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# Customer Intention on Service Robots' Technology in the Hospitality Industry: A Study in Kuala Lumpur

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## ABSTRACT

Though frequently discussed, technology is often misunderstood beyond its basic forms, such as machinery and electronic devices. In the context of rapid advancements in digital tools and frontier technologies like artificial intelligence (AI) and robotics, understanding their impact on various industries is crucial. This study is based on the service robots' influence on customer intentions in Kuala Lumpur, Malaysia. This research used a quantitative approach involving a survey through Google Forms. The survey was also distributed via social media platforms like WhatsApp and Telegram. This study measured customer intention, trust, performance expectancy, and perceived value using a 5-point Likert scale for the survey. Thirty respondents were asked for the pilot study, which helped to ensure clarity and refine the questionnaire. Using SPSS, the reliability test was used as the values of Cronbach's Alpha are between 0.8 and 0.9. The findings show a relationship between trust and perceived value with customer intention, as mentioned in previous studies that said significant roles in technology adoption. Performance expectancy also showed a relationship with customer intention, though to a lesser extent. This suggests that while Kuala Lumpur residents are receptive to service robots in the hospitality sector, the impact of expected performance is somewhat less influential. This study provides insights into the acceptance of service robots in Malaysia's hospitality industry. It underscores the need for further research on the evolving role of technology in enhancing service experiences. The results contribute to understanding technology adoption in emerging markets and offer a basis for future studies on technological advancements in hospitality.

***Keywords:*** *Service Robots, Customer Intention, Trust, Performance Expectancy, Perceived Value*

## 1.0 INTRODUCTION

Technology is a word that's often used but not always well understood. When people think of "technology," they typically picture things like machinery, electrical gadgets, or industrial systems (Agar, 2020). While defining technology can be tricky, most people can distinguish something man-made and something that occurs naturally (Rivers, 2022). However, "technology" can also refer to the practical application of knowledge or methods for getting things done (Işman, 2012). Over the past few decades, technological advancements have surged, bringing digital devices and "frontier technologies" like artificial intelligence (AI), robotics, biotechnology, and nanotechnology. These advancements are driving development across various industries at an unprecedented pace (UNCTAD, 2021), making technology a key player in the global economy (Verma et al., 2021).

In particular, the tourism and hospitality industry has been transformed by technology, becoming one of the fastest-growing economic sectors (Ghildiyal et al., 2022). According to Dalal (2017), the hospitality industry has wide services such as event planning, transportation, accommodation, theme parks, and more. While Kansakar et al., (2019) said that the revenue from the services is a crucial part of the economy, whether it is local or global. Nowadays, digital transformation and smart technology are making hotels and tourism more intelligent and reshaping the hospitality business (Elkhwesky & Elkhwesky, 2023). Fang & Partovi, (2022), said that the transformation is quick and evolving, and the hospitality industry needs to adapt quickly. Customers now depend more on technology and make it an important part of the hospitality experience (Shin et al., 2022). According to Elkhwesky & Elkhwesky, (2023) Shortly, advanced and smart technologies such as artificial intelligence (AI), machine learning, service robots and self-service technologies will have a big impact and transform the hospitality industry.

Service robots have become trending in the food and beverage business and offer autonomous systems to interact with customers (Jembere et al., 2023). The use of robots has many roles, such as checking guests in hotels or airports, greeting customers in restaurants, cooking in the kitchen, and also delivering food or items in the hotel (Said et al., 2024). Other than that, they can handle simple tasks such as security, entertainment, and maintenance (Choi et al., 2023). However, not all see eye to eye on this matter, and said that robots can take away the human touch that is defined as good service (Cabrilo et al., 2024). Intention to use was based on Fishbein, M., & Ajzen, (1975), which is the strength of a person's intention to perform a certain behaviour and supported by Ling et al., (2021). Understanding why customers choose service robots can predict how widely robots are adopted in the industry. Intention is a main factor in behaviour-predicting (Ling et al., 2021). Although there is an increase in service robots, there is little research on customer intentions in Malaysia.

This study aims to fill that gap by exploring how different variables can influence customers' intentions. Although it lacks a thorough rationale for why the rise of service robots is particularly relevant to Malaysia, especially in Kuala Lumpur, the problem statement remains underdeveloped. The study can help in understanding why the local adoption patterns of using such technologies. Other than that, to align the study with Malaysia's current technology a strong justification is required by using the Technology Acceptance Model (TAM) provides a valuable framework for understanding how Malaysian businesses and consumers might adopt service robots (Martin, 2022). The study can explore how service robots' characteristics and their ability to enhance service efficiency can affect their acceptance among both consumers and businesses in Malaysia.

## 2.0 LITERATURE REVIEW

### 2.1 Service Robots in the Hospitality Industry

Service robots are becoming more common in the hospitality industry, but researchers describe them in different ways. Della Corte et al., (2023), talk about social robots, which are partially or fully automated machines that interact with people and add value through these interactions. Subramony et al., (2023) Call them conversational agents, which include robots and voice assistants that can have real conversations with customers. Blut et al., (2021) Describe service robots as autonomous agents, either physical like actual robots or virtual like chatbots. These robots are unique because they connect with customers and offer services in a way that's different from traditional technology (Pitardi et al., 2022).McLeay et al., (2021) Mention that service robots are not the same as any other form of technology because they can provide

interactive services and also can be considered as delivering services agents. Service robots can achieve their abilities by utilising a variety of Artificial intelligence (AI)-powered technologies such as computer vision, language processing, machine learning and smart work routines (Pitardi et al., 2022).

Li et al., (2019) Said that AI is the intelligence of technologies and robots that can scan anything from all of their surroundings and make decisions to solve the problem in business-related problems. AI-powered service robots have become more popular and will soon take the place of human service providers in all forms of services (Pitardi et al., 2022). In the hospitality industry, AI also refers to the use of chatbots that can provide personalised services (Tussyadiah, 2020). According to Somin et al., (2024), service robots uniquely combine technology with service features and the values customers seek. The researcher Zhong et al., (2020) highlights concerns about how guests accept and connect emotionally with service robots. Recently, Malaysia launched the first KEENON robotics showroom in Southeast Asia, introducing the BUTLERBOT W3. This robot is designed to enhance the guest experience in hotels by providing features like autonomous lift use and a focus on contactless delivery (PR Newswire, 2023).

By taking into account both the practical and psychological factors that drive technology adoption, incorporating TAM into the research allows for a more comprehensive understanding of how service robots can be integrated into Malaysia's service sector. Furthermore, the findings of this study could also inform other Southeast Asian nations who were facing similar challenges in adopting automation technologies and broadening the study's relevance and impact.

### 2.2 Types of Service Robots

Service robots are designed to imitate human behaviour, express emotions, and provide services to customers through an internal control system (Seo, 2022). According to Kang et al., (2023), service robots can be classified into three main categories: machine-like, semi-human-like, and human-like robots. Machine-like service robots do not possess human traits and typically include basic features such as articulated hydraulic arms. An example of this type is the robot barista used by "Dal. komm," a coffee chain in Korea, which operates as a dual-arm machine to brew espresso (Hwang et al., 2021).

Semi-human-like service robots resemble a blend of human and robotic characteristics, featuring a human-shaped body paired with a cartoon-style face and metal skin. A notable example is Pepper Parlour, a popular semi-humanoid robot employed at a Japanese luxury café that greets and serves customers at their tables (Chang & Kim, 2022). Human-like service robots come closest to resembling real humans, complete with hair, facial features, limbs, and other human attributes. The Henn-na Hotel, a Japanese hotel chain, uses such robots to facilitate contactless check-in and check-out services and interact multilaterally with guests (Yu, 2022).

In Malaysia, robot servers have become increasingly prevalent in restaurants (Durai, 2022). Among them are BellaBots, charming delivery robots with cat-like faces, produced by Pudu Robotics and managed by Toshiba Tec Malaysia. Customers can place orders through their phones or at self-order kiosks, with the adorable robots serving their delicious meals.

### 2.3 Technology Acceptance Model

Researchers often use the Technology Acceptance Model (TAM) to measure how people accept technology. This model, introduced by Davis (1985), builds on earlier theories about why people adopt new behaviours and focuses on two main factors: perceived usefulness (PU) and perceived ease of use (PEOU). Aslam et al. (2023) Said that TAM forecasts and explains the use of information technologies-based studies Fishbein, M., & Ajzen, (1975), which is the theory of reasoned action (TRA). TAM is used widely to understand whether people accept or reject new technology (Saari et al., 2022). Fernandes & Oliveira (2021) said that the model was modified because it was criticised for simplicity, and TAM2 was created with the addition of subjective norm while TAM3 was added to the idea context dependent proposed as a result. TAM also studied how people adopt technology, and their effectiveness can differ depending on context (Viswanathan & Sreekumar, 2019).

There is much-existing research that focuses on positive responses from customers to service robots (Wang et al., 2023). Other than that, Cabrilo et al. (2024) defined acceptance of robots as the extent to which customers positively evaluate frontline service robots in terms of trustworthiness and usefulness, and later, they established a robot acceptance model (RAM). Zhong et al. (2020) also said that the experimental method should be applied to assess the impact of robot services in hotels on customer buying behaviour.

To summarise, using TAM in this study is appropriate because there were few studies on TAM based on customer acceptance of robots.

### 2.4 Trust

In an earlier study, trust is defined as a customer's trust in the dependability and quality of an organisation's services (Arthur et al., 2024). This study was supported by Lee et al., (2022); in their perspective, trust can be described as an individual's willingness to accept the behaviour of another party, which is given their expectations and the trustee's capacity to control or supervise the other party's specific action. Kraus (2023) states trust has grown by including human interaction with technology. Many factors can influence trust, such as intentions, trust in institutions, perceptions of trustworthiness, and general tendency to trust (Giang-Do & Thu-Hien, 2024). Trust is an essential factor in whether customers are willing to accept technology, and trust is typically a significant component in service and partnership settings, such as connections between buyers and sellers and human-social relationships. (Ling et al., 2021). Genfen et al. said that trust can help explain and predict customers adopting new technologies. Trust can also affect whether people are willing to use robots (Arthanat et al., 2020).

#### *2.4.1 Relationship between Trust and Customer Intention*

Huang (2022) said trust is essential in influencing customers' decisions using tourism services, online platforms, or self-service technologies. There is a strong relationship between trust and customer intention in using and accepting robots (Musa et al., 2024). According to Ou et al. (2024), many technology adoption models also consider trust an essential factor in determining customer intention. The same goes for Arthanat et al. (2020), who also found that trust can influence the intention of customers to use robots. Trust is also crucial when introducing new technology (Park & Stangl, 2020). Zheng et al. (2023) said that trust mediates the relationship between innovation services and customer satisfaction. In their study, trust has a gap between technological advancement and customer willingness to try new services, such as robot-delivered services.

### 2.5 Performance Expectancy

According to Safira & Sari (2024), performance expectancy is the extent to which a person thinks using a particular technology would help users carry out specific tasks. Perceived usefulness, intrinsic motivation, work fit, relative benefit, and outcome expectation are the five fundamental concepts around which performance expectation is built (Ling et al., 2021). Prior research has also shown that performance expectancy is the most effective predictor of IT usage intention (Safira & Sari, 2024). According to Arthanat et al. (2020), when researching healthcare robots, performance expectancy also has a positive effect on the intention to use robots. The researchers concluded that performance expectancy had a crucial role in usage intention since robots can improve overall outcomes by increasing productivity, improving service performance, and performing duties successfully. According to (Ling et al., 2021), strong empirical evidence supports the considerable effect of performance expectancy on usage intention. Hence, this study wants to examine whether there is a relationship between performance expectancy and customer usage intention.

#### *2.5.1 Relationship between Performance Expectancy and Customer Intention*

Performance expectancy is the degree to which an individual believes that the application of a given technology will benefit users in executing certain activities (Safira & Sari, 2024). According to (Molitor & Renkema, 2022), when technology improves daily living, the likelihood of embracing and valuing it rises and technology, in our case, robots, have to make jobs easier, increase convenience, and complement daily activities carried out in groups. Arthanat et al. (2020), who are researching healthcare robots, found that performance expectancy positively affects the intention to use robots. Strong empirical evidence supports the considerable effect of performance expectancy on usage intention (Ling et al., 2021).

### 2.6 Perceived Value

When customers judge the utility of a product or service based on their views of worth, this is referred to as perceived value (Said et al., 2024) (He, 2024). Perceived value is a multidimensional idea encompassing numerous variables (Chuah et al., 2022). One part of perceived value is the value chain, while others include the value of people, entertainment, and other factors. (De Kervenoael et al., 2020). According to He (2024), perceived value is "the consumer's overall assessment of a product's utility based on the perception of what is given and received." Perceived value has been employed in hotel robot research because it shows the

benefits of social robotics in offering more excellent service quality (De Kervenoael et al., 2020). There has been limited study on the link between perceived value and intention to use service robots, the two variables are inferred from research from the closest areas of study. (Ling et al., 2021). According to Ali et al. (2021), intelligent lockers significantly positively affect customers' intentions to use them. Next, based on a study conducted by (De Kervenoael et al., 2020), perceived value has a strong positive impact on the intention to utilise robots, which appears to be the highest impact among the other variables in the study. Therefore, in this study, we want to examine whether there is a relationship between perceived value and customer intention to use service robots.

### *2.6.1 Relationship between Perceived Value and Customer Intention*

Perceived value can be defined as when customers judge the utility of a product or service based on their views of worth (He, 2024). Previous research has shown that perceived value has an impact on user intention (Huang, 2022). There is limited research on the relationship between perceived value and intention to employ service robots. Therefore, the relationship between the two variables is inferred using research from related fields (Ling et al., 2021). Y. Wang et al. (2023) discovered a significant relationship between perceived value and users' intent to participate in a shared ride service, and it can conclude that the users' intention to use technology is influenced by its perceived value. In addition, Ali et al. (2021) conducted a study on intelligent lockers, and they found that smart lockers have a significant positive effect on customers' intentions to use them. For this study, we want to determine whether a relationship exists between perceived value and customer intention to use service robots in Malaysia.

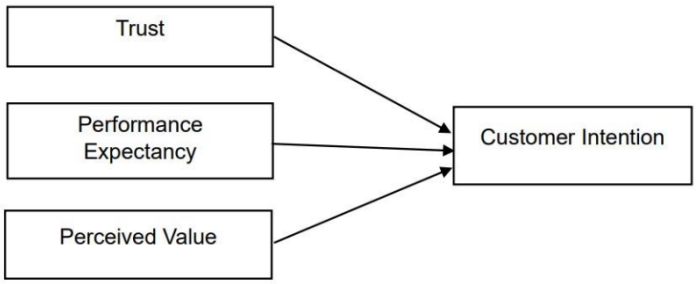


**Figure 1: Theoretical Framework adapted from Ling et al., 2021**

## 3.0 METHODOLOGY

A quantitative research approach was used, and all respondents were given the same survey. Correlations are used to examine the relationships between the independent and dependent variables. The survey was conducted online using Google Forms and distributed through social media platforms like WhatsApp and Telegram. According to Taherdoost (2024), questionnaires are helpful for getting specific answers to specific questions, allowing us to gather quantitative data on the issue at hand. The self-administered nature of the questionnaire helped us obtain more responses. We ensured that the questions were written in clear, unbiased language so that respondents could easily understand them. The survey measured customer intention, performance expectancy, perceived value, and trust with items adapted from Ling et al. (2021). All responses were collected using a 5-point Likert scale.

In this study, the focus is on individuals as the unit of analysis. The respondents were residents of the Kuala Lumpur area, and the aim was to explore their willingness to accept service robots as replacements for human workers in the hospitality industry. The population targeted includes adults living in Kuala Lumpur. According to the Department of Statistics Malaysia (DOSM), the metro area population of Kuala Lumpur in 2020 was approximately 1,982,112, with around 1,231,000 adults aged 20 to 59. Kuala Lumpur was chosen due to its status as the city with the country's highest number of hotel rooms and its ranking as fourth in the number of hotels. Statista reported that Kuala Lumpur had 456 hotels in 2021.

Additionally, Kuala Lumpur has the largest population compared to other cities and is the capital of Malaysia. Recognised by the World Bank as the most developed city in the country, Kuala Lumpur is likely to be a prime location for service robots. This study aims to understand whether residents are open to service robots replacing human workers in the hospitality industry.

A non-probability sampling technique, specifically convenience sampling, was employed for sampling. Since the goal was to measure residents' openness to service robots, anyone living in Kuala Lumpur was eligible to participate in the survey, regardless of their experience with service robots. The Krejcie and Morgan table was used to determine the sample size, indicating that 384 respondents were needed to represent the 1,231,000 adults living in Kuala Lumpur.

A pilot study with 30 respondents was conducted to check if the questions were straightforward and easy to understand. The pilot study was done before collecting data from the total sample of 400 respondents. This step helped in refining the main study. The responses from the 30 participants were analysed using SPSS version 26.0. A reliability test was conducted to check each variable's Cronbach's Alpha value, ensuring the questions were reliable before moving forward with the primary data collection. The Cronbach's Alpha values from the pilot study ranged from 0.8 to 0.9, showing good reliability. No questions were removed, and the only changes made were to reword sentences that could be confusing or have a double meaning. A normality test was done first to check for any outliers in the study. Two outliers were found and removed from the final data.

## 4.0 RESULT AND DISCUSSION

### 4.1 Demographic of Respondents

The demographic profile for this research was examined based on age, gender, residency in Kuala Lumpur, marital status, and employment. Frequency analysis was used to review the data. Table 1 shows that most respondents are between 18 and 25 years old (67.0%), followed by those aged 26 to 35 years (24.5%) and 36 to 45 years (5.2%). The smallest group is those aged 45 and above, with only ten respondents (3.3%). Most respondents are male (53.3%), while females comprise 46.7%. Most are single (76.5%), with the remaining being married (23.5%). In terms of employment, most are employed (47.7%), followed by students (46.4%). The fewest are unemployed (5.9%).

**Table 1: Demographics of Respondents**

| Category | Frequency | Percent (%) |
|---|---|---|
| **Age** | | |
| 18 – 25 years old | 205 | 67.0 |
| 26 – 35 years old | 75 | 24.5 |
| 36 – 45 years old | 16 | 5.2 |
| 45 years old and above | 10 | 3.3 |
| **Gender** | | |
| Male | 163 | 53.3 |
| Female | 143 | 46.7 |
| **Marital Status** | | |
| Single | 234 | 76.5 |
| Married | 72 | 23.5 |
| **Employment** | | |
| Employed | 146 | 47.7 |
| Unemployed | 18 | 5.9 |
| Student | 142 | 46.4 |

### 4.2 Descriptive Analysis

Descriptive analysis was used to examine each item in customer intention, trust, performance expectancy, and perceived value variables. This analysis includes the mean and standard deviation based on a 5-point Likert scale, where one means "strongly disagree," 2 means "disagree," 3 means "neutral," 4 means "agree," and five means "strongly agree." In this study, customer intention is the main focus. Table 4.2 shows that the mean scores range from 3.84 to 4.10. Most respondents agreed with the statements about customer intention, except for item number five, where they were neutral. Detailed results for customer intention are shown in Table 2.

**Table 2: Mean Score for Trust**

| Code | Item | N | Mean | Standard Deviation |
|---|---|---|---|---|
| T1 | The information provided by the service robots will be more accurate | 306 | 4.13 | .832 |
| T2 | I had a belief that I could rely on the service robots to execute their jobs | 306 | 3.90 | .968 |
| T3 | If the service robots gave me advice, I would believe them | 306 | 3.56 | 1.048 |
| T4 | If the service robots gave me advice, I would follow the advice | 306 | 3.51 | .995 |
| **Total Trust** | | | **15.10** | **3.835** |

Table 2 shows that the total mean score for trust is 15.10, with a standard deviation of 3.835. The highest mean score is for T1 (Mean=4.13, SD=0.832), where respondents agreed that the information from service robots is more accurate. The next highest mean score is for T2 (Mean=3.90, SD=0.968), where respondents were neutral about whether they believe they can rely on service robots to do their jobs. The third highest score is for T3 (Mean=3.56, SD=1.048), showing that respondents were also neutral about believing advice from service robots. The lowest mean score is for T4 (Mean=3.51, SD=0.995), where respondents were neutral about following advice given by service robots.

**Table 3: Mean Score for Performance Expectancy**

| Code | Item | N | Mean | Standard Deviation |
|---|---|---|---|---|
| PE1 | The reliability of artificially intelligent machines like service robots will surpass people | 306 | 4.14 | .993 |
| PE2 | Service robots will offer more consistent service than people | 306 | 4.08 | .838 |
| PE3 | Service robots will have a solid system | 306 | 4.09 | .855 |
| PE4 | Service robots will deliver information that is more accurate and has fewer human errors | 306 | 4.21 | .867 |
| PE5 | Service robots will be easier to interact with after hours or during hectic periods | 306 | 4.13 | .859 |
| **Total Performance Expectancy** | | | **20.65** | **4.412** |

Table 3 indicates that the total mean score for performance expectancy is 20.65, with a standard deviation of 4.412. The highest mean score is for PE4 (Mean=4.21, SD=0.867), where respondents believe that service robots will deliver more accurate information with fewer errors. The next highest score is for PE1 (Mean=4.14, SD=0.993), showing that respondents think the reliability of service robots will surpass that of humans. The third highest score is PE5 (Mean=4.13, SD=0.859), with respondents agreeing that service robots will be easier to use during busy times or after hours. The fourth highest score is PE3 (Mean=4.09, SD=0.855), indicating that respondents think service robots will have a robust system. The lowest mean score is for PE2 (Mean=4.08, SD=0.838), where respondents agree that service robots will provide more consistent service than people.

**Table 4: Mean Score for Perceived Value**

| Code | Item | N | Mean | Standard Deviation |
|---|---|---|---|---|
| PV1 | The usage of service robots in a service setting will be beneficial to me compared to a traditional service | 306 | 3.96 | .891 |
| PV2 | Service robots use in a service environment will result in a positive customer experience | 306 | 4.00 | .873 |

| | | | | |
|---|---|---|---|---|
| PV3 | When compared to the cost of the service I must pay, the use of robots in a service context offers superior value for money | 306 | 3.94 | .942 |
| Total Perceived Value | | | **11.90** | **2.706** |

According to Table 4, the mean score for perceived value is 11.90, with a standard deviation of 2.706. The highest mean score is for PV2 (Mean=4.00, SD=0.873), where respondents felt that using service robots leads to a better customer experience. The second highest mean score is for PV1 (Mean=3.96, SD=0.891), indicating that respondents were unsure if service robots are more beneficial than traditional services. The lowest mean score is for PV3 (Mean=3.94, SD=0.942), where respondents were also uncertain if service robots offer better value for money compared to the cost of traditional services.

**Table 5: Mean Score for Customer Intention**

| Code | Item | N | Mean | Standard Deviation |
|---|---|---|---|---|
| CI1 | It is a good idea to use a service robot in a service environment | 306 | 4.10 | .932 |
| CI2 | If given the chance, I want to use service robots in a service environment | 306 | 4.06 | .940 |
| CI3 | In the future, I want to use service robots in a service environment | 306 | 4.10 | .943 |
| CI4 | In the future, I intend to use service robots | 306 | 4.07 | .995 |
| CI5 | In the future, I intend to use service robots in service environments more frequently | 306 | 3.84 | .937 |
| **Total Customer Intention** | | | **20.17** | **4.747** |

According to Table 5, the total mean score for customer intention is 20.17, with a standard deviation of 4.747. The highest mean scores are for CI1 (M=4.10, SD=0.932) and CI3 (M=4.10, SD=0.943). This means respondents think using service robots in a service environment is a good idea and would like to use them in the future. The second highest mean score is for CI4 (M=4.07, SD=0.995), indicating that respondents plan to use service robots in the future. CI2 (M=4.06, SD=0.940) has the third highest mean score, showing that respondents would want to use service robots if given the chance. The lowest mean score is for CI5 (M=3.84, SD=0.937), where respondents are neutral about their intention to use service robots more often in the future.

### 4.3 Relationship between Dependent Variable and Independent Variable

The main objective of this research is to analyse whether there is a relationship between the dependent and independent variables. Pearson correlation analysis is used to test the following hypothesis of this research:

$H_1$: There is a relationship between trust and customer intention.

$H_2$: There is a relationship between performance expectancy and customer intention.

$H_3$: There is a relationship between perceived value and customer intention.

This section answered the first and third research objectives, including the research questions. Table 6 shows the Pearson correlation analysis output to test the hypothesis.

Table 6 shows that the correlations between the variables range from 0.685 to 0.749. All the independent variables—trust, performance expectancy, and perceived value—are connected to the dependent variable, customer intention. Trust (0.716) and perceived value (0.714) have strong correlations with customer intention, while performance expectancy (0.685) has a moderate correlation. The study's results are generally positive, likely because most respondents are between 18 and 25 years old and are more inclined toward technology. This suggests the hypothesis is supported, as all the independent variables are related to the dependent variable.

**Table 6: Pearson Correlation Analysis**

| Variable | Customer Intention | Trust | Performance Expectancy | Perceived Value |
|---|---|---|---|---|
| Customer Intention | 1.000 | .716** | .685** | .714** |
| Trust | .716** | 1.000 | .737** | .749** |
| Performance Expectancy | .685** | .737** | 1.000 | .718** |
| Perceived Value | .714** | .749** | .718** | 1.000 |

*Note: **. Correlation is significant at the 0.01 level (2-tailed); N=306. Correlation: Very high correlation (0.9 to 1); high correlation (0.7 to 0.9); moderate correlation (0.5 to 0.7); low correlation (0.3 to 0.5); very low correlation (0.0 to 0.3)*

## 4.4 DISCUSSION

### 4.1 The Relationship between Trust and Customer Intention

The first objective of this study is to identify the relationship between trust and customer intention that is based on the first hypothesis that "there is a relationship between trust and customer intention". Trust is described as a person's willingness to accept the behaviour of another party (trustor) based on their expectations and the trustee's ability to supervise or regulate the other party's specific activity (Lee et al., 2022). Based on the findings in Chapter 4, a relationship between trust and customer intention has the same result as the previous study by Musa et al. (2024). A survey by Musa et al. (2024) showed strong correlations between trust, and trust was also included as a predictor of robot usage and acceptability. Other than that, Ou et al. (2024) also claimed that trust is a predictor of usage intention in several variations of the technology adoption model. In addition, Arthanat et al. (2020), also discovered that trust influences the usage intention of robots. Trust is a critical antecedent variable when introducing new technology into the hotel service industry (Park & Stangl, 2020).

### 4.2 The Relationship between Performance Expectancy and Customer Intention

To determine the second objective, a second hypothesis was created that there is a relationship between performance expectancy and customer intention. Based on the findings in Chapter 4, the Pearson correlation analysis results show a relationship between performance expectancy and customer intention. Performance expectancy is the degree to which an individual believes that the application of a given technology will benefit users in executing certain activities (Safira & Sari, 2024). Arthanat et al. (2020), a researcher researching healthcare robots, found that performance expectancy positively affects the intention to use robots, which is in line with our findings in Chapter 4. Strong empirical evidence supports the considerable effect of performance expectancy on usage intention (Ling et al., 2021).

### 4.3 The Relationship between Perceived Value and Customer Intention

Lastly, to analyse the third objective in this study, the third hypothesis was formulated, which is that there is a relationship between perceived value and customer intention. Perceived value can be defined as when customers judge the utility of a product or service based on their views of worth (He, 2024). Referring to the findings in Chapter 4, the results show a relationship between perceived value and customer intention. The findings were similar to Y. Wang et al. (2023), who discovered a relationship between perceived value and users' intent to participate in a shared ride service, and it can conclude that the users' intention to use technology is influenced by its perceived value. Previous research has shown that perceived value impacts user intention (Huang, 2022). Ali et al. (2021) conducted a study on intelligent lockers, and they found that the value of smart lockers has a significant positive effect on customers' intentions to use them.

### 4.4 Limitations and Recommendations

One limitation of this study is its focus solely on Kuala Lumpur. Expanding the research to include other regions or a nationwide sample could offer a more comprehensive understanding of how Malaysians perceive service robots. This would provide a broader perspective on the variations in acceptance and adoption across different cultural or socioeconomic backgrounds within Malaysia. Additionally, the limited research on service robots in Malaysia compared to other countries highlights the need to explore local

perspectives, especially as technology evolves rapidly. Understanding how Malaysians respond to new technologies is crucial for the country's readiness to adapt and compete in a globalised world. This study provides initial insights into the factors influencing service robot adoption in Malaysia, laying the groundwork for future research. However, more research is necessary to capture the fast-changing technological landscape and its effects on consumer behaviour. By investigating how service robots are perceived and used in diverse Malaysian contexts, future studies can build on this research to better inform businesses, policymakers, and researchers about the potential for service robots in the country.

## 5.0 CONCLUSION

In summary, service robots are becoming increasingly common, and this study highlights three key factors that significantly influence customers' intention to use them: trust, performance expectancy, and perceived value. Each variable is critical in shaping customers' attitudes toward adopting service robots.

Trust is a central factor because it directly affects how confident customers feel about the reliability and safety of these robots. When customers trust the service robots, they are more likely to rely on them for tasks that traditionally require human involvement. Trust also eases concerns about privacy and data security, which are often associated with automated technologies. Performance expectancy refers to the belief that service robots can effectively assist customers in completing specific tasks. If customers feel that robots can perform their tasks efficiently and accurately, their likelihood of using these robots increases. This expectation ties directly to the perceived efficiency and effectiveness of the service robots in providing value. Perceived value is another significant factor, as it involves comparing the usefulness of service robots to human-provided services. Customers evaluate whether the robots offer better, equal, or lesser value than traditional services. If customers perceive service robots as offering convenience, cost-effectiveness, or superior functionality, their intention to use them grows stronger. The results of this study suggest that all three variables—trust, performance expectancy, and perceived value—are positively related to customers' intention to use service robots. It also indicates that customers already show a degree of trust and willingness to engage with these services. This research provides valuable insights into the factors driving the adoption of service robots, offering a clearer understanding of why customers may choose to use or avoid them, which can help businesses improve robot-based services in the future.

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