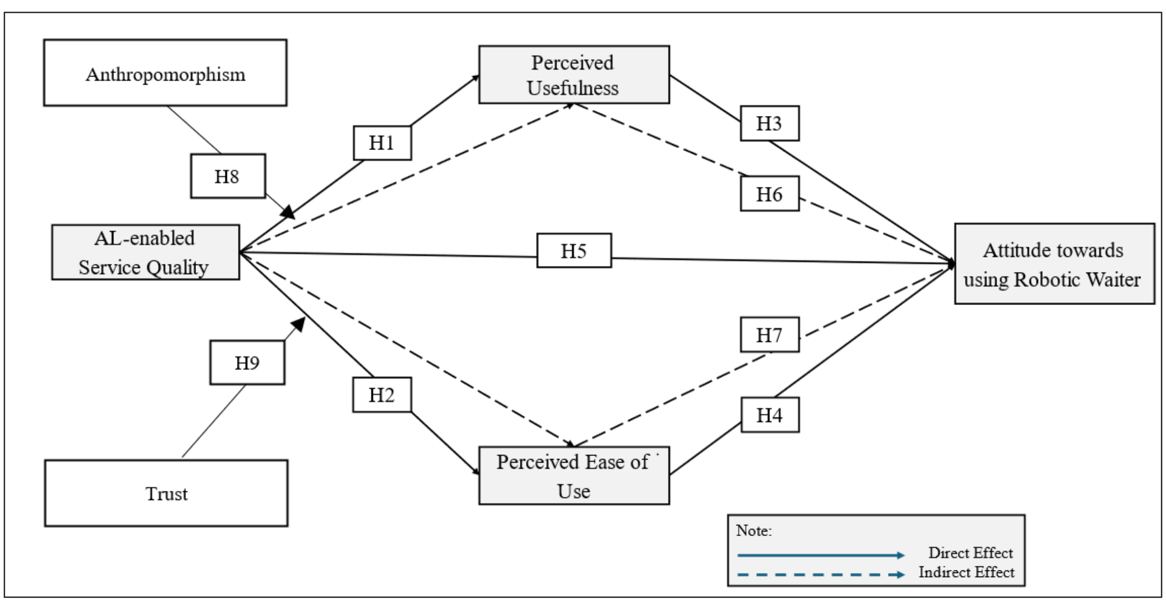

Fig. 1: Conceptual Framework

METHODOLOGY

A quantitative method was applied to explore the drivers influencing customer perception toward robot waiters in restaurants. The sample respondents were patrons from restaurants in Kuala Lumpur, Malaysia, where robot waiters are utilized. The selection of Kuala Lumpur was due to its status as a nation's capital city, influenced by a high level of travel, tourism, and technology adoption, thus having a suitable environment to analyse AI-powered service within the hotel industry.

The current study utilized convenience sampling as its methodology. The approach is specifically suitable in exploratory studies where the key aim is to obtain data from a targeted and easily accessible population (Klar & Leeper, 2019). The use of this approach made it possible to conduct effective collection from people with exposure to robot waiters, ensuring both response data relevance and reliability. According to Hoyle, Lin, et al. (2020), a sample size of between 200 to 400 respondents can be acceptable in studies using structural equation modelling (SEM), a core analysis approach in this study. Thus, a total of 300 questionnaires were administered to restaurants within Kuala Lumpur, securing a response of 278 completed forms. After excluding incomplete returns, a remaining 267 valid responses were achieved for further analysis.

Measure

The research model consists of six constructs: AI-enabled service quality, PU, PEOA, anthropomorphism, trust, and attitudes towards usage. Each construct was assessed utilizing items derived from established scales in the literature, so ensuring both reliability and validity. A 5-point Likert scale was used to evaluated all the item, indicating strong disagreement to strong agreement (1 to 5), in accordance with the guidelines established by Hair et al. (2017), Simms et al. (2019), and Taherdoost (2019).

AI-Enabled Service Quality (AESQ): This construct reflects the perceived quality of service provided by AI systems, such as robotic waiters. Aspects like efficiency, reliability, and responsiveness have a major impact on customer impressions (Enholm et al., 2021; Uzir et al., 2021). In line with the IS Success Model, the robot waiter operates with precision and competence, allowing users to rely on it for quality service, besides giving timely responses to questions.

Perceived Usefulness (PU): Described in the Technology Acceptance Model (TAM), Perceived Usefulness measures users' cognitions about how much the AI-empowered service would improve their experience or allow them to do something more effectively (Davis, 1989; Jang & Lee, 2020). Representative examples include: I think having a robotic waiter would be useful in improving my dining experience, using the robotic waiter allows me to conduct my dining activities more effectively, and the robotic waiter would be useful in providing me with the services I need (Davis, 1989).

Perceived Ease of Use (PEOU): This construct measures the level of simplicity and lack of effort needed for user interaction with the AI system (Davis, 1989; Ventre & Kolbe, 2020). The measures used to gauge this construct include: working with the robotic waiter is straightforward and easy, I find it easy to learn the skills needed to use the robotic waiter, and the robotic waiter is user-friendly (Davis, 1989).

Anthropomorphism: This trait scores how much the robot waiter is seen to have humanlike qualities. These qualities arguably can have a strong impact upon customer perception with respect to intuitiveness and relatability (Gursoy et al., 2019; Lin et al., 2020). The measures used to determine anthropomorphism include the following statements: The robot waiter seems to have humanlike qualities, I think I am interacting with the robot waiter in a way I would with a human, and the robot waiter seems to understand me in a way I would expect with a human.

Trust: In this context, trust denotes the extent to which users view the robotic waiter as capable of executing its functions consistently and safely, which can profoundly affect perceived utility and attitudes toward its utilization (Gefen et al., 2003; Lee & See, 2004). For this construct, I believe the robotic waiter is safe to operate, I feel confident it will work as intended, and I trust it to consistently complete jobs.

Attitudes Toward Use (ATU): Accounts for the general positive or negative orientation people have toward the use of AI services (Venkatesh & Davis, 2000; Maruf et al., 2021). An example would be saying: "I have a positive attitude toward using robot waiters because I think it's a fantastic idea, and I'm looking forward to having them in restaurants" (Venkatesh & Davis, 2000).

Data Acquisition

Data were collected using a mall-intercept survey approach. This method involves approaching potential respondents in public spaces, in this case, shopping malls, where demographic profiles are expected to match those of the targeted population. The mall-intercept method is most useful for data collection in a multicultural, dynamic environment like Kuala Lumpur, which is famous for its cosmopolitan food culture. The use of this mall-intercept approach relies on its ability to access a heterogeneous segment of targeted subjects within a relatively short period of time, thus providing a diversified sample representing the targeted population. In addition, this approach allows researchers to identify particular cohorts—namely, dining patrons who have had access to robot-waiter services—thus ensuring data relevance as well as accuracy (Bush & Hair, 1985).

Research assistants trained in handling surveys were strategically stationed at restaurants located at shopping malls in Kuala Lumpur to approach potential respondents. Participants were explained in depth about the purposes of the study, with assurances of confidentiality. Respondents were invited to fill out the survey at point of access, using a tablet device brought by assistants or a physical questionnaire handed directly to them. Participants were also granted permission to fill out their surveys at a later time through a Web link supplied by them, if they so wished. This multi-pronged approach greatly enhanced response levels, allowing data collection at once while at the same time allowing respondents to clarify any uncertain questions. A pilot survey of 30 participants who were acquainted with RoboKitchen robot waiters was carried out before full-scale data collection to gauge clarity in the questionnaire. The findings from this initial phase resulted in a few minor adjustments, thus ensuring a comprehensible yet concise final survey.

Data Examination

In initial evaluation stages, SPSS-23 was used then exploratory, descriptive statistics and reliability tests were conducted for data analysis. On the other hand, hypothesis testing and validation of the measurement model were conducted using structural equation modeling (SEM) with the use of AMOS-SEM. The use of two methodologies served to provide a thorough evaluation of relationships within the constructs, enhancing the generalizability and integrity of findings. Path analysis, within the context of SEM, was utilized to evaluate hypotheses, a key component in determining direct and mediated relationships by the constructs.

Demographic Features

The study's sample consisted of 267 respondents, with a higher proportion of females (53.6%) comparing with males (46.4%). The age distribution was diverse, with the largest group (25.8%) aged between 24 and 29 years, followed by those aged 36 to 41 years (20.2%). The smallest age group was 48 to 53 years (7.5%), and a notable 12.4% were aged 54 and above. Regarding marital status, a majority (76.5%) were single, with the remaining 23.5% married. In terms of occupation, the highest proportion of respondents were unemployed (30.0%), followed by students (21.7%), and the self-employed (19.1%). Service holders accounted for 15.7%, while housewives made up 13.5% of the sample. Income levels varied, with the majority (32.6%) earning between RM 8,000 and RM 9,000 monthly. The next largest group (20.6%) earned between RM 6,000 and RM 7,000, while only 1.9% reported earning more than RM 10,000. Table 1 represents demographic profile.

Table 1: Respondents' Demographic Profile

Attributes	Category	FQ	%
Gender	Male	124	46.4%
	Female	143	53.6%
Age	18-23	25	9.4%
	24-29	69	25.8%
	30-35	38	14.2%
	36-41	54	20.2%
	42-47	28	10.5%
	48-53	20	7.5%
	54 and above	33	12.4%
Occupation	Service	42	15.7%
	Housewife	36	13.5%
	Student	58	21.7%
	Self-employed	51	19.1%
	Unemployed	80	30.0%
Income	Less than 2k	37	13.9%
	2k-3k	33	12.4%
	4k-5k	50	18.7%
	6k-7k	55	20.6%
	8k-9k	87	32.6%
	10k and above	5	1.9%

Exploratory Factor Analysis

An Exploratory Factor Analysis (EFA) was performed to investigate and delineate the underlying structure of the dataset, analyzing the interrelationships among the variables (Auerswald & Moshagen, 2019; Rashid et al., 2020; Ozbekler & Ozturkoglu, 2020; Haque et al., 2025). The Kaiser-Meyer-Olkin (KMO) measures the sampling adequacy while Bartlett's test of sphericity evaluates the appropriateness of the data for factor analysis. In Table (2), KMO value was 0.681, surpassing the minimum criterion of 0.50, hence signifying the appropriateness for factor analysis (Choi et al., 2019).

Table 2: KMO and Bartlett's Test

KMO		0.681
Bartlett's Test of Sphericity	Chi-Square (estimated)	1694.804
	df	78
	Sig.	0.000

The results obtained from Bartlett's test indicating statistical significance ($p < 0.001$) to signify that there was enough inter-correlation among variables to enable the conduct of EFA. The EFA was carried out through principal component analysis augmented with varimax rotation according to guidelines outlined by Badar et al. (2020). Eigenvalues above 1.0 and factor loadings above 0.50 were acceptable for use in this analysis. The EFA revealed six unique factors corresponding to designations presented in the model. However, a few items—namely PU2, ATU3, and PEOU4—were removed from analysis because factor loadings were not acceptable, leading to a streamlined factor structure as evident from Table 3.

Table 3: Comprehensive Explanation of Total Variance

Component	1	2	3	4	5	6
PU3	0.947					
PU2	0.938					
PU1	0.840					
ATU2		0.886				
ATU1		0.868				
ATU4		0.854				
PEOU2			0.897			
PEOU1			0.870			
PEOU3			0.868			
AESQ3				0.749		
AESQ4				0.706		
AESQ1				0.698		
AESQ2				0.629		
ANT1					0.812	
ANT2					0.795	
ANT3					0.780	
TRU1						0.850
TRU2						0.835
TRU3						0.820

Reliability and Validity

Reliability and validity tests ensure the robustness of measurement model. Cronbach's alpha was used to assess each construct's reliability through SPSS, and Composite Reliability (CR) was calculated through AMOS. According to Daud et al. (2018) and Taber (2018), a Cronbach's alpha value exceeds 0.60 that is considered acceptable. Table 4 shows that all construct's Cronbach's alpha and CR values achieved above the minimal criterion, affirming the reliability of the scales used.

Table 4: Factor Loading, AVE, and CR for Constructs

Constructs	Items	Factor Loading	Cronbach's α	AVE	CR
PEOU	PEOU1	0.89	0.86	0.78	0.92
	PEOU2	0.90			
	PEOU3	0.87			
AESQ	AESQ1	0.70	0.67	0.50	0.79
	AESQ2	0.63			
	AESQ3	0.75			
	AESQ4	0.71			
PU	PU1	0.84	0.90	0.82	0.93
	PU2	0.94			
	PU3	0.95			
ATU	ATU1	0.87	0.86	0.75	0.90
	ATU2	0.89			
	ATU4	0.85			
Anthropomorphism	ANT1	0.81	0.85	0.73	0.88
	ANT2	0.80			
	ANT3	0.78			
Trust	TRU1	0.85	0.88	0.76	0.91
	TRU2	0.84			
	TRU3	0.82			

The standardized factor loadings for all items exceeded the threshold of 0.50, confirming that the constructs are reliable and free from significant reliability concerns. We further evaluated the validity of the constructs through CR with Average Variance Extracted (AVE). As detailed in Table 4, the AVE values for Perceived Ease of Use (PEOU) (0.78), AI-Enabled Service Quality (AESQ) (0.50), Perceived Usefulness (PU) (0.82), Attitudes Towards Use (ATU) (0.75), Anthropomorphism (0.73), and Trust (0.76) all met or exceeded the required thresholds, establishing strong convergent validity. CR values ranged from 0.79 to 0.93, well above the 0.60 threshold, further affirming the reliability and validity of the constructs (Shrestha, 2021; Baistaman et al., 2020).

Measurement Model

The measurement model measures both reliability and construct validity of the variables, including exogenous variables and endogenous variables. The variable for AI-enabled service quality was determined to be the exogenous variable, while perceived utility and PEOU were determined to be mediating variables, with users' attitudes toward robot waiters being categorized as the endogenous variable. Anthropomorphism and trust were found to be moderator variables. A thorough assessment of the measurement model was made to determine construct validity, including convergent and discriminant validity testing, along with reliability testing. According to Table 5, the model yielded a satisfactory fit, demonstrated by a Comparative Fit Index (CFI) value of 0.942 and a Root Mean Square Error of Approximation (RMSEA) value of 0.079, signifying a strong-measurement model. The statistic for chi-square was found to be 147.108 with a df value of 55, giving a normed-chi-square value of 2.675, within the acceptable value. These results confirm that essential dimensions related to AI-enabled service quality, perceived utility, perceived ease of use, attitudes, anthropomorphism, and trust are effectively represented by the constructs. Data collection was done using SPSS-23 and AMOS-SEM. Data analysis was done using SPSS first, including descriptive statistics analysis and reliability testing. The later use of AMOS-SEM was done to verify the measurement model and to investigate hypotheses through structural equation modelling (SEM). Path analysis using SEM clarified the direct impacts and mediating impacts of the components.

Table 5: Summary of Measurement Model Results

Model Fit Indices	Value
CFI	0.942
RMSEA	0.079
Chi-square	147.108
Degrees of Freedom	55
Normed Chi-square	2.675

All constructs exhibited high reliability with validity reinforcing the robustness of the measurement model for later structural analysis.

RESULTS

Structural Model

Appropriateness of the structural model was assessed against the dataset. Fig. 2 shows that the adjusted structural model yielded a CFI value of 0.941, above the 0.90 threshold value, thus implying a good fit. The RMSEA had a value at 0.079, within acceptable ranges, thus further validating adequacy in the model. The normalized Chi-square statistic was found to be 2.662, below the cut-off value of 5, thus implying a sound model fit. The model had a 56-degree freedom accompanied by a value for a chi-square at 149.064. Combined, these indices imply a fit between the structural model and data, thus providing a sound premise for testing hypotheses in this study.

The path estimations shown in Table 6 are derived from the SEM study, which is shown in Fig. 2 and details the relationships among the components.

Table 6: Path Estimation

Hypothesis	Path	Standardized Regression Weight	Standard Error (SE)	Critical Ratio (CR)	P-Value	Result
H1	AI-Enabled Service Quality → Perceived Usefulness	0.14	0.07	1.97	<0.05	Supported
H2	AI-Enabled Semce Quality → Perceived Ease of Use	0.26	0.11	2.40	<0.05	Supported
H3	Perceived Usefulness → Attitude Towards Use	0.31	0.07	4.10	<0.001	Supported
H4	Perceived Ease of Use → Attitude Towards Use	-0.02	0.06	0.89	0.375	Not Supported
H5	AI-Enabled Service Quality → Attitude Towards Use	0.57	0.12	4.81	<0.001	Supported

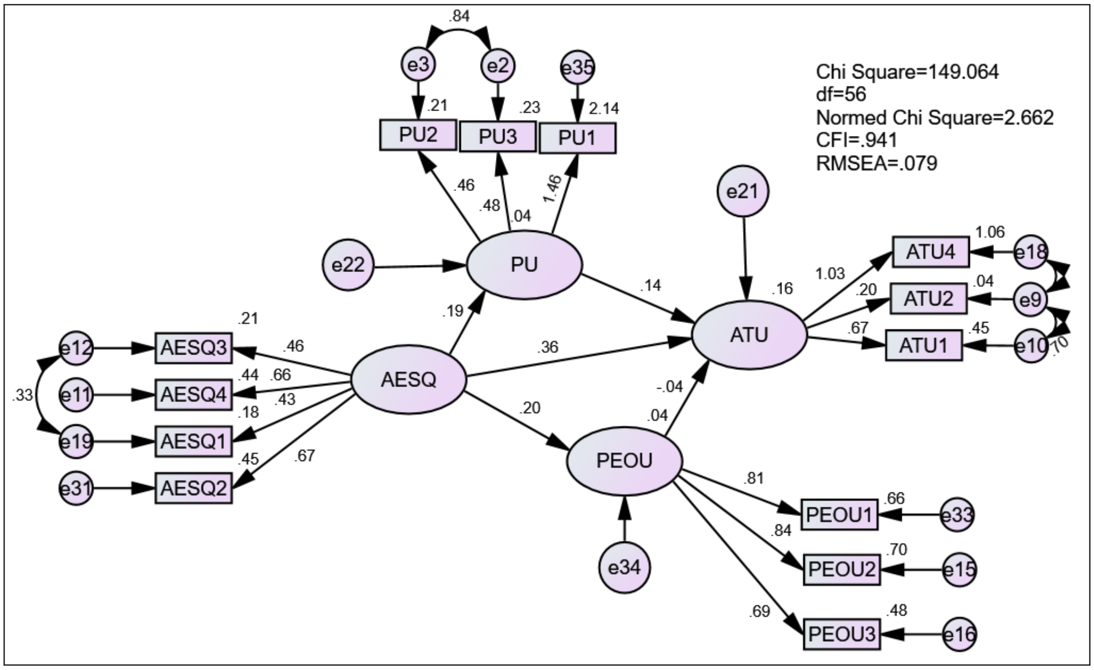

Fig. 2: Structural Model

Hypothesis Testing

According to the study, perceived usefulness (β = 0.14, p < 0.05) is much favorably influenced by AI-enhanced service quality. This supports H1 and shows that improved customer view of the use of artificial intelligence technology, including robotic waiters, results from high service quality in them. This result is consistent with earlier studies that underline how directly the perceived quality of AI services increases their perceived utility (Prentice et al., 2020; Chen & Aklikokou, 2020). This implies that service providers have to give the quality of AI-enabled interactions a priority so that consumers view these technologies as positive.

PEOU (β = 0.26, p < 0.05) was likewise found to benefit from AI-enabled service quality, therefore supporting H2. This suggests that excellent service quality in artificial intelligence systems not only makes these technologies seem more valuable but also facilitates interaction with them. This outcome is in keeping with the body of current research, according to which good service quality improves the user-friendliness of artificial intelligence systems (Pillai et al., 2020; Ameen et al., 2021). Practically, this means that by increasing the accessibility and simplicity of these technologies, thereby lowering user resistance by boosting the quality of AI systems.

Attitudes toward using robotic waiters (β = 0.31, p < 0.001) were much predicted by perceived utility, hence validating H3. This result emphasizes the important part that apparent value plays in forming good user attitudes. According to the literature on technology acceptance, people who find a technology useful are more likely to grow positive opinions about its adoption (Ivanov et al., 2022; Choe et al., 2022). The findings support the need of proving the clear advantages of AI-enabled services to support favourable consumer sentiments and raise the possibility of adoption.

Against predictions, PEOU had no appreciable effect on views toward using robotic waiters (β = -0.02, p = 0.375), thereby generating H4 not being supported. This implies that in this setting, perceived usefulness or service quality shapes user attitudes more so than the convenience and effortlessness of employing robotic waiters. This result adds to the current conversation on technology acceptance by underlining that, particularly in environments where the perceived utility and service quality of the technology are more salient, ease of use may not always be a key factor (Suleman & Zuniarti, 2019; Taufik & Hanafiah, 2019; Tahar et al., 2020).

The study finally confirmed a strong favourable link between views of the use of robotic waiters (β = 0.57, p < 0.001), therefore providing significant support for H5. AI-enabled service quality validated. This result emphasizes how very important good service quality is for creating favourable impressions of AI-powered products. This result is consistent with earlier studies showing that consumers who see high levels of AI technology service quality are more likely to develop positive opinions of their application (Prentice et al., 2020; Nguyen & Malik, 2022). This emphasizes how important it is for practitioners to make investments in better AI solutions to raise customer satisfaction and encourage adoption.

The results show overall the significance of artificial intelligence-enabled service quality as a main driver of both good user attitudes and perceived utility. Although in this specific scenario perceived simplicity of use was shown to be less important, the general results highlight that in the hotel sector acceptance and implementation of AI technologies depend much on service quality and perceived utility. These revelations not only add to the increasing corpus of research on artificial intelligence-human interaction but also have pragmatic ramifications for companies trying to maximize consumer contact with AI-enabled products.

Mediate Impact Analysis

The mediation study sought to determine if PEOU and PU mediate the link between attitude toward use (ATU) and AI-enabled service quality (AESQ). The study followed the three-steps as suggested by Carranza et al. (2018) to assess the direct impact of the independent variable (AESQ) on the dependent variable (ATU), the indirect influence of the independent variable on the dependent variable by the mediator (PU or PEOU), and the correlation between the mediator and the dependent variable. Table 7 shows the summary of the SEM model.

Table 7: Mediating Path Estimation

Hypothesis	Path	Standardized Regression Weight	Standard Error (SE)	Critical Ratio (CR)	p-Value	Mediation
H6	AESQ → PU → ATU	0.31	0.07	4.15	<0.001	Supported
H7	AESQ → PEOU → ATU	0.05	0.06	0.89	0.375	Not Supported

The study of Hypothesis Six (H6) aimed to ascertain whether attitude toward usage (ATU) moderates the relationship between artificial intelligence-enabled service quality (AESQ). Examining the direct impact of AESQ on PU—found to be statistically significant—with a path coefficient of 0.14 and a critical ratio (CR) of 1.97 ($p < 0.05$). This result shows that users' opinions of their utility are favourably influenced by the perceived service quality of AI-enabled solutions. Following that, the direct association between AESQ and ATU was also noteworthy, with a path coefficient of 0.57 and a CR of 4.81 ($p < 0.001$), so demonstrating that the quality of AI-enabled service directly improves favourable attitudes towards utilizing these systems. With a path coefficient of 0.31 and a CR of 4.15 ($p < 0.001$), the indirect effect of PU on ATU was assessed last and also showed to be significant. This implies that users' opinions of utilizing AI-enabled services are much influenced by perceived utility. PU mediates the link between AESQ and ATU, it was decided considering the important interactions in all three stages. Thus, Hypothesis Six is validated since perceived usefulness of AI-enabled service quality influences attitudes towards use both directly and indirectly.

Hypothesis Seven (H7) sought to investigate if PEOU moderates the association between ATU and AESQ. With a path coefficient of 0.26 and a CR of 2.40 ($p < 0.05$), first the direct impact of AESQ on PEOU was investigated and shown to be statistically significant. This suggests that more perceived ease of use follows from better perceived service quality in AI-enabled systems. Testing the direct association between AESQ and ATU came next; this, as earlier noted, was significant with a path coefficient of 0.57 and a CR of 4.81 ($p < 0.001$). With a route coefficient of 0.05 and a CR of 0.89 ($p = 0.375$), the last step—which evaluated the indirect influence of PEOU on ATU—showered that this link was not statistically significant. This lack of relevance implies that the association between attitudes toward use and AI-enabled service quality is not mediated by apparent simplicity of use. Therefore, Hypothesis Seven is not supported, meaning that even if AI-enabled service quality affects opinions of ease of use, this has no appreciable impact on attitudes towards employing the technology.

Moderation Effect of Anthropomorphism

Table 8: Moderation Effects Testing Results

Hypothesis	Path	Standardized Regression Weight	Standard Error (SE)	Critical Ratio (CR)	p-Value	Result
H8	Anthropomorphism × AI-Enabled Service Quality → PU	0.18	0.08	2.25	<0.05	Supported
H9	Trust × Perceived Usefulness → Attitude Towards Use	0.22	0.09	2.44	<0.05	Supported

Hypothesis 8 proposed that anthropomorphism will modify the association between AI-Enabled Service Quality (AESQ) and Perceived Usefulness (PU). The analysis corroborates this prediction, as the interaction (Table 8) effect is both positive and significant ($\beta = 0.18$, $p < 0.05$). This indicates that when the robotic waiter is perceived as more human-like, the positive impact of service quality on perceived usefulness is strengthened. In other words, anthropomorphic features enhance the perceived value of the service provided by the AI, making it seem more useful to customers.

Hypothesis 9 stated that Trust would regulate the link between Perceived Usefulness (PU) and Attitude Towards Using. The statistics also corroborate this theory ($\beta = 0.22$, $p < 0.05$). The results indicate that increased trust in the robotic waiter enhances the positive correlation between perceived usefulness and user attitudes. This means that when customers trust the AI-enabled service, they are more likely to develop favourable attitudes toward using it, particularly when they already perceive it as useful. Overall, these moderation effects demonstrate the importance of Anthropomorphism and Trust in enhancing customer perceptions and attitudes towards AI-enabled services.

IMPLICATIONS

Managerial Implications

First of all, artificial intelligence systems must be of highest quality. Hotel managers have to give maintenance and frequent updates of artificial intelligence systems top priority if they are to guarantee consistent and effective performance. AI should not only be functional but also provide a good emotional connection with consumers as the sector investigates advanced AI capabilities including empathic AI that improves user experience by giving psychological comfort (Law et al., 2023). Maintaining service standards depends on regular inspections and updates since obsolete systems could cause customer discontent and a drop in the quality of services.

Furthermore, crucial for hospitality companies is their efficient communication of the benefits of artificial intelligence to its guests. Although artificial intelligence and automation can improve service delivery, the human element is still absolutely important (Jabeen et al., 2021). Companies should explain how these technologies enhance human relationships as well as the efficiency of artificial intelligence—that is, faster service and accurate order delivery. This strategy can help all customers overcome any concerns about the application of robotic solutions.

Another important component of effective application of artificial intelligence technologies is user friendliness. On-site help and well-defined directions can greatly improve client interaction with artificial intelligence systems. Studies on consumer opinions of mechanical artificial intelligence in hotel operations emphasize the need of user experience in forming customer happiness (Mariani & Borghi, 2021). Customers are more inclined to accept artificial intelligence systems if they find them simple and straightforward to use, therefore driving higher utilization and satisfaction.

Furthermore, very important is building confidence and familiarity between consumers and artificial intelligence technologies (Fuentes et al., 2018). Programming polite greetings and tailored encounters helps companies create robotic waiters that seem more personable. Building trust—a necessary component of consumer acceptance—depends on humanizing technology. Making sure artificial intelligence technologies are seen as dependable and safe can help to build good client impressions, thereby improving their whole experience.

Moreover, the constant improvement of AI services depends on constantly seeking and including client feedback. Development of good artificial intelligence systems depends on an awareness of consumer wants and preferences (Liu, 2024). Frequent feedback helps companies to customize their AI products to more satisfy consumer expectations, hence strengthening loyalty and satisfaction. By means of this iterative development process, artificial intelligence systems become more efficient and match consumer needs.

At last, industry leaders and legislators have to set criteria and offer incentives to enable a more consistent and dependable client experience. Driven by artificial intelligence, the fourth industrial revolution has fundamentally changed service companies including hotel operations (Teng, 2023). Stakeholders working together will help to establish an environment that promotes innovation and raises consumer satisfaction by means of this transition.

Theoretical Implications

This work makes a substantial contribution to the domain of technology acceptance research. Traditionally, the TAM has concentrated on the direct impacts of PU and PEOU on attitudes toward technology. This research enhances the model by integrating AI-enabled service quality as a pivotal element affecting these constructs. The results indicate that AI-enhanced service quality substantially influences perceived utility and perceived ease of use, therefore affecting user sentiments. This extension enhances the explanatory power of TAM, particularly in the context of AI and robotic technologies in service environments.

Moreover, this study introduces anthropomorphism and trust as moderating variables—an area that has been scarce in previous research. While prior studies have mainly examined the direct effects of anthropomorphism and trust on technology acceptance (Gursoy et al., 2019; Lin et al., 2020), this research demonstrates their moderating roles. The findings indicate that anthropomorphism enhances the favourable correlation between AI-enabled service quality and perceived usefulness. This indicates that when robotic waiters are regarded as more anthropomorphic, their service quality is more likely to be considered beneficial. This discovery enhances the Technology Acceptance Model by emphasizing the significance of psychological and relational elements in technology acceptance (Gursoy et al., 2019; Lin et al., 2020).

The study similarly demonstrates the significance of trust in improving the relationship between PU and attitudes toward technology. Trust is demonstrated to enhance the beneficial impact of perceived usefulness on user attitudes. When people trust AI technologies, they are more inclined to view them as advantageous, resulting in more positive views towards their utilization. This discovery deepens our comprehension of trust's significance in technological acceptance, especially within AI-enabled service contexts (Gefen et al., 2003; Goundar et al., 2021). The findings suggest that enhancing human-like qualities in AI and fostering trust are crucial for improving user acceptance and the effectiveness of AI technologies in service environments.

RESEARCH LIMITATIONS AND FUTURE APPROACH

Though some limits have to be admitted, this work provides important insights. The focus on robotic waiters in the hotel industry could limit the general relevance of the results to other AI-driven businesses or services. Future studies should investigate several artificial intelligences uses in different service environments to ascertain whether the found associations apply in other situations.

Second, by including objective measures or longitudinal data, the dependence on self-reported data could be resolved in next investigations. This would support the validation of the results and offer a more whole picture of user interactions throughout time using artificial intelligence systems.

Third, a more varied sample comprising people from several cultural backgrounds and different degrees of knowledge of artificial intelligence technology would enrich the study. This would provide a better knowledge of user opinions on AI-enabled services and improve the external validity of the results.

Fourth, the study neglected other possible elements even although it looked at the mediating effects of PU and simplicity of use coupled with the moderating roles of anthropomorphism and trust. Further variables like hedonic motivation and social impact should be investigated in next studies to improve understanding of the factors influencing artificial intelligence acceptance.

At last, this study has carried out in Malaysia, a particular technological and cultural setting that might evolve with time. The fast development of artificial intelligence technology and changes in society attitudes toward AI call for continuous research to guarantee that theoretical models remain current and fairly depict user perceptions in various surroundings. Future research ought to take cross-cultural comparisons and the effect of technology developments on consumer perceptions of AI-enabled services under consideration.

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