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# AI, Robots and Innovation: Are Consumers Ready to Embrace Service Robots Technology?

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**ABSTRACT**

As service robots continue to automate and transform the food and beverage industry, these technological innovations will fundamentally alter the existing practices of service practitioners, inherently changing service management and marketing strategies. The current study investigates the relationship between trust, performance expectancy, perceived value, social influence and perceived enjoyment towards consumers' usage intention of service robots in the food and beverage industry. A total of 300 sets of questionnaires were distributed through online platforms with 264 sets used for subsequent analysis. Four constructs were significant in influencing consumers' intention to use service robots (trust, perceived value, social influence, and perceived enjoyment); while performance expectancy did not. The outcome provides meaningful theoretical and practical insights which will contribute towards sustainable development of the F&B industry in the future.

*Keywords: Artificial Intelligence (AI), Service Robots, Innovation, Technology*

## INTRODUCTION

Robots have recently seen adoption into the service industry after a decades-long process of use throughout many sectors (Belanche et al., 2019). Robotics, artificial intelligence (AI), and service automation technologies have created opportunities for the modern industry to integrate various interactive technologies into the service environment, thereby replacing or increasing a large amount of manpower (Ivanov et al., 2018, p. 26). Robots commonly belong to three different categories - professional, industrial and personal service. Industrial robots have been widely used among the manufacturing sectors, while professional and personal service robots have been introduced more recently into the economic and service sectors as well.

The International Federation of Robotics (2018) predicted that as the sales of service robots continue to grow at an annual growth rate of between 30 to 35 percent per year, the use of service robots for professional and personal (domestic tasks) will be further expanded in the next ten years. According to Schwab (2017), robots and AI are expected to play an even bigger role in the economy in the next 10 to 15 years, due to the Fourth Industrial Revolution with profound economic, social, and political implications (LaGrandeur & Hughes, 2017;

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Leonhard, 2016). Malaysia is also embracing Industry 4.0 and focuses on AI innovation and development with emphasis in areas such as education and business (Hasnan, 2019).

There are many applications of service robots in various industries such as elder care (Glende et al., 2015), medicine (Schommer et al., 2017), farming (Driessen & Heutinck, 2015), financial trade (Dunis et al., 2016), carriage (Maurer et al., 2016) and tourism and hospitality (Ivanov et al., 2017). Wirtz et al. (2018) suggested that AI devices enabled organizations to offer its services with greater productivity, efficiency, and efficacy. Service robots may resolve several human labour issues such as the high cost of hiring and difficulty in retaining employees in the food and beverage industry (Cheong et al., 2016). Conversely, with the wider use of robots in various industries, there will be challenges in regards to social, economic and labour. Consumers may oppose using robots as a substitute for human employees in organizations as well as frontlines service employees. They may be unwilling to fully accept service robots due to various reasons such as the lack of 'humanity', difficulty in understanding and controlling robots and other ethical concerns (e.g., potential increase in unemployment rate when robots enter the human labour market).

Professional service robots are now being utilized in service industries such as finance, retailing, healthcare, education and tourism and hospitality sector. When consumers are exposed to front-line service interactions that support AI, there is a need to have a deeper understanding of their thoughts, feelings and behaviours (Ostrom et al., 2019). Although the application of AI and robotic technologies in the F&B industry is still at its infancy, it is actively developing, bringing an increasing number of businesses implementing such technologies. This AI revolution and the adoption of AI applications in service encounters attracted great attention from various researchers (Wirtz et al., 2018; Huang & Rust, 2018). Service and technology literature tend to focus on the positive attitude of AI application usage, while the economic literature tend to focus on the impact of AI technology towards human labour and job replacement (Colby et al., 2016; Marinova et al., 2017; Rafaeli et al., 2016).

Despite the growing interest, studies on service robots in the food and beverage industry remained under-researched. Previous studies explored several issues regarding AI application such as consumers' perception and AI utilization in service delivery (Duan et al., 2019). Past researchers mainly focused on the role of service robots in service encounters (Wirtz et al., 2018), application of robots in tourism and hospitality (Murphy et al., 2017), impacts of AI technology on frontline employee-customer interactions (Marinova et al., 2017), or put forward a theory to explain the development of AI technology and artificial replacement (Huang & Rust, 2018). Academics have also investigated customer's willingness to use service robots in service encounters (Lu et al., 2019).

Many past studies focused on the application of robots in the travel and hospitality sector (Murphy et al., 2017). For instance, Ivanov et al (2018) looked at the attitude of young Russians towards the introduction of robots in hotels, Tussyadiah, & Park (2018) and Garenko (2017) on consumers' evaluation of hotel service robots and Ivanov and Webster (2017) on cost-benefit analysis of robot adoption in tourism and hospitality companies. Most studies are either concepted or exploratory, while the empirical research in the field of service robot's usage in the F&B industry are very limited. To address this gap, this research aims to examine the application of service robots in the F&B industry, specifically looking at factors that may influence consumers' usage intention towards the AI application in the service encounters. This research adopts a demand-side perspective, focusing on the views of consumers.

## LITERATURE REVIEW

### Overview of Service Robots

Wirtz et al. (2018) mentioned that “service robot is a technology that delivers service with system-based autonomy that enable an organization’s customers to communicate and interact with”. In this case, the degree of autonomy refers to the ability of the robot to perform tasks without human intervention. This autonomy may be affected by the complexity of the robot's operating environment and the inherent characteristics of the robot (e.g., intelligence, mobility, and senses capabilities). Sensors are built-in devices that allow robots to understand and interact with their environment. The key tasks of the robot usually determine the demand for certain sensors. Such sensors are typically like human perception and it may include light sensors (vision), pressure sensors (touch), taste, and hearing sensors (Ruocco, 2013). For instance, service robots that provide food and beverages can continuously analyse and respond to the environment.

All robots can be classified into two major categories: (1) industrial robots and (2) service robots. As the name suggests, industrial robots are designed to perform industrial tasks such as welding, palletizing, and other related tasks in manufacturing and production (Murphy et al., 2017). On the contrary, service robots aim to support and serve humans through physical and social interaction. Service robots can also be divided into professional service robots (i.e., robots employed by companies) and personal service robots (i.e., robots used by individuals for non-commercial tasks). Jörling et al. (2019) reaffirmed that service robots can provide “customized services by performing physical as well as non-physical tasks with a high degree of autonomy”. Examples of this includes service robots in virtual contexts such as voice-based digital assistance (i.e., Alexa and Siri), text-based chatbots (i.e., websites Chabot), and algorithms assistance (i.e., robot advisors for investment services).

Physical robots often appear as humanoid robots in the tourism and hospitality service context to provide directions and information. All the above examples clearly show that the service industry is altering, and more and more companies are considering reorganizing their organization’s frontline service from a more traditional mode to innovative ways (i.e., service robots involved). According to Schneider (2019), by 2025, approximately 85 percent of customer interactions will be conducted without human intervention.

### Service Robots in the F&B Industry

Service robot is one of the most transformative technological innovations to date in the context of hospitality service (Ivanov & Webster, 2019). Driven by the advancement of electromechanical engineering and computer science (i.e., novel technologies and processes such as machine learning or deep neural networks), robots have overcome the limitations of factories and are becoming more adaptive to human dynamics and environment (Wirtz et al., 2018; Ivanov et al., 2019). In recent years, service robots have accelerated the development of the F&B industry (Murphy et al., 2017; Bowen & Whalen, 2017). There are robots that serve customers in the frontline and robots that cook complex meals in the kitchen (Bowen & Morosan, 2018). For instance, a burger robot that can process up to 120 orders per hour and a barista robot that can serve up to three beverages in 40 seconds was developed by a California-based inventor in the United States (Troitino, 2018; Canales, 2018). Past studies also mentioned the application of service robots in the F&B Industry. For example, the birth of a new generation of electronic waiters was explained and analysed from a technical perspective (Malik et al., 2016). Iqbal et al. (2017) analysed service robots in the F&B industry from a system aspect. Thanh et al. (2019) studied the development of sensors to assist robots in maintaining a stable service speed in the F&B industry. It can be concluded that service robot technology has gained prominence in the F&B industry.

**Underlying Theories**

Technology Acceptance Model (TAM) developed by Davis et al. (1989), was adapted from Fishbein & Ajzen (1975) "Theory of Reasoned Action" (TRA), specifically tailored for predicting user acceptance of new technology. TAM seeks to deliver an explanation of the elements of technology acceptance, explaining the way people behave based on their attitudes towards certain new technology (Davis et al., 1989). TAM is mainly determined by key variables: (1) perceived usefulness and (2) perceived ease of use (Davis et al., 1989). TAM has been widely used in subsequent research to predict the perceived usefulness and usage intention of technology by adding various individual context-specific variables, such as past experience, social influence and subjective norms (Venkatesh & Davis, 2000; Marangunić & Granić, 2014). However, the simplicity of TAM is often criticized (e.g., Bagozzi, 2007), for being unable to involve other relevant aspects, such as the influences of social processes and subjective norms. To addressed this concern, TAM 2 was subsequently developed by Venkatesh & Davis (2000), with additional theoretical variables (e.g., social factors and cognitive factors) to improve the insufficient interpretive power. TAM 2 integrates the influences of subjective norms (e.g., social influence) and made significant contributions to the field of AI adoption theories for future researchers to develop their conceptual framework such as the adoption of service robots by potential users.

Venkatesh et al. (2003) unified eight theoretical models that incorporate the most reliable constructs (combination of TAM and TPB) as the key-dependent to form a new model called "Unified Theory of Acceptance and Use of Technology" (UTAUT) and (UTAUT 2) (Venkatesh et al., 2012). This theoretical model was developed by using the essential elements of the eight theoretical models to study both consumer usage intention and actual use within new technology acceptance in both organizational and consumer contexts. UTAUT was established with four key variables (1) performance expectancy, (2) effort expectancy, (3) social influence, and (4) facilitating conditions with various individual moderators such as age, gender, experience, and voluntariness to make the effect of a construct on usage intention stronger or weaker (Heerink, 2010). This theoretical model provides a basic construct and definitions of consumer technology acceptance and uses context. UTAUT model has been widely used in previous research such as the acceptance of robots (i.e., the iChat) (de Ruyter et al., 2005; Looijie et al., 2006). The UTAUT model is a good foundation for researchers to start exploring factors that determine consumers' usage intention of service robots. This is due to its extensive validation and the potential applicability of the model to human-robot interaction (Heerink et al., 2010). For UTAUT 2, it integrated three additional constructs to the UTAUT model, which is only emphasizing the importance of extrinsic motivation (i.e., utilitarian value) (Venkatesh et al., 2012). Intrinsic or hedonic motivation, price value, and habit were added to UTAUT 2, as these three variables had shown to be critical factors in predicting consumer technology use context by subsequent researchers (Brown & Venkatesh, 2005; Dodds et al., 1991; Kim et al., 2005).

**Consumers' Usage Intention (CUI) towards Service Robots**

Intention to use is based on the definition of behavioural intention by Fishbein and Ajzen (1975), as "the strength of one's intention to perform a specified behaviour". Intention is crucial in predicting an individual's usage goal and it has been well proven in IT literature and reference disciplines (Cham, Cheng, & Ng, 2020; Venkatesh et al., 2003). The UTAUT model attempts to explain usage intention, as well as subsequent usage behaviour. Thus, all TAMs including UTAUT and UTAUT2 rest on the three main constructs; (1) factors affecting personal intentions, (2) intention of using service robot, and (3) actual use. Service providers should encourage usage when users are willing to use the service robot's application and utilise them. Based on previous studies, robotics system usage is largely influenced by behaviour, hence factors that affect consumers' intention to use the application of service robots play an important role in predicting future usage of service robots in the F&B Industry.

In the past, several researchers conducted studies regarding the usage intention of service robots in different contexts and countries. As reported by Alaiad et al. (2013), researchers have studied the stakeholders' usage intention of home healthcare robots by applying the UTAUT model. Moreover, these studies were mainly based on the technical viewpoint of service robots which have been conducted in an organisational context, where the main purposes for using the systems are effectiveness, efficiency, and usefulness. When the purpose is to explore consumers' intention to use service robots in their daily life, the robotics research must be supplemented by other theories. These theories include both non-utilitarian motives and utilitarian motives. Thus, this research aims to further study trust, performance expectancy, perceived value, social influence, and perceived enjoyment of consumers' usage intention towards service robots in the F&B industry.

**Trust (T)**

Trust is defined as an "individual's willingness to accept the actions of the other party (trustor) to perform, based on their expectation, and the trustee ability to monitor or control the other party (trustor) specific action" (Mayer et al., 1995). Doney & Cannon (1997), iterated trust as the perceived competence (i.e., reliability) and kindness of the trust target. Trust is related to derivative fundamentals: (1) disposition to trust, (2) institution-based trust, (3) trusting beliefs, and (4) trusting intention (Susanto et al., 2016). Common among those definitions are the combination of trusting dispositions, cognitions, and willingness or intentions (McKnight et al., 2002). Trust is also recognised as a relationship in which an entity called trustor, relies on someone or something called trustee (Cho et al., 2015; Deeparechigi et al., 2018; Goh et al., 2017; Tan et al., 2019). According to Gefen et al., (2003), trust is a primary motive for acceptance. Trust often acts as a key element in relationships and service contexts, such as in seller-buyer relationships (Siau & Shen, 2003), and human-social interactions (Hengstler et al., 2016). Trust also includes ways people interact with new technology (Cham et al., 2018; Li et al., 2008； Siau et al., 2004). The definition of trust has now been widely used in several research areas, especially in fields such as automation, computing and engineering that looks at trust of a human towards a machine's automated operations. For instance, trust in human-automation interaction (Schaefer et al., 2016), trust in automation, trust in human-robot interaction (Aroyo et al., 2018), and trust in artificial intelligence.

Prior studies often explain robotics relationship with flow theory (Nakamura & Csikszentmihalyi, 2014). When people interact with robots, the sense of participation they feel will enable people to have higher perceptual trust and interactivity. In turn they will enter a state of flow; a state of high enjoyment, which fundamentally motivates people to intend to use the service (El Shamy & Hassanein, 2017; Zhou et al., 2010). Trust is an essential factor in the IT interaction environment to explain or predict the degree of users' adoption of technology (Alaiad & Zhou, 2014; Lim & Cham, 2015). Past literature demonstrated the impact of trust on the adoption of technology (Wu et al., 2007; Armida, 2008). As stated by Gefen et al. (2003), trust is included in multiple versions of the technology acceptance model as a predictor of usage intention. Past research identifies trust as a strong determinant in predicting intention to use service and service robots (Gefen et al., 2003; Han & Conti, 2020; Kaushik & Rahman, 2015; Wirtz et al., 2018). Alaiad & Zhou (2014) discovered that trust has a positive effect on the usage intention of home healthcare robots. Based on the above review, the following hypothesis is proposed:

**H1:** *There is a significant positive relationship between trust (T) and consumers usage intention (CUI).*

**Performance Expectancy (PE)**

Venkatesh et al. (2003) defined performance expectancy (PE) as "the degree to which an individual believes that the use of a specific technology will provide benefits to users in the execution of certain activities". Performance expectancy is a construct based on five different fundamental models: (1) perceived usefulness (2) extrinsic motivation (3) job-fit (4) relative advantage and (5) outcome expectations. Researchers may use alternative terms to represent PE (e.g., quality of task outcomes, outcome expectations, effectiveness, and increased self-competency). According to Lu et al. (2019), performance expectancy was characterised as the degree to which robots can provide constant and reliable service to consumers. When service robots are performing services as a frontline employee, their competency performance is closely related to the perceived service quality and the perceived benefits and experience that customer received by using such devices. This factor is an extended item from perceived usefulness in TAM/TAM2 and is a fundamental item in influencing an individual's attitude towards the application of new technology.

Prior studies also demonstrated that PE is the strongest predictor of usage intention of IT (Venkatesh et al., 2003). In line with Alaiad & Zhou (2014), PE has a positive effect on the intention to use home healthcare robots. The researchers claimed that PE played an important role in relation to usage intention as robots can improve the overall outcomes by its productivity, enhance service performance, and are able to perform tasks effectively. Another research by Alaiad et al. (2013), showed that PE positively predicted usage intention. Pragmatic and usefulness tend to be important in influencing an individual's technology acceptance decisions. Consumers tend to adopt technologies that are useful for their own need (Alaiad et al., 2013). There is also extensive empirical evidence that supports the significant effect of PE on usage intention (Wills et al., 2008; Rahman et al., 2011; de Veer et al., 2015). Hence, the following hypothesis is proposed:

**H2:** *There is a significant positive relationship between performance expectancy (PE) and consumers usage intention (CUI).*

**Perceived Value (PV)**

Perceived value (PV) is one of the most important measures for gaining competitive advantage (Parasuraman, 1997). PV is a complicated perception that encompasses many areas, including human value, entertainment value, and the value chain (de Kervenoael et al., 2020). Several past studies determined that consumers' satisfaction is related to their overall perception of value (Woodruff, 1997). This concept is widely applied in hospitality and tourism services, and is usually seen as a trade-off between multiple benefits (Han et al., 2017). For Zeithaml (1988) perceived value is defined as "the consumer's overall assessment of the utility of a product based on the perception of what is received and what is given". Parasuraman and Grewal (2000) conceptualised perceived value as a dynamic structure composed of four value types: (1) acquisition value, (2) transaction value, (3) in-use value, and (4) redemption value. In the product or service life cycle, the relevance of each of the four dimensions is different (i.e., the purchase and transaction value are the most prominent in the purchase process). Parasuraman et al. (1988) stated that PV is a ratio of perceived benefits to perceived costs. PV is regarded as dependent on different situations, including technology types, promises of service types, and tangible assets. By introducing an overall assessment of responsive cues in robots, it provides direction for cognition (Kim et al., 2007). Thus, PV represents the benefits of social robot technologies towards a higher service quality by defining overall perceived gains or losses (de Kervenoael et al., 2020).

Due to limited research on the relationship between PV and intention to use service robots, the relationship between the two variables is inferred based on research conducted in other similar fields. Researchers in the past investigated PV extensively (employing attention and usage intentions, such as in the mobile industry (i.e., smartphone) (Kim et al., 2013; Sweeney & Soutar, 2001). Yuen et al. (2019) research showed a significant positive effect on customers' intention to use smart lockers. Past researchers also pointed out that customers' intention to use can be improved by providing tangible benefits (e.g., improve utility). PV is a composite of economy, function, hedonic, and social utility, which can greatly improve consumers' usage intention (Cheng et al., 2019; Yuen et al., 2019). Based on de Kervenoael et al. (2020) study, PV was found to have a significant positive impact on intention to use robots, which seems to be the largest impact among other variables in the study. Hence, the following hypothesis is developed:

**H3:** *There is a significant positive relationship between perceived value (PV) and consumers usage intention (CUI).*

**Social Influence (SI)**

According to Venkatesh et al. (2003), SI is defined as the degree to which the opinion and believes of significant others may influence users' perception and intention on using certain technology (i.e., service robots). In other words, SI refers to the degree to which consumer's social group (e.g., family, friends, etc.) believes that using AI devices (i.e., service robots) in service delivery is relevant and congruent with group norms (Gursoy et al., 2019). SI is also related to the extent to which consumers' social groups believe they should use service robots in a service encounter. Venkatesh and Morris (2000) state that the role of an individual's social influence in technology adoption decisions can be complex and dependent on the context. For instance, in mandatory contexts (e.g., employees), society's positive influence on intentions can be attributed to compliance with the organisation's operational policies; however, in the involuntary contexts (e.g., customers), social perceptions may influence consumer's decision towards the new technology (Cham, Cheng, Low, & Cheok, 2020; Cheing et al., 2020; Lim, Ng, Chuah, Cham, & Rozali, 2019; Lu et al., 2019).

Multiple studies showed that social influence in technology acceptance decisions is complex and subject to a wide range of contingent influences. For instance, compliance, internalisation, and identification may affect consumers' perceptions of technology (Venkatesh & Morris, 2000; Venkatesh et al., 2003). Consumers will internalise the subjective culture and belief of their reference group and thus decide accordingly (Jeon et al., 2017). In the current situation, reference groups play a role in decision-making support or rejection of this new technology and may influence consumers' perceptions of service robots. Past studies also discovered that family and friends are one of the most important sources of information in consumer decision-making process (Gursoy et al., 2016). Consumers tend to adopt the culture, values and norms of their preferred groups to make corresponding behavioural decisions (Jeon et al., 2017). Thus, consumers are likely to conform to their group's norms by forming an initial positive attitude toward AI devices. Previous research indicated that SI is critical in shaping individuals' intention to use new technologies (Thompson et al., 1991; Taylor & Todd, 1995). Alaiad et al. (2013) found that SI significantly predicts usage intention of home healthcare robots, while in an educational context, Han & Conti (2020) also support that SI is significant in influencing pre-service teachers' intention to use a telepresence robot. Alaiad et al. (2013) stated that individuals' usage intention is relatively affected by their friends' and peers' opinion among their respective societies. Hence, the following hypothesis is formulated:

**H4:** *There is a significant positive relationship between social influence (SI) and consumers usage intention (CUI).*

**Perceived Enjoyment (PENJ)**

PENJ is defined as "the extent to which the activity of using the particular technology is perceived to be pleasant and enjoyable, apart from any performance consequences that can be expected" (Davis et al., 1992; Venkatesh, 2000). Based on this definition, enjoyment perception is an intrinsic motivation that can lead to emotional arousal (Lee et al., 2005). In addition, Ryan and Deci (2000) also defined enjoyment as a type of intrinsic motivation present when a person does something that is inherently interesting. Numerous researchers proposed the inclusion of intrinsic motivation (i.e., perceived enjoyment) to explain robots' acceptance and usage intention (Lu et al., 2019; van Pinxteren et al., 2019). In line with Arkin et al. (2003) and Bruce et al. (2002), they stated that humans may be motivated by inherent attention and interests during human-robot interactions. Furthermore, Kehr (2004) projected that when there is a correspondence between implicit (unconscious) motivation and explicit (conscious) motivation, intrinsic motivation (i.e., perceived enjoyment) will increase. When a person is intrinsically motivated, he or she will act for the fun or challenge it brings, not because of external products, pressure, or rewards (Santos-Longhurst, 2019). In other words, when people enjoy what they consider important on both levels, they are internally motivated, which makes the process of engaging in this activity less laborious, because there is no voluntary adjustment (i.e., self-regulation, willpower) needed (Kehr et al., 2018).

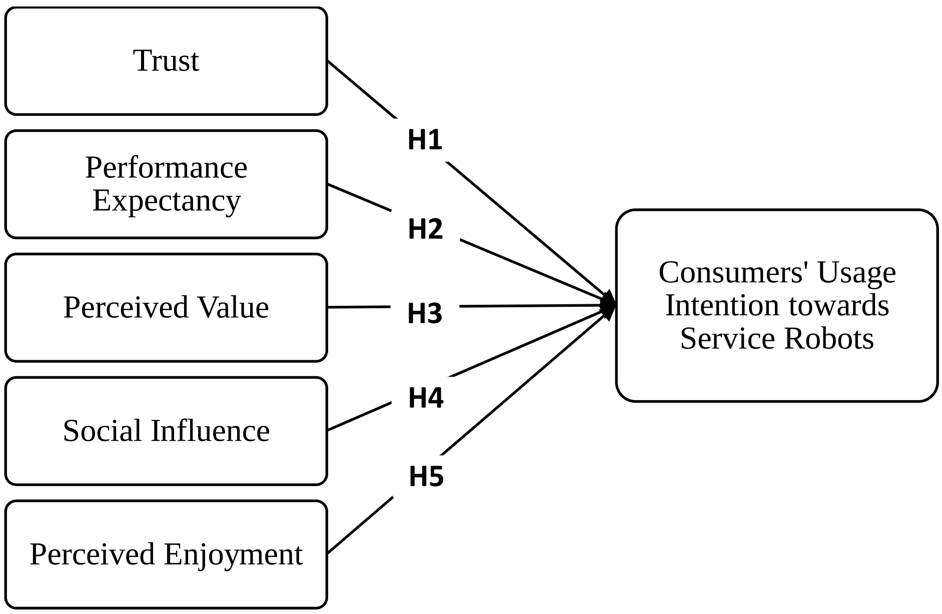
Intrinsic motivation (i.e., perceived enjoyment) is the main driving force for technology use (Venkatesh et al., 2012). PENJ has been widely used by past researchers to predict pleasure received by consumer and employee while interacting with a technological device (i.e., service robots) (Lim, Cheng, Cham, Ng, & Tan, 2019; Lu et al., 2019; van Pinxteren et al., 2019; Turja et al., 2020). Turja et al. (2020), discovered that 0.73 Spearman's correlation at

<0.001 p-values for PENJ, which indicated that PENJ correlated the most with the intention to use care robots among older adults. A study by van Pinxteren et al. (2019) showed positive relationship between PENJ and intention to use ($\beta$= 0.396, p< 0.01; R2= 0.196) in using a humanoid service robot in a service context. Heerink et al. (2010) conducted a regression analysis experiment and found that the more enjoyable a participant is with a socially expressive robot (i.e., iCat), a higher degree a person will intend to use the robot. When service robots act as frontline employees, which oversee delivering human-like interactions, the interactional value will be central to consumers' experience (Lu et al., 2019). Hence, the following hypothesis is proposed:

**H5:** *There is a significant positive relationship between perceived enjoyment (PENJ) and consumers usage intention (CUI).*

The proposed conceptual model is displayed in Figure 1.

**Figure 1:** Proposed Research Model




## RESEARCH METHOD

In this study, a questionnaire-based approach was applied. The unit of analysis was individual consumer aged 17 and above. Due to the nature of the study, the use of self-administered questionnaire was more effective as it allows researchers to collect more responses from consumers. The questionnaire was designed using simple and unbiased wording so that the respondents could understand the questions easily. Question items were adapted from earlier studies with modifications after initial pilot study and pre-test. Items that measured consumers usage intention were adapted from Venkatesh et al. (2003), performance expectancy, perceived enjoyment and social influence from Lu et al. (2019), perceived value from Sweeney and Soutar (2001) and finally trust from van Pinxteren et al. (2019). All the constructs were measured using a 5-point Likert scale of 1- strongly disagree to 5 - strongly agree. The final version of all measurement items is attached in the Appendix.

Convenience sampling method was used to ensure largest possible sample with the least amount of administration and were distributed via online Google form. The final refined questionnaire was distributed to 300 participants and 264 sets were eventually used for the final analysis. The final demographic composition of respondents is as follows: gender (50.4 percent male and 49.6 percent female), age (81 percent in the age group of 17 to 38) and education level (majority 77 percent has bachelor's degree). The proposed conceptual model was then tested using Smart-PLS and SPSS.

## RESULTS

### Measurement Model Assessment

The first step in PLS-SEM is to assess the measurement model. This will ensure the reliability and validity of the model (Benitez et al., 2019). Hair et al. (2017) recommended that the Cronbach's Alpha and Composite Reliability should be ≥ 0.70 to be reliable. The Average Variance Extracted (AVE) tested the convergent validity and the value should be ≥ 0.50. The results showed that Cronbach's alpha ranged from 0.771 to 0.832 while Composite Reliability values extended from 0.844 to 0.879. The AVE values ranged between 0.511 and 0.584. All measurements for the reliability as well as validity of each construct were achieved (Table 1). Next, discriminant validity was tested through Heterotrait-Monotrait Ratio (HTMT) (Dijkstra, 2014). To be significant, the HTMT value should be ≤ 0.90 (Hair et al., 2017). From Table 2, none of the value was higher than 0.90, and thus, confirmed the discriminant validity of the model.

**Table 1.** Cronbach's Alpha, Composite Reliability and AVE of the Measures

| Construct | Cronbach's Alpha | Composite Reliability | Average Variance Extracted (AVE) |
|---|---|---|---|
| Usage Intention | 0.813 | 0.866 | 0.511 |
| Trust | 0.789 | 0.860 | 0.543 |
| Performance Expectancy | 0.771 | 0.844 | 0.512 |
| Perceived Value | 0.808 | 0.877 | 0.564 |
| Social Influence | 0.785 | 0.850 | 0.524 |
| Perceived Enjoyment | 0.822 | 0.869 | 0.574 |

**Table 2.** Discriminant Validity (Heterotrait-Monotrait Ratio (HTMT))

| Construct | T | PE | PV | SI | PENJ |
|---|---|---|---|---|---|
| Trust (T) | | | | | |
| Perf Expect (PE) | 0.425 | | | | |
| Percv Value (PV) | 0.640 | 0.320 | | | |
| Soc Influence (SI) | 0.411 | 0.745 | 0.655 | | |
| Percv Enjoy (PENJ) | 0.248 | 0.321 | 0.256 | 0.380 | |

### Structural Model Assessment

Hair et al. (2019) advised researchers that in the structural model assessment, the first thing to do was to measure its predictive power. This was done through measuring the $R^2$, $Q^2$ and $f^2$ values. $R^2$ value should be at least ≥ 0.25 to be significant (Hair et al., 2017). $Q^2$ value larger than zero was considered meaningful while for $f^2$, the minimum should be ≥ 0.02 to be meaningful. In this research, all the values achieved the required level.

### Hypothesis Testing

Hypothesis testing was conducted to test the relationship among variables which was evaluated by the T Statistics. Bootstrapping was also carried out to test if the constructs fit the data. For bootstrapping, the actual sample size was increased to 5,000 as suggested by Hair et al. (2017). Table 3 showed the results of the structural model. This study was a one-tailed analysis and the minimum T-Statistics required to be significant was ≥ 1.65 (Hair et al., 2012). The result indicated that trust (T-Statistics = 3.800; P = 0.000), perceived value (T-Statistics = 3.465; P = 0.001), social influence (T-Statistics = 3.886; P = 0.000) and perceived enjoyment (T-Statistics = 5.552; P = 0.000) were significant contributors towards usage intention. However, performance expectancy (T-Statistics = 1.550; P = 0.085) was insignificant towards usage intention.

**Table 3:** Total Effects

| | Standard Beta | Standard Error | T Stat | P | Outcome |
|---|---|---|---|---|---|
| T->CUI | 0.197 | 0.050 | 3.800 | 0.000 | Supported |
| PE->CUI | 0.101 | 0.060 | 1.550 | 0.085 | Not Supported |
| PV->CUI | 0.201 | 0.055 | 3.465 | 0.000 | Supported |
| SI->CUI | 0.188 | 0.043 | 3.886 | 0.000 | Supported |
| PENJ->CUI | 0.297 | 0.050 | 5.552 | 0.000 | Supported |

## DISCUSSIONS

Trust has a positive influence on consumers' intention to use service robots; thereby confirming previous literature on UTAUT in the service robot's context (Alaiad & Zhou, 2014; Han & Conti, 2020; Kaushik & Rahman, 2015; Wirtz et al., 2018). The finding is also supported by Everett et al. (2017) and Morgan (2017), that lack of trust is often seen as a major obstacle, which prevent consumers from using service robots. Past researchers also pointed out that reliability, trustworthiness, and effectiveness of robots would help eliminate consumers' doubts about new technologies and encourage usage intention (Alaiad & Zhou, 2014).

PE is not a contributor towards consumers usage intention. This finding seems surprising and inconsistent with several past research that shows PE is significant predictor of the intention to use service robots (Alaiad & Zhou, 2014; Alaiad et al., 2013; Lu et al., 2019). However, there are studies that do not confirm the relationships between PE and CUI in the technology acceptance context (Cheng et al., 2011; Attuquayefio & Addo, 2014; Mensah, 2019). The results could mean that in the context of this study, PE seems not to be an influencing factor for consumers in their usage intention towards service robots. One possible reason may be due to the sample in this study focusing on CUI instead of employees' perspective in which consumers have less consent on the use of a service robot that would enhance their job performance (Venkatesh et al., 2003). Another possible reason may be that there is no favourable environment and fascinating features of service environment for consumers to appreciate (the benefits they will enjoy), or they might be unaware how such technology will improve their performance through service transactions (Mensah, 2019). AI applications are still regarded as emerging technologies in the F&B industry especially in Malaysia. Most of the service robot can only deliver food, and yet consumers must manually remove food from the robot tray which could reduce the perceived usefulness from consumers' perspective. In addition, only a few restaurants have adopted this advanced application in Malaysia.

PV has a significant positive influence towards consumers' usage intention which is in line with prior studies by de Kervenoael et al. (2020). They revealed that PV was the most significant predictor in shaping an individuals' intention to use robots. These findings justify how PV can be used as an effective tool to foster the relationship with service robots in a service environment; thereby making a positive contribution to consumer experience. The researchers also pointed out that, although PV is sometimes taken for granted in today's services, it still deserves attention in conditions in which radical innovations reveal themselves (de Kervenoael et al., 2020). Other researchers also proposed that a rational consumers' intention to use a service is chiefly determined by individuals' evaluation of the associated costs and benefits of existing service offerings (Hartono & Raharjo, 2015; Reid et al., 2014).

SI has a significant positive impact on intention to use. This result is supported by the original construct of UTAUT-1, tested most in the robot framework, and its influence on usage intention has garnered considerable support (Alaiad et al., 2013; Han & Conti, 2020). Recent study by Turja et al. (2020) found that SI has a higher influence on intention to use care robots among healthcare professionals. The relationship between SI and intention to use is also supported in Alaiad & Zhou (2014) research, indicating that SI to be the strongest determinant. They claimed that social media platforms (e.g., forums, online communities, and social networks) may play a major role in contributing to the result, as individuals may make decisions based on the opinions of others. Moreover, when the referent's power status is relevant to the individual; or when the individual has insufficient knowledge or experience with these technology, referents' opinions will become the main factor affecting consumers' usage intention (Lu et al., 2019). This shows that peer opinions are an important factor in encouraging early adopters to use the technology as well as inviting their friends and colleagues to participate.

The result also indicates that there is a significant positive relationship between PENJ and CUI. The finding is consistent with previous studies that indicate positive relationship between PENJ and CUI in the service robot's context (Palau-Saumell et al., 2019; Turja et al., 2020; van Pinxteren et al., 2019). Users will have positive intentions to use service robots if they perceived such applications as entertaining, fun, and enjoyable (Palau-Saumell et al., 2019). One of the possible reasons may due to the enjoyment and delight that these consumers perceived when adopting new technologies (Han & Conti, 2020). Past studies also pointed out that joy and delight (i.e., PENJ) that an individual perceived from a new application will generate greater expectations and induce CUI towards a new technology (Davis et al., 1992). The finding shows that the pleasure and enjoyment of interacting with robotic staff pertain to be a core principle in encouraging CUI in the F&B industry.

This study adopted the theoretical framework of Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT-1 & UTAUT-2). Based on prior conceptual framework, a new integrated framework with the variables of trust, performance expectancy, perceived value, social influence, perceived enjoyment, and consumers' usage intention were adopted. The study aims to examine the factors that influence the CUI towards the application of service robots in the F&B industry. As there are limited prior studies conducted on service robots; this research is expected to ensure a positive dining experience by introducing new variables and related theories, thereby expanding the field of research on service robots and consumer intentions.

The outcome of this study will also provide additional information for researchers who are interested in studying the adoption of these robotics technologies in the future. Theoretically, the research provides a model for explaining the usage intention of service robots, which not only strengthens the theoretical foundation of service robots research but also extends the applications of technology adoption theory to the field of robots' services. This study has identified and empirically verified several new constructs, such as trust and perceived enjoyment, to explain the application of service robots. However, this study also shows that PE has less impact on consumers' intention to use service robots. Thus, future researchers should consider this issue in their future studies. For instance, replacing another related variable that may have a significant impact on consumers' adoption of new technologies. Besides, future researchers should emphasise the study on work-related benefits by applying PE as a variable in their research instead of emphasizing in the context of consumers.

## MANAGERIAL IMPLICATIONS

The insights gained from this study can directly benefit both restaurant practitioners and robot designers. Most importantly, due to the Covid-19 pandemic, contactless services seem to have become the focus of the service industry. Thus, this study allows service marketers to better understand service robots and evaluate factors that consumers are concerned about when adopting this advanced technology. The findings will be important guide in formulating business strategy that benefit marketers and consumers.

Trust has been shown to have a significant positive relationship with CUI. Considering the important role of trust, control ability, and reliability in the adoption of restaurant service robots, this study proposes that robot designers and service providers should develop appropriate mechanisms to enhance these features. Furthermore, results also indicated that perceived value has a significant relationship with CUI towards service robots in the F&B industry. This highlights the importance of human-oriented PV and perfect service value expected by consumers (Čaić et al., 2018). Thus, service practitioners should constantly evaluate their services strategies to meet consumers' expectations and increase users' perceived value through unique dining experiences. As the research results show that consumers with higher PV will tend to use new technologies, practitioners should improve the service environment to provide a satisfactory dining experience at an appropriate service cost, so that consumers feel value for money, and at the same time obtain value through service. For instance, consumer feedback is essential for service practitioners to enhance their business strategies.

Social influence is shown to have a significant relationship with CUI. Based on these findings, robot manufacturers need to identify individuals with strong (formal or informal) personal influence on consumers and motivate them to become advocates for robot adoption. For instance, service practitioners should utilise popular social media platforms, such as Facebook, Instagram, YouTube and TikTok to attract potential consumers and encourage users to interact with each other to establish social connections, thereby increasing consumers' intention to use service robots. Having pleasant and enjoyable service experience will encourage consumers to share voluntarily (e-WOM) strategy) with their peers and so enhance the exposure to the usage of service robots.

Innovative robots design and service strategy coupled with innovative experience in service transactions will increase the level of consumer enjoyment. Robot designers and service practitioners should focus on the design aspects that may enhance perceived enjoyment since entertainment is found to be a construct that significantly influence usage intention in robotic technology. Due to the COVID-19 pandemic, contactless services have become the norm in service transactions. Therefore, service robots may become a competitive advantage for F&B practitioners in the future. However, since the technology is still new to local consumers, robot manufacturers, designers and adopters should continue to study the market's consideration of serving robots to enhance the intention of local consumers to use them.

## FUTURE RESEARCH DIRECTIONS

This study examined restaurant service robots from consumers' perspective. Future researchers could investigate from the perspective of employees and explore their opinions on using robots in a shared working environment. Studies could also include additional constructs such as cultural factors and anthropomorphism, as well as moderating effects of demographic factors as an extension to the current conceptual framework. Moreover, researchers should explore longitudinal studies using different robot designs in different contexts to further investigate users' perceptions of service robots and other psychological factors that may affect consumers' intentions to use such technologies. As the research is based on non-probability sampling methods, the findings cannot be generalized to the general population of the country. It is recommended that scholars use on-site probability sampling methods and perhaps comparative studies between various different countries such as China and the United Kingdom. The research model in the study is based on the Malaysian context. Thus, when the study is extended to other countries or regions, the outcome might be inherently different due to the differences in culture, traditions or even openness of to embrace new technologies. The survey conducted is a cross-sectional study based on consumers' memory experience of dining at a service robot restaurant in the past 6-8 months, and this might not accurately capture consumers experience (i.e., interactive process). Using different data collection strategies such as focus groups discussion or combining both the quantitative as well as the qualitative (personal interview) to solicit richer response might need to be explored in the future.

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## APPENDIX

Measurement Scales

Trust
1. The service robots provided accurate information.
2. I felt I could rely on the service robots to do what was supposed to do.
3. I would trust the service robots if it gave me advice.
4. I would follow the advice the service robots give me.

Performance Expectancy
1. Artificially intelligent devices such as service robots will be more dependable than human beings.
2. Artificially intelligent devices such as service robots will provide more predictable service than human beings.
3. Artificially intelligent devices such as service robots will have reliable systems.
4. Information provided by service robots will be more accurate with fewer human errors.
5. Service robots will be approachable during busy hours or off-business hours.

Perceived Value
1. Compared to a traditional service is provided, the use of robots in a service environment is worthwhile to me.
2. The use of robots in a service environment delivers a satisfactory experience.
3. Compared to the cost of service I need to pay, the use of robots in a service environment offers value for money.

Social Influence
1. People who are important to me would encourage me to utilize service robots during a service transaction.
2. People who influence my behaviour think that I should use the service robots.
3. People who are important to me think that I should use the service robots.
4. Utilizing service robots will be a status symbol in my social networks (e.g., friends, family, and co-workers).
5. I will use service robots during a service transaction if a significant proportion of my friends use it.

Perceived Enjoyment
1. Interacting with artificially intelligent devices such as service robots will be fun.
2. Interacting with artificially intelligent devices such as service robots will be enjoyable.
3. Interacting with artificially intelligent devices such as service robots will be entertaining.
4. Using artificially intelligent devices such as service robots will bring innovative experience in service transactions.

Consumers’ Usage Intention Towards Service Robots
1. Using service robot’s in-service environment is a good idea.
2. Given the opportunity, I will use service robots in a service environment.
3. I am likely to use service robots in a service environment in the future.
4. I intend to use service robots in a service environment more and more in the future.
5. I plan to use the service robots in the future.