

DETERMINANTS INFLUENCING CUSTOMERS' INTENTION TO USE AI-DRIVEN ROBOTIC SERVICE IN MALAYSIAN RESTAURANTS

SHIAU WEI CHAN¹, HIROHIKO MORI², WAN THENG LOH³, MD FAUZI AHMAD⁴

^{1,4}Faculty of Technology Management and Business, Universiti Tun Hussein Onn Malaysia, 86400 Batu Pahat, Johor, Malaysia

²Department of Intelligent Systems, Tokyo City University, Tokyo 158-8557, Japan

³Sineurope Pte Ltd, 4 Tuas Bay Walk, SINGAPORE 637767

E-mail: ¹swchan@uthm.edu.my, ²hmori@tcu.ac.jp, ³wantheng28@gmail.com,

⁴mohdfauzi@uthm.edu.my

ABSTRACT

As artificial intelligence (AI) and service robotics increasingly permeate the restaurant industry, new IT-enabled service models are emerging. In IT research, customer acceptance is critical; a robotic system's value extends beyond mere functionality, requiring users to perceive the technology as useful, easy to use, trustworthy, enjoyable, and low-risk. But there are practical issues as well. For example, customers at two restaurants reported that robots struggled to accommodate special requests for additional items like sauces or tableware and frequently caused order confusion by delivering food to the wrong customers. This study aimed to explore the expected level of customers' intention to use AI-driven robotic services and the determinants that influence that intention in restaurant contexts in Batu Pahat, Johor, Malaysia. A sample of 307 restaurant customers who had experienced robotic services at two restaurants was surveyed using questionnaires, and the data were analyzed quantitatively by employing SPSS software. The study found a high level of intention among customers to use AI-driven robotic services. Results indicated positive correlations of intention to use with perceived usefulness (0.743), perceived ease of use (0.624), perceived need for interaction with the technology (0.516), perceived enjoyment (0.645), and perceived trust (0.609); in addition, a weak negative correlation was found between intention to use and perceived risk (0.197). For IT contribution, the contribution of this study was based on the contextual extension and empirical testing of a TAM-based acceptance framework integrating functional, interactional, hedonic, trust, and risk factors within an understudied restaurant setting in Malaysia.

Keywords: *Determinants, Intention to use, AI-driven Robotic Service, Restaurants*

1. INTRODUCTION

Trends in robotics in recent years, especially those that leverage artificial intelligence (AI), have revolutionized the field of robotics. The emergence of more capable AI-driven robotic systems fuses autonomous physical behavior with more innovative information-processing tasks. Robots in restaurant contexts constitute a key IT application, as their payoff depends on the interaction between humans (guests and hospitality staff), service encounters, and digital-physical resources. More importantly, a robot's service success not only hinges on engineering performance but also on the willingness of guests to adopt it, which involves guest expectations, perceptions, and continuance intention [1–4]. In that sense, customer intention becomes an

important IT-related perspective on whether or not to apply robotic service to translate technological capacity into service capability.

The advancement of technology has propelled the restaurant sector toward a sustainable future where robotics can be utilized at every level of the service process [5]. The primary aims of adopting robotic services in restaurants are to differentiate the business from other restaurateurs and attract a new segment of technologically savvy and creative customers [6]. Additionally, implementing robotic services can offer professional and friendly service to customers [7]. Consequently, the adoption of robotic technology in the restaurant sector is growing rapidly, with an increasing number of restaurants integrating robotics into their operations and customer interactions [8]. The utilization of robotic

workers in the restaurant sector will lead to a fundamental change that will disrupt the way traditional restaurants operate [9]. Robotic workers can assist businesses in attracting technology-savvy customers, addressing employee shortages, providing services to customers, and creating new prospects in the restaurant sector [10]. Furthermore, robotics can solve the problem of customer congestion during peak hours in restaurants [11], which has particularly attracted the attention of customers during lunch hours [12].

Choi et al. [13] noted that experiencing robotic service is an interesting and novel experience. Therefore, customers may desire to interact with robotics as they find robotic services enjoyable and have a positive perception of robotics [5]. Despite advances in robotics, some individuals are still unfamiliar with robotic services and, as a result, do not interact with them on a routine basis [14]. According to Cha [15], customers' intentions to utilize robotics in restaurants are influenced by their perceived trust towards robotics, enjoyment of communicating with robotics, and behaviors toward the usage of robotics. Research indicates that customer satisfaction in robotic service restaurants is influenced by several factors, including time savings, service efficiency, monetary value, and security [16].

To identify the real problems customers faced when utilizing robotics, the researcher conducted a preliminary study by interviewing those who had used robotic services at two restaurants in Batu Pahat, Johor. Customers who had used the robotic services at these two restaurants explained the actual problems they encountered. Firstly, robotics could not fulfill special customer requirements, such as requests for additional tableware, napkins, and extra food sauces. Although the robotics automatically delivered food to customers, it could not accommodate special requests for extra cutlery or other needs. As a result, customers had to either take these items on their own or request them from the employees. Additionally, customers at these two restaurants discovered a risk of receiving the wrong food since the robots delivered food to multiple customers simultaneously. Even though the robotics delivered food to the correct table, customers still had to take the food themselves, leading to potential confusion about which food belonged to whom. Consequently, this situation could affect customers' intention to use robotic services. AI-driven systems have significantly improved operational efficiency and service quality across service industries; however, challenges related to technology

implementation, data security, and user acceptance remain major barriers to successful adoption [17].

In addition, the researcher found a serious deficiency of studies that examine the acceptance of robotic service in Malaysian restaurants. Most previous research was conducted in Korea [5, 9, 19, 20], Taiwan [18], and China [22, 23]. Since 2025, literature has extended its scope to more general technology-acceptance models, including social presence, anthropomorphism, food-safety perceptions, privacy, and effects of service contexts [1–19]. For instance, an extended TAM was used to examine customer acceptance of restaurant robot waiters in 2025 and this study revealed that customer acceptance remained a significant concern despite the large number of robot restaurants available in 2025 [1].

A study in 2025 also identified social presence, appearance, anthropomorphism, precision, perceived intelligence, personalisation, and automation as influential factors on acceptance of restaurant service robots [2]; a recent meta-analysis of 46 empirical research investigated various contextual and cultural influences of consumers' responses to restaurant service robots, and confirmed the importance of considering contextual factors in applying empirical evidence from research findings [3]; another study published in 2025 also found that transparency of AI function, privacy, and customers' control of robots potentially affect behavioral intention to AI-powered hospitality robots [4]; another study suggested that service complexity and trust affected customers' acceptance of services in different service contexts [19].

These advances have allowed this study not to claim a full model of robotic-service acceptance, but to show the empirical evidence of customers who have had experience of robotic services in two Batu Pahat restaurants and to investigate the rather narrow integrated effects of the TAM-inspired functional factors, interaction, enjoyment, trust, and risk. Consequently, this study contributes especially to the evidence of Malaysian customer acceptance in the specific local context, which can later be used to compare with other evidence from different nationalities and service contexts.

2. LITERATURE REVIEW

2.1 Overview of AI-Driven Robotic Service

According to the International Organization for Standardization [20], a robot can be defined as a mechanism programmed with a degree of autonomy, operating within its environment to accomplish specific tasks. Conversely, the International Federation of Robotics defines a

service robot as a robot that provides beneficial functions for people or equipment [21]. Some robots are capable of detecting, testing, and predicting changes in their environment. Additionally, robots can enhance the customer experience by assisting employees, replacing workers, automating tasks for efficiency, and providing improved services [22]. AI-driven robotics signifies a transformative shift, offering immense future potential while raising critical ethical concerns, as AI integration enables robots to function not merely as tools but as extensions of human cognition and interaction [23]. Beyond technological advancement, successful AI implementation requires organizations to consider technological, organizational, and environmental conditions that collectively influence technology adoption and long-term sustainability [24].

Robots are typically designed to perform hazardous, repetitive, and monotonous tasks [25]. They can be programmed to execute a wide range of complex tasks traditionally performed by humans, such as lifting heavy objects and interacting with customers [26]. Robots excel at performing repetitive tasks more efficiently than human workers and offer various benefits [27]. For example, they can serve customers continuously without taking sick or annual leave, thereby enhancing the customer experience and ensuring quality control [28].

From an engineering perspective, Xue et al. [29] investigated ice cream serving robots. Conversely, from a technical standpoint, Neeti et al. [30] detailed the development of a new generation of robotic waiters. In the restaurant sector, Iqbal et al. [31] studied the features of serving robot systems. Morita et al. [32] explored a tea house robot system. Thanh et al. [33] researched the creation of sensors to assist robots in the restaurant sector in maintaining consistent service speed. Therefore, it is evident that the majority of previous studies have focused on the engineering aspects of serving robot technology.

2.1.1 Robotics at the front of the restaurant

As per Murphy et al. [34], robots serving at the front of restaurants are known as service robots. As frontline employees, robots provide various services to customers, such as greeting, taking orders, delivering food to tables, and entertaining customers. Robots are capable of moving around restaurant tables. Choi & Kwak [35] defined anthropomorphic robots as robots that imitate human actions and cognitive abilities. Therefore, a robot with anthropomorphic characteristics can resemble a human worker in communicating with customers [8].

Two types of robots work in front of restaurants, namely robotic hosts and robotic food runners [8]. The responsibility of a robotic host is to serve as a host at the front of the restaurant. Additionally, robotic hosts can greet customers, take orders, and respond to customer inquiries. For instance, in Dubai, United Arab Emirates, the robotic host at Tanuki restaurant serves customers by greeting them, singing, dancing, and offering food vouchers [36]. Robotic hosts are commonly used at restaurants to provide a futuristic experience and entertain guests. Hence, human workers might be replaced by robotic hosts at restaurants.

A robotic food runner is another type of robot that operates in front of restaurants [8]. The primary role of a robotic food runner includes delivering meals to customers' tables and returning soiled plates to the kitchen. Kitchen workers place the dishes on robotic trays, while human workers in the front of the restaurant interact with customers, retrieve dishes from the robotic food runner, and clean the table once customers have finished their meals. Using a robotic food runner to deliver meals can help restaurateurs save time, encourage human workers to spend more time interacting with customers, and improve the customer experience. In the future, robots will handle the entire restaurant service experience without human assistance [25].

2.1.2 Robotics at the back of the restaurant

According to Kim et al. [8], robotics operating behind restaurants is called industrial robotics. A robotic kitchen worker will accomplish repetitive tasks in the restaurant. For example, sushi robotics will carry out repetitive jobs such as rolling and cutting the sushi [37], while burger robotics will flip or grill burgers on the grill [38]. The robotic kitchen workers conduct repetitive work, whereas all other tasks are performed by human workers.

The robotic kitchen workers combine many procedures into a single system. Robotics at the back of the restaurant can replace the chef by executing the food preparation procedure. For instance, robotic kitchen workers are utilized to prepare the cooking ingredients and cook them following the programmed recipes [8]. Therefore, using robotics in restaurants can help reduce the time to prepare or cook the ingredients, minimize mistake rates, enhance efficiency, and maintain food quality [8].

Kim et al. [8] mentioned that a robotic cleaner at the back of the restaurant is another utilization of robotics. The robotic cleaner can be used to clean the floor and various surfaces in restaurants. Robotic cleaners have been commonly used in households, but they are rarely utilized in

restaurants. However, Oracle [26] mentioned that 47% of restaurateurs strongly believe that robotic cleaners will be extensively employed in restaurants by 2025.

2.2 Determinants

2.2.1 Perceived usefulness

Perceived usefulness can be determined as the degree of trust in adopting a certain technology, where the technology is found to be useful for people who utilize it in services [39]. An individual will utilize a technology if he or she is confident that the technology will be beneficial to him or her. Conversely, if a person feels that the technology is less beneficial to him or her, then he or she will not utilize it [40]. Davis [41] presented perceived usefulness as an influential variable in acceptance of technology; therefore, some researchers have proved that perceived usefulness is a significant determinant of technology adoption and usage, especially in terms of the Internet, Internet of Things (IoT), artificial intelligence (AI), robots, and Computer-Mediated Environment (CME) [42].

2.2.2 Perceived ease of use

According to Zuniarti et al. [39], perceived ease of use is defined as the degree of an individual's perception that technology may be easily comprehended. The frequency of usage and interaction between customers and the technology might contribute to the ease of use of the technology. Mahanani & Sari [43] determined that the notion of employing technology will be based on business, known as perceived ease of use. As seen from this definition, perceived ease of use is also a notion about the decision-making process [43]. An individual will use an information system if they believe that the information system is easy to use. Conversely, if an individual finds that the information system is difficult to use, they will not adopt it [40]. Perceived ease of use meets individual demands in developing the effectiveness of robotic technology [44]. However, some users are not familiar with the use of robotics. Thus, they assume that interacting with a robot is difficult and requires certain digital abilities to communicate with it effectively [42].

2.2.3 Perceived need for interaction with technology

The need for interaction can be defined as an individual's desire to interact with a service employee during the delivery process. Interaction between a customer and a service provider is necessary to deliver excellent service [45].

Interaction can strengthen the interpersonal relationship between service employees and consumers [46]. Currently, robotics cannot communicate with customers in the same way as human employees do. Nevertheless, robotics will potentially develop to the stage where it can generate human emotions [15]. A previous study has shown that pleasure and social interactions between robotics and guests are essential in a restaurant [15]. Robotics can be even more useful if they use humor to create emotional interactions with guests or compliment them on their menu selection. Restaurants that adopt robotics should be aware of this critical component in the interaction between robotics and customers and make efforts to enhance the usefulness of robotics [15]. Therefore, the interaction between robotics and guests has become a major challenge for restaurateurs operating their businesses.

2.2.4 Perceived enjoyment

As per Venkatesh & Davis [47], perceived enjoyment can be described as the degree to which an individual enjoys utilizing a technology. Perceived enjoyment refers to the use of technology to execute a task that is considered enjoyable, regardless of the consequences of the activity [48]. Conversely, Kim et al. [49] defined perceived enjoyment as the level of pleasure felt when utilizing technology, irrespective of the predicted result. Perceived enjoyment is a situation in which a person utilizes technology in their daily activities to enhance their sense of comfort, also known as hedonic in technology [50]. The use of technology may offer consumers comfort, which can lead to greater intensity of technology usage [51]. The higher the comfort level of information technology users, the higher their attitude will be subsequently connected to system technology acceptance [52]. Feeling comfortable and having fun when adopting information technology systems will increase the effectiveness and efficiency of users in completing a job [53].

2.2.5 Perceived trust

Trust is defined as the belief that technology will function with personal integrity and reliability, and will execute tasks efficiently [54]. Yuen et al. [55] describe an individual's belief in a certain technology as trust. Customers with vigilant characteristics carefully evaluate the reliability of information before purchasing new goods and services [56]. Robots with better social abilities are perceived as more trustworthy due to their intelligence [57]. Pillai & Sivathanu [58] define trust

as a feeling of credibility and trustworthiness when interacting with a robot. Tuomi et al. [59] state that trust is an individual's perception of a technology's capability to meet their expectations. If a robot can execute tasks correctly and effectively without errors, customers will assume that the services provided by the robot can meet their expectations [60]. Consequently, customers are more inclined to trust robots [61]. However, customers might lose faith in robots if they do not fulfill their expectations [58].

2.2.6 Perceived risk

Based on Sung & Jeon [62], perceived risk refers to the subjective and psychological risk that customers perceive in a certain buying situation. Generally, risk perception is associated with fear of loss or uncertainty resulting from decision-making. Hwang et al. [9] explain that risk perception can lead to unpredictable consequences. Since the concept of perceived risk was proposed by Hwang et al. [18], several researchers in diverse fields have conducted studies on why customers are unwilling to adopt new technology-based services. Perceived risk has been shown to have a significant influence on the utilization of new technology-based services [18]. Previous researchers have investigated the significance of perceived risk in various fields, including self-service kiosks in hotels [63], acceptance of digital payment [64], and drone food delivery services [65]. However, only a few prior studies have focused on the perceived risk of robotics in restaurants. Therefore, evaluating perceived risk toward robotics in restaurants is important and necessary [9].

2.3 Theoretical model in current research

Although there are numerous theoretical models, such as the Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT), the researcher focused on the fundamentals of the Technology Acceptance Model (TAM), extension of TAM, and extension of UTAUT in current research. The fundamentals of the TAM model, extension of TAM, and extension of UTAUT are used in this research because these models are usually used to predict users' use and acceptance of new technologies [62].

Furthermore, another reason for the researcher to study the fundamental aspects of the TAM model in this research is the limited number of studies conducted on the TAM model in the context of robotic services in restaurants [66]. This assertion

is supported by Marangunić & Granić [67], where TAM has been predominantly researched for the acceptance of technology in the tourism and hospitality sector. For example, TAM has been applied in studies concerning hotel front desk systems [68], consumer-generated content adoption [69], self-service hotel technology [45], tablet applications for hotels [70], and mobile tourism applications [71]. According to Fuentes-Moraleda et al. [72], although TAM has been widely used in previous studies to forecast customer acceptance of information technology (IT) products, it is rarely used to predict customer acceptance of robotic services.

According to Kaushik et al. [45], while TAM has been utilized in several studies for predicting users' acceptance of technology, it has a drawback in that it does not adequately consider the influence of numerous exogenous factors, thus making the TAM model unable to accurately predict the adoption of new technologies. To address this limitation, the researcher decided to incorporate the variables from the extensions of TAM and UTAUT presented by Sung & Jeon [62] and Slade et al. [73].

In the fundamental TAM model, perceived usefulness and perceived ease of use are the major determinants that influence a customer's intention to use a technology [74]. Meanwhile, perceived enjoyment and perceived need for interaction with technology are variables from the extensions of TAM used to predict customers' use and acceptance of new technologies [62]. Additionally, perceived risk and perceived trust are common variables from the extensions of UTAUT, according to Slade et al. [73]. Therefore, the development of this research framework is based on the fundamental TAM model, along with its extensions.

2.4 Conceptual framework and hypotheses development

Figure 1 shows the conceptual framework. The independent variable is the determinants influencing customers' intention to use AI-driven robotic service in restaurants, which consist of perceived usefulness, perceived ease of use, perceived need for interaction with technology, perceived enjoyment, perceived trust, and perceived risk. While the dependent variable consists of only one variable, which is the customers' intention to use AI-driven robotic service in restaurants. Below are the hypotheses developed in the study:

2.4.1 Perceived usefulness and intention to use

Perceived usefulness is seen as a factor that influences a customer's intention to use a technology

[75]. An individual will regard beneficial technology innovation as good and worthwhile, while ineffective technology innovation could be considered as bad and worthless. Therefore, high usefulness will enhance customers' intention to use the technology innovation; nevertheless, low usefulness will reduce customers' intention to use the technology innovation [76]. The essential variable influencing customers' intention to adopt robotics is perceived usefulness [57]. Perceived usefulness is an important factor in explaining the intention to use because robotics is found to be beneficial and effective for humans [77]. Customers will not have a high intention to adopt robotics if the robotics is useless [57].

Perceived usefulness is the key indicator that affects customers' intention to use robots. Since robotics offers a variety of services, such as taking orders and delivering food, the perceived usefulness of robotics could enhance the intention to adopt it [78]. The utilization of robotics in the restaurant sector is considered advantageous since it can reduce the risk of disease transmission [79]. Customers are more inclined to use new technology if they believe robotics will benefit them [6]. Previous researchers recorded that perceived usefulness had a positive influence on customers' intention to use robotic services [57]. Based on these statements, hypothesis H1 is:

H1: There is a significant relationship between perceived usefulness and customers' intention to use AI-driven robotic service in restaurants.

2.4.2 Perceived ease of use and intention to use

According to Piasek & Wieczorowska-Tobis [80], perceived ease of use is one of the determinants that influence customers' intention to use robotics. People will consider user-friendly technology innovation as good and take pleasure in using it, whereas non-user-friendly technology innovation could be regarded as bad and not enjoyable to use. Consequently, good ease of use will improve customers' intention to adopt the technology innovation, while bad ease of use will minimize customers' intention to adopt the technology innovation [76].

Kervenoael et al. [81] discovered that perceived ease of use influences users' intention to adopt robotics. The function of robotics is to assist humans in completing tasks. Robotics can expend greater effort to complete the complicated jobs that humans consider tough and demanding [82]. Consequently, customers are more inclined to interact with a robot if the robot is simple to

understand, easy to use, and involves little effort [58]. The previous study by Zhou [78] showed that there is a positive relationship between perceived ease of use and customers' intention to use robotic services. Based on the above statement, hypothesis H2 is:

H2: There is a significant relationship between perceived ease of use and customers' intention to use AI-driven robotic service in restaurants.

2.4.3 Perceived need for interaction with technology and intention to use

As stated by Suarez et al. [83], the need for interaction is a determinant that influences the intention to adopt technology. Since human interaction is common in restaurants, using new technologies such as robotics in restaurants can be challenging for customers. Customers still prefer human-to-human interaction because they believe robots are less empathetic [15]. However, Barton & Sinha [84] found that robotics is highly preferred by younger generations compared to human interaction. Choi et al. [13] discovered that robotics has a high level of acceptability in restaurants.

As technology has advanced, customers' perceptions of robotics have gradually changed, even in the restaurant sector. Robotics is used to provide services and interact with customers in various ways, including receiving orders, delivering food and beverages, entertaining, hosting, and cleaning [15]. An individual needs a high level of interaction with technology, and the intention to use robotics is enhanced. Whereas if an individual needs a high level of interaction with humans, the intention to adopt robotics will be attenuated [78]. The perceived need for interaction with technology has a positive effect on customers' intention to use robotic services [85]. Based on these statements, hypothesis H3 is:

H3: There is a significant relationship between perceived need for interaction with technology and customers' intention to use AI-driven robotic service in restaurants.

2.4.4 Perceived enjoyment and intention to use

Perceived enjoyment has been found to influence the intention to use technology [54]. The enjoyment of utilizing information technology in restaurants is the process of adopting the technology, which is joyful, and consumers are always pleased while using it [52]. If consumers are enjoying the process, they will exert more effort in it [86]. Previous researchers have indicated that robotics is attractive because it creates an enjoyment

perception, which could be regarded as motivation to adopt robotics [87].

Perceived enjoyment is one of the determinants that influence customers' intention to use robotics [54]. Customers are more likely to communicate with robotics when they find interactions with robotics inherently engaging [42]. Customers with a high level of enjoyment when using advanced technology can improve their intention to utilize new technology [88]. Cha [15] concluded in a previous study that perceived enjoyment positively influenced customers' intention to adopt robot services in restaurants. Based on the above statement, hypothesis H4 is:

H4: There is a significant relationship between perceived enjoyment and customers' intention to use AI-driven robotic service in restaurants.

2.4.5 Perceived trust and intention to use

Perceived trust is a significant factor influencing the intention to adopt technology [54]. Consumers are the most fundamental factor to consider when developing an information technology system. Technology cannot thrive without considering consumers' acceptance, feelings, and trust. If a customer has a higher level of trust in robots and expects them to execute tasks as expected, they will perceive robots as useful and easy to use [18].

The intention to adopt is directly or indirectly influenced by perceived trust [88]. Since robotics is a modern technology in the market, perceived trust is a significant determinant in measuring customer intention [89]. If an individual believes that robotics is trustworthy, they will feel more secure, leading to a pleasant feeling [90]. Conversely, if an individual perceives that robotics is untrustworthy, they will not intend to utilize it in the future [57]. Perceived trust has been shown to positively influence the intention to utilize robot services in restaurants [88]. Furthermore, AI-enabled services that provide timely, personalized, and contextually relevant interactions are more likely to strengthen users' trust and satisfaction, thereby encouraging continued engagement with the technology [91]. Based on these statements, hypothesis H5 is:

H5: There is a significant relationship between perceived trust and customers' intention to use AI-driven robotic service in restaurants.

2.4.6 Perceived risk and intention to use

According to Jeong & Ha [92], perceived risk influences the intention to use service robots. Since the utilization of new technology-based

services depends on the degree of risk perceived by customers, perceived risk plays a significant role in the field of new technologies. Customers are reluctant to use new service technologies when risk is involved in the service process [28]. However, robotics can provide services to customers without making errors because robotics is based on an automated system [93]. Thus, customers perceive low risk in such services [5].

When customers perceive low risk in the use of robotics, they are more likely to have a high desire to adopt and spend more at restaurants that provide robotics services. Conversely, customers with high perceived risk towards the use of robotics are less likely to utilize or spend less at restaurants that offer robotics services [5]. The previous study by Cha [15] indicated a relationship between perceived risk and customers' intention to utilize robot services in restaurants. Based on the above statement, hypothesis H6 is:

H6: There is a significant relationship between perceived risk and customers' intention to use AI-driven robotic service in restaurants.

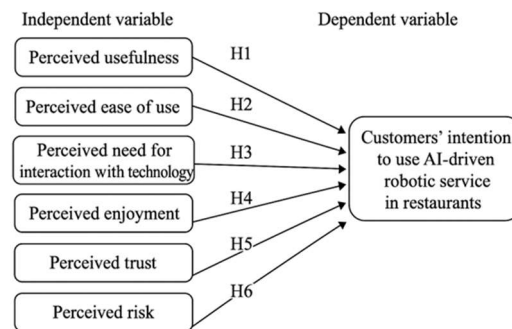


Figure 1: Conceptual Framework

3. METHODOLOGY

3.1 Research Design

A research design serves as a structured blueprint for achieving the objectives of a study. It provides a systematic framework for identifying and analyzing the relationships among the variables under investigation [94]. The first objective of this research is to determine the level of customers' intention to use AI-driven robotic services. The second objective of this study is to identify the determinants influencing customers' intention to use AI-driven robotic services in Batu Pahat restaurants. To conduct this research, the researcher employed the quantitative method. Quantitative research focuses on measuring the quantity, frequency, or magnitude of a phenomenon and forms the foundation of statistical analysis, relying heavily on the quality of measurement instruments used in

observations, surveys, and experimental tests [94]. Additionally, descriptive analysis was conducted in this research to calculate the mean and standard deviation. After collecting the data, the researcher used correlation analysis to examine the relationship between the independent variables and the dependent variable.

3.2 Population and Sample

Based on Schindler [94], the target population can be described as the entire group for which information is required, and a conclusion is drawn. Recruiting the entire target population is frequently unacceptable in research. On the contrary, the researcher chooses a sample of people from the target population for their research. However, the population for this research was still unknown. This is because the researcher was required to identify and select the potential respondents since the sample consisted of the customers who had used the robotic services at two restaurants. A sampling frame can be defined as a list of items from which a sample is taken, and it must accurately represent the population [94]. The researcher distributed the survey questionnaire to customers who had used the robotic services at two restaurants in Batu Pahat, Johor. The reason for choosing this location to conduct the survey is that there are only two restaurants in Batu Pahat that provide robotic services to their customers.

According to Schindler [94], the sample size can be determined as the number of samples involved in research. The target respondents of this research are customers who have used the robotic services at these two restaurants. The unit of analysis is the individual who consumes food at the two restaurants. According to Krejcie & Morgan [95], a sample size of 384 should be sufficient for this research because the population of this research was unknown. A total of 384 survey questionnaires were distributed to the target respondents through a hardcopy survey. Out of these, 307 respondents agreed to participate in the research. As a result, the survey return rate was 80%.

3.3 Instrumentation

A questionnaire is a type of data collection tool commonly used in normative studies. It comprises a set of questions designed on a research topic that respondents answer [94]. There are two types of questionnaires: closed-ended questions and open-ended questions. Closed-ended questions can only be answered by choosing from the provided options, typically multiple-choice questions and the Likert scale. Open-ended questions allow

respondents to provide answers based on their opinions [94]. In this research, the researcher chose closed-ended questions because they only require respondents to select from the provided answers, making it easier to obtain higher response rates.

Section A: Demographic respondent (this section was identified using multiple-choice options)

Section B: Level of customers' intention to use robotic service (this section was identified using a 7-point Likert scale)

Section C: Determinants influencing customers' intention to use robotic service in Batu Pahat restaurants (this section was identified using a 7-point Likert scale)

Additionally, the scale of measurement used in this research was a seven-point Likert scale, ranked from 1 = strongly disagree to 7 = strongly agree. Finstad [96] demonstrated that the seven-point Likert scale is more reliable, simple to use, and provides a better depiction of the respondent's true evaluation.

3.3.1 Content Validity

Content validity refers to the degree to which a measurement instrument adequately encompasses the investigative questions guiding the study; greater alignment between the instrument and the research questions indicates stronger content validity [94]. The researcher sent the questionnaire to two experts for validation. Expert A is an associate professor from Universiti Tun Hussein Onn Malaysia with a research interest in technological innovation, while Expert B is a senior lecturer from the same university with a research interest in Industry 4.0. Both experts provided valuable insights and suggestions regarding the research questionnaire. Since the instrument is written in English, two language experts also assisted in validating the language accuracy. Finally, the researcher incorporated the corrections based on the feedback provided by the experts.

3.3.2 Internal Consistency Reliability

A pilot study is an initial phase in research methodology, typically involving a smaller study aimed at helping to design and modify the research. Pilot testing of the measurement instruments allows for their refinement prior to the commencement of the main research study [94]. Researchers commonly use pilot studies to assess the appropriateness of their proposed methods and processes. Therefore, a well-designed and conducted pilot study can aid in estimating sample size by identifying previously unknown variables and evaluating the strength of relationships between each variable [97].

This research conducted a pilot study by distributing a survey questionnaire to 30 respondents. Johanson & Brooks [98] suggest that having 30 representative individuals from the population of interest is an acceptable minimal requirement for pilot research aimed at developing a scale or conducting a preliminary survey. Subsequently, Cronbach's alpha was computed to assess internal consistency reliability. Based on George & Mallery [99], Cronbach's alpha for perceived usefulness, consisting of 4 items, is 0.749, which is considered acceptable. The Cronbach's alpha values for perceived ease of use and perceived need for interaction with technology, with 4 items and 3 items, respectively, are 0.884 and 0.929, indicating good and excellent reliability, respectively. For perceived enjoyment, comprising 3 items, Cronbach's alpha value is 0.933, indicating excellent consistency and reliability. Additionally, the 4 items measuring perceived trust show a Cronbach's alpha value of 0.889, signifying good consistency and reliability. Furthermore, the variables perceived risk and intention to use, each consisting of 4 items, have Cronbach's alpha values of 0.924 and 0.937, respectively, indicating excellent reliability. The overall reliability of this study is 0.904, with a total of 26 items, which is considered excellent. Consequently, the survey questionnaire used in this study is deemed suitable for the respondents and has achieved reliability and validity.

3.4 Data Analysis

According to Calzon [100], data analysis is the process of gathering, modeling, and analyzing data to derive insights that aid decision-making. The researcher utilized IBM Statistical Package for the Social Sciences (SPSS) version 26 to analyze the collected data. Descriptive analysis, as described by Rawat [101], is a type of data analysis that helps explain, illustrate, and summarize data effectively. There are several objectives when conducting descriptive analysis, such as highlighting the potential relationship between each variable and providing essential information about a dataset's variables. Schindler [94] indicated that there are numerous types of descriptive analysis, including measures of Central Tendency and variability. Central Tendency refers to a number that summarizes the entire dataset, with mean, median, and mode being the three measures. Variability, on the other hand, refers to the range of values within a set of data, with range, variance, and standard deviation being the three measures of variability. Hence, descriptive analysis was conducted in this

study to help summarize the large dataset in a sensible approach.

Correlation analysis, as explained by Schindler [94], measures the extent to which two variables are related. Karl Pearson first formulated and explored correlation analysis in 1896 [102]. When two variables correlate, it may result in a positive or negative relationship. For example, if a variable's trend is positive and similar to that of other variables, there is a possibility of a positive relationship, leading to a positive correlation. Conversely, if a variable's trend is positive and other variables trend negatively, there is a possibility of a negative relationship, resulting in a negative correlation [94]. Therefore, correlation analysis was conducted to examine whether there is a correlation between the determinants and intention to use.

3.5 Threats to Validity and Justification of the Critique Criteria

Several threats to validity should be acknowledged while interpreting the results. First, the external validity was compromised because the sample was retrieved from two restaurants in Batu Pahat and the target population was not known. Results can only generalize to the customers who had experienced robotic service in the sample establishments, and are not transferable to all Malaysian restaurant customers, other Malaysian states, other restaurant formats, or all robot types. Second, the cross-sectional survey design only captured perceptions at the time of collection and therefore cannot generalize to temporal change or establish causality.

Third, the use of self-reporting responses based on a single questionnaire contained potential for common-method and response biases. Fourth, despite 307 usable responses, the face-to-face convenience sampling method might have incurred sample selectivity because customers who agreed to participate in the survey may have been systematically different from customers who refused to participate. Fifth, because the study considered AI-driven robotic service as a customer-facing restaurant technology, the AIs involved could be dissimilar in capabilities or range of AI autonomy, and so the results should be interpreted more narrowly with the specific robotic service encounters instead of with all AI-robotic services. The validity of the critique criteria-such as functional usefulness, ease of use, interaction, enjoyment, trust, risk, contextual relevance, and methodological scope-was based on their correspondence to the key constructed variables in the research and the integration of TAM extensions supporting the conceptual framework

[48, 54, 55, 68, 79]. They further resulted in a balanced evaluation of statistical evidence and restaurant robotics practice.

Spearman's rho was adopted to assess associations between variables in the research; it was appropriate because of the ordered Likert-scale responses and the purpose of analyzing the strength and direction of monotonic relationships. Therefore, the conclusion can be read as an association instead of causality that a change in the independent variable should lead to a change in the dependent variable.

4. RESULTS AND DISCUSSIONS

4.1 Level of customers' intention to use AI-driven robotic service

The first objective of this study was to determine the level of customers' intention to use AI-driven robotic services, which was performed using descriptive analysis. Table 1 indicates the mean and standard deviation for the items of intention to use. The mean values ranged from 5.62 to 5.66, while the standard deviation values were in the range of 1.147 to 1.185. The results indicated that the level of customers' intention to use AI-driven robotic services is high, despite numerous determinants that might influence customers' intention to use AI-driven robotic services. Previous researchers have proven that customers' intention to use AI-driven robotic services can be influenced by a range of factors, such as compatibility and anxiety, as well as perceived value and attitude, as declared by Kwak et al. [103]. Karjaluoto et al. [104] also mentioned that understanding customers' intention to use is significant for business managers to make strategic decisions and predict sales of current and forthcoming goods and services. Therefore, by focusing the marketing strategy on customer intention, business managers can maximize the opportunities available to the company [105].

Table 1: Level of agreement mean measurement

Intention to use items	Mean	Std. Deviation	Interpretation
ITU1	5.65	1.185	High
ITU2	5.62	1.184	High
ITU3	5.62	1.152	High
ITU4	5.66	1.147	High
Average mean	5.64		High

4.2 Determinants influencing customers' intention to use AI-driven robotic service

The second objective of this study was to identify the determinants influencing customers' intention to use AI-driven robotic services in Malaysian restaurants. According to Table 2, the results showed that all the determinants were correlated with intention to use. There is a significant correlation between all the independent variables and customers' intention to use AI-driven robotic services, especially for perceived usefulness, which had a strong positive correlation with customers' intention to use AI-driven robotic services. In other words, perceived ease of use, perceived need for interaction with technology, perceived enjoyment, perceived trust, and perceived risk are correlated with customers' intention to use AI-driven robotic services. Regarding perceived usefulness, it had a strong positive correlation with the intention to use, consistent with the findings of Zhou [78]. Zhou [78] declared that the majority of customers are optimistic about technological advancement and believe that new technologies will be advantageous. Hence, high usefulness will enhance customers' intention to use the new technologies [76].

Regarding perceived ease of use, it had a moderate positive correlation with the intention to use, similar to the findings of Kervenoael et al. [81]. Customers are more likely to interact with a robot if the robot is simple to understand, easy to use, and involves little effort [58]. Therefore, a high level of perceived ease of use makes it easier to increase customer satisfaction and adoption of robotic services [72].

Moreover, the perceived need for interaction with technology was found to have a moderate positive correlation with the intention to use. This is in agreement with the findings of Zhou [78]. According to Zhou [78], the intention to use robotics increases when there is a high level of technology interaction with an individual. Barton & Sinha [84] highlighted that robotics is highly preferred by the younger generations compared to human interaction.

Furthermore, perceived enjoyment was also discovered to have a moderate positive correlation with the intention to use, supporting the findings of Cha [15]. One of the possibilities could be the enjoyment and delight these customers felt when utilizing new technology [54]. As a result, customers will be more inclined to adopt robotic services if they perceive these technologies to be interesting, enjoyable, and fun [106].

In addition, the perceived trust had a moderate positive correlation with the intention to use, as in the findings reported by Cha [15]. Lack of trust is usually viewed as a significant barrier that

prohibits customers from utilizing robotic services [107]. Wirtz et al. [25] declared that the possibility of adoption seems to increase when robotics is perceived as more reliable and as prioritizing the interests of customers.

Last but not least, perceived risk had a very weak negative correlation with the intention to use, in line with the findings of Karjaluoto et al. [104]. Perceived risk is a significant psychological barrier to the acceptance of new technologies, and lowering perceived risk can directly increase the adoption of new technologies [62]. However, customers are reluctant to use the new service technologies when risk is involved in the service process [28].

4.3 Critical Evaluation and Differences from Recent Prior Work

The highest value is for perceived usefulness ($\rho = 0.743$), followed by perceived enjoyment (0.645), perceived ease of use (0.624), perceived trust (0.609), perceived need of interaction with technology (0.516), and perceived risk (0.197). These imply that restaurant sample consumers seem to be more interested in the usefulness of robot service rather than risk reduction. The fact that the simple relationship for perceived risk is weak suggests that risk may not play a role as a main determinant in this situation. Although only showing that risk does not seem to be a significant predictor, it is not inconsistent with evidence from Seo and Lee [108] that trust, risk, satisfaction, and TAM constructs can become determinants through the mediatory effect of more general attitudes in a robot-based restaurant. Because the present research did not examine mediating influences, it would be mistaken to conclude that risk was irrelevant to restaurant robot service.

The study showed that customers who had experience with AI technology in their meals in two Batu Pahat restaurants had a high intention to accept and use the technology. The six proposed determinants all significantly predicted customer intention to use the technology. The positive relationships between intention to use and four factors – perceived usefulness (best predictor with $\rho=0.743$), perceived enjoyment (0.645), perceived ease of use (0.624), and perceived trust (0.609) – were unsurprising. Two other factors, perceived need for interaction with technology (0.516), and perceived risk (weak negative relationship of -0.197) were also significant. These findings offered the two test results that both functional and experiential perceptions of service were relevant in determining customer acceptability and intention to use the technology.

The research also has pragmatic strengths in that it uses respondents who have experienced restaurant robots without entirely abstracting the model in hypothetical scenarios; it has 307 valid responses, and acceptable internal consistency was found for the constructs used. A blend of usefulness, ease of use, interaction, enjoyment, trust, and risk encompasses the perceived functional, experiential, relational, and uncertainty attributes of acceptance. However, the research has significant shortcomings: data were obtained from only two restaurants in a single city; the design is cross-sectional and correlational; the variables are self-reports; and the study does not test demographic moderation, robot form, task complexity, service quality, privacy, social presence, or actual continued usage. The negative implications are significant because recent research indicates that customer reactions shift according to the type of service, robot form, and quality of the customer-robot interaction [2–19]. While the study provides important contextual insights, it does not give an outright AI acceptance model to be used to model future restaurants.

Table 2: Summary of the results of the hypotheses

Hypothesis	Spearman's rho correlation	Result
H1: There is a significant relationship between perceived usefulness and customers' intention to use robotic service in restaurants.	0.743	Accepted
H2: There is a significant relationship between perceived ease of use and customers' intention to use robotic service in restaurants.	0.624	Accepted
H3: There is a significant relationship between perceived need for interaction with technology and customers' intention to use robotic service in restaurants.	0.516	Accepted
H4: There is a significant relationship between perceived enjoyment and customers' intention to use robotic service in restaurants.	0.645	Accepted
H5: There is a significant relationship between perceived trust and customers' intention to	0.609	Accepted

use robotic service in restaurants.		
H6: There is a significant relationship between perceived risk and customers' intention to use robotic service in restaurants.	-0.197	Accepted

5. CONCLUSION

At the conclusion of this research, both the research objectives and the six hypotheses had been satisfactorily achieved. The first research objective aimed to determine the level of customers' intention to use AI-driven robotic services. The results indicated that the level of customers' intention to use robotic services is high, although several determinants influenced customers' intention to use robotic services. Moreover, the second research objective aimed to identify the determinants influencing customers' intention to use AI-driven robotic services in Batu Pahat restaurants. The results showed that all the determinants were significantly correlated with intention to use.

The main contribution of this study to IT research is the contextual use of a TAM-based framework that combines perceived usefulness and perceived ease of use with interaction, enjoyment, trust, and risk in a Malaysian restaurant context. This study contributes new evidence to the literature by researching customers who have real experiences of restaurant robotic service in Batu Pahat. At the same time, cross-comparison with recent literature reveals that acceptance is complex and context-dependent; recent research has also included perceived social presence, anthropomorphism, personalization, privacy, food safety, service complexity, and demographic factors [1–19]. Therefore, this framework should be viewed as a 'specific model' rather than a comprehensive explanation of customer acceptance.

The major strength of the research is its practical implications and its close accordance with practical use, alongside solid, theoretically based determinants and acceptable reliability. The main limitations are the limited geographical and organizational breadth, the cross-sectional, self-report nature of the survey, the correlational, not causal approach, and the failure to include variables recently suggested as significant. Specifically, the results can only tell us that raising the mentioned variables does not necessarily lead to higher intention to use and cannot be projected immediately onto other Malaysian states, other restaurant formats, customer types, or other robot types.

Pragmatically, restaurant practitioners could use the results as guidance to focus on robot service's functional accuracy and usability while providing suitable human support for tasks that cannot be performed by robots, such as special requests or service recovery. But the evidence does not support customers' acceptance of serving tasks with more robotics. Not-too-much, not-too-little human service design is still crucial as a variety of tasks could require different interactions with robots.

Future research should build on these studies by addressing the previous limitations listed above: using larger and more diverse sample across other states of Malaysia and other forms of restaurants, empirically testing other types of service robots, adopting longitudinal and/or experimental research designs where appropriate, using mixed methods research, and exploring the roles of social presence, anthropomorphism, personalization, privacy and transparency, food safety, service complexity, service quality, demographic moderators, and actual continued usage [1–19]. Larger sample sizes and structural equation modeling or other multivariate approaches can be adopted to test the direct, indirect, and moderating effects, which can be inferred in correlational studies. This kind of research can further shed light on when, why, and how robotic services with AI can deliver value for customers and restaurant establishments.

ACKNOWLEDGEMENT

This research was supported by Universiti Tun Hussein Onn Malaysia (UTHM) through Tier 1 (vot Q913).

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