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Service robots in full- and limited-service restaurants: Extending technology acceptance model

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ABSTRACT

As the role of service robots has become increasingly important in service encounters, existing literature has widely adopted the technology acceptance model to understand customers' acceptance of robotic services. However, it remains unclear how customers' responses to service robots can vary in different service contexts. This research seeks to address this issue by experimentally examining customer-robot encounters in two different types of service contexts, full and limited services. The results of our multi-group SEM analysis show that customers who perceive having quality interaction with a service robot are more likely to perceive the robot as useful, form positive attitudes toward using the service robot, and experience rapport with the service robot in a full-service context than a limited-service context. Our findings contribute theoretically to the literature on robotic services and the technology acceptance model and provide implications for incorporating service robots into the design of full- and limited-service contexts.

1. Introduction

Over the last several years, artificial intelligence (AI) technologies have changed the nature of service interactions at an accelerated speed (Huang & Rust, 2018; Li et al., 2021). As an important innovation enabled by AI technologies, service robots can be understood as a mechanical device designed to perform physical tasks (Belanche et al., 2020), such as offering autonomous or semi-autonomous services to customers (Haidegger et al., 2013). The advance in AI technologies enables service robots to deliver services with greater productivity, efficacy, and efficiency (Wirtz et al., 2018) as compared to human employees (Calderone, 2019). As a result, an increasing number of firms begin to adopt service robots to perform tasks in different contexts, such as schools, homes, hospitals, and hotels (Bera et al., 2018; Forlizzi & DiSalvo, 2006).

To examine the extent how users would accept robotic technologies, technology acceptance model has been widely used, indicating that people are likely to adopt a technology as they form positive attitudes toward the technology based on the perceptions that the technology is useful and easy to use (Davis et al., 1989; Stock & Merkle, 2017). However, one key issue that has largely been overlooked in the literature on the technology acceptance model is whether customers' adoption of robotic technology can differ depending on service contexts. Specifically, we expect that customers' reactions can vary in full- and limited-restaurant-service contexts because these two types of restaurant services are different by nature and can provide distinct benefits to customers. For example, customers tend to focus more on the quality of interaction with the service provider in a full-service context (Kim & Qu, 2020), whereas limited-service customers are more likely to evaluate a service situation based price-related attributes (Tanford et al., 2012). Our research aims to examine this issue by studying how customers' responses to robotic technology can vary in the contexts of full- and limited-restaurant services. Examining this issue is important because the role of service robots can vary across types of service encounters (Belanche et al., 2020; Huang & Rust, 2021).

In addition, because service encounters usually require interactions between customers and service providers, service robots are often programmed to engage in social interactions, such as using human language, in order to allow humans to use their existing interpersonal skills to interact with robots (Seo et al., 2017). Human-robot interaction can be understood as individuals' perception of engaged relationships and perceived quality of interacting with robots (Bartneck et al., 2020; Patompak et al., 2019). Even though the extant literature (e.g., Lee et al., 2012; Nomura & Kanda, 2014, 2016) have studied the nature of the

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interactions between human and robots, very little attention has been paid to customer-robot interaction quality. In this research, we follow Brady and Cronin (2001) to refer interaction quality to customers' perceptions of the quality of their interactions with service providers and conceptualize customer-robot interaction quality as the perceived level of excellency with respect to the interaction between a service robot and a customer during service delivery (Choi et al., 2019). Because it remains unclear whether the quality of customer-robot interaction can influence customers' responses to service robots and subsequently facilitate the building of customer-robot rapport, especially in the restaurant setting, our study also seeks to add a fresh perspective to the existing literature by investigating the antecedent role of customer-robot interaction quality in affecting the relationships proposed in the technology acceptance model and the positive outcome of customer-robot rapport. It is important to consider these factors because they are key to building relationships with customers, which suggest the possibility that customers' willingness to build relationships with a service robot can be another key aspect of customer technology acceptance to consider.

Through the current research, we seek to provide meaningful contributions. First, we broaden the technology acceptance model by identifying user-technology interaction quality as an antecedent that affects the usefulness and ease of use perceptions. Second, we extend the service robot literature by demonstrating how the effects of customers' cognitive evaluations of a service robot on customers' intention to use the robot can vary depending on the nature of restaurant service contexts (i.e., full vs. limited services). Third, we contribute to the literature that examines the human-robot rapport by showing how interaction quality can increase the rapport through the customers' positive perceptions and attitudes towards robotic services. Finally, our research findings offer implications for service practitioners to encourage positive customer responses to robotic services, as well as providing tailored robotic service environments in response to different service settings.

2. Literature review

2.1. The role of robots in service encounters

Technologies have changed how service providers interact with customers, and service robots play a critical role in this fast transition, resulting in an emerging reality of incorporating robots into the service delivery process. Service robots refer to "system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers" (Wirtz et al., 2018, p. 909). The revolution of AI has enabled service robots to offer services with greater productivity, efficacy, and efficiency (Wirtz et al., 2018). In turn, robotic assistants have been adopted in a variety of service fields, such as hotel services (Palvia & Vemuri, 2016), retail services (Grewal et al., 2018), and airport services (Frick, 2015).

Companies can benefit from adopting robotic services because service robots are capable of executing many tasks currently performed by human employees in a more efficient and effective manner, given that the robots can work 24-7 and have not only stronger physical abilities but also faster computing power (Huang & Rust, 2018). With these characteristics, service robots are able to increase a company's productivity, operate automatic processes, and perform dangerous tasks (Calderone, 2019). In response to robotic services, customers can perceive the quality of robotic services to be similar to that of human services (Choi et al., 2019) and be willing to use robotic services (Ivanov & Webster, 2018). In fact, customers have been found to develop positive attitudes towards different types of robots, such as domestic service robots (Brengman et al., 2021), health care robotic assistants (Broadbent et al., 2010), robotic restaurant servers (Hwang et al., 2020), and hotel service robots (Fuentes-Moraleda et al., 2020).

Existing literature has examined factors that can influence customers' responses toward service robots. One critical stream of research examines the role of functions performed by service robots in driving customers' usage of robotic services, such as communication skills (Saunderson & Nejat., 2019), systems' programming level (Pineda et al., 2015), and task performance (Park et al., 2010). With respect to tasks performed by robots, people tend to view that proper jobs for service robots are information provision, housekeeping activities, and processing bookings, payments, and documents (Ivanov & Webster, 2018). Although service robots can perform various tasks (Dautenhahn et al., 2005) and play different roles in different service contexts (Belanche et al., 2020; Huang & Rust, 2021), how customers' reactions to service robots can vary in different service encounters remain a key question that has received little attention. Limited research (e.g., Huang & Kao, 2021; Longoni & Cian, 2022) that attempts to examine the role of frontline agents enabled by AI technology in different contexts has primarily focused on the utilitarian and hedonic nature of service encounters. We further inform this literature by considering the contexts of full and limited services, one of the most frequently used categorizations of services, based on the guideline of North American Industry Classification System (NAICS, 2017).

2.2. Full-vs. limited-service encounters

Full services refer to offering a full range of services to please customers (NuWire, 2012). Based on NAICS Code 722511, a full-service restaurant suggests that customers order and are served while seated, and pay after eating, yet the restaurant also provides alcoholic beverages, carryout services or live nontheatrical entertainment. On the other hand, limited services can be understood as offering basic utilities without further services. For example, a restaurant offering limited services will likely require customers to engage in self-service when it comes to placing an order and making a payment (Parsa et al., 2020).

Customers can react differently to full and limited services and, because of the differences in expectations, full and limited services are associated with distinct satisfiers and dissatisfiers (Kim, Kim, & Heo, 2016) as well as different behavioral intentions. For example, customers were found to have a stronger intention to revisit a full-service restaurant as compared to a limited-service restaurant (Marinkovic et al., 2014) because additional opportunities to interact with frontline agents can lead customers to view a full-service provider more positively (Andaleeb & Conway, 2006). In the context of robotic services, Lin et al. (2020) demonstrated that customers' positive emotions toward robotic services play a key role in affecting their evaluations of the services and the influence varies depending on whether service contexts are full or limited by nature. However, it remains unclear how the impact of customers' cognitions of service robots on their acceptance of the robots can vary depending on the nature of service contexts. In our study, we seek to extend this literature by proposing a research framework that further studies how full-vs. limited-service contexts can affect the extent to which customers' cognitions (i.e., perceived usefulness and perceived ease of use of a service robot) influence their intention to use the robots based on the technology acceptance model (Davis et al., 1992).

2.3. Technology acceptance model

Davis et al. (1992) introduced the technology acceptance model to help understand how individuals use and accept a specific technology. The model argues that an individual's attitudes and intentions toward trying to learn to use new technology are determined by his/her considerations of the perceived related advantages of the technology. Because the nature of the model is to examine people's psychological mechanisms to new technologies, it has been widely adopted to study human-robot interaction, especially in restaurant/hotel settings (Abou-Shouk et al., 2021; Omar Parvez et al., 2022). According to this theory, the most critical determinant of an individual's behavioral intention is his/her attitude toward a technology, which is a function of perceived usefulness and ease of use of the technology toward the behavior (Davis, 1989; Bagozzi et al., 1992).

According to this model, a key antecedent of individuals' attitudes toward adopting technology is their perceived usefulness of the technology, which refers to a person's evaluation of using a particular system that would enhance his or her outcome of the experience (Davis et al., 1992). People tend to hold a positive attitude toward adopting a technology when they believe it is useful. On the other hand, when they consider that the technology provides only limited advantages, they will likely form negative attitudes toward the technology.

Another important antecedent is perceived ease of use, which is defined as users' perceptions of the level of complexity associated with using a specific technology (Lund, 2001). In other words, perceived ease of use is determined by an individual's beliefs on how easy and straightforward they can learn to use the subject (Davis et al., 1992). People tend to show a positive attitude toward the adoption of technology when they feel they can learn how to use it quickly and easily. When the opposite is true, people are more likely to view the technology adoption negatively.

Drawing on the technology acceptance model (Davis et al., 1992)), we propose that customers' perceived usefulness and ease of use toward service robotics are key to determining their attitude toward interacting with the service robotic assistant and therefore to influence their adoption intention. Based on recent hospitality literature that applies the technology acceptance model to study robotic services, we define perceived usefulness as an individuals' evaluation of the related usefulness of the service robotic assistant, and perceived ease of use as an individual's consideration to the degree of complexity of using the service robot (Abou-Shouk et al., 2021; Hwang et al., 2020; Omar Parvez et al., 2022; Sun et al., 2020).Our research expands upon the literature in two ways. First, it studies the technology acceptance model in different service contexts. Second, we contribute to this body of literature by further suggesting the need to take interaction quality and rapport with the service robotic assistant into consideration.

3. Theoretical framework and hypothesis development

3.1. The antecedent effect of interaction quality

It is important to understand the interpersonal interactions between frontline employees and customers in service encounters as these employees' actions play a key role in satisfying a customer's consumption needs (Ghlichlee & Bayat, 2020; Jung et al., 2021; Xiong et al., 2021). Interaction quality refers to customers' perceptions of the degree of excellence in how service is delivered from the service encounter during the time of interacting (Brady & Cronin, 2001; Joon Choi & Sik Kim, 2013; Lemke et al., 2010). From the service perspective, a two-way interpersonal interaction between a customer and interactive service provider, interactive service procedure, and interactive service device, can be conceptualized as an action of perceiving interaction quality (Brady & Cronin, 2001; Lehtinen & Lehtinen, 1991). In this research, we focus on the interaction quality between customers and service robots, frontline service agents enabled by AI technologies, and define interaction quality as a customer's perceived quality of their interaction with a service provider (i.e., a service robot in this research) (Brady & Cronin, 2001), which can be understood as the perceived excellency of the interaction between a customer and a service robot during the service delivery period.

Because the technology acceptance model suggests that a well functioning external variable can generate direct effects on users' perceived usefulness and ease of use of a technology (Davis & Venkatesh, 1996), interactional quality can be viewed as such an external variable to influence customers' perceptions of robotic technology. In this context, perceived usefulness refers to a person's evaluations of using a particular technology that would enhance his or her outcome of the experience (Davis et al., 1992) whereas perceived ease of use is defined as users' assessment of the complexity level associated with using a specific technology (Lund, 2001). Since humans can learn to appreciate a robotic assistant through experiences interacting with it (Qiu et al., 2019), we expect interaction quality to positively influence customers' perceived usefulness and ease of use with respect to a service robot. This argument is based on the stimulus–organism–response paradigm (Mehrabian & Russell, 1974), which suggests that stimuli in an environment (e.g., service environment) can affect the internal states of an organism (e.g., a customer) and drive the organism's responses to the environment. Because interaction quality can serve as a situation whereby a service provider creates physical, virtual, or mental engagement with customers (Grönroos & Voima, 2012), interaction quality can be viewed as cues in a service environment that trigger customers' evaluations of a service robot (i.e., perceived usefulness and ease of use). Our argument is also consistent with the existing literature studying the interaction between humans and robots, which suggests that after interacting with a robot, individuals are more likely to view the robot positively (Stafford et al., 2013). Thus, we propose:

Hypothesis 1 (H1a). Customers' perceived interaction quality with a service robot exerts a positive effect on their perceived usefulness of the service robot.

Hypothesis 2 (H2a). Customers' perceived interaction quality with a service robot exerts a positive effect on perceived ease of use toward the service robot.

In addition, we expect the positive influence of interaction quality on the usefulness and ease of use perceptions to vary depending on the types of services provided (i.e., full vs. limited services). Previous literature has suggested that customers' responses to a service provider can vary depending on the nature of the services, such as strong and positive customer attitudes and intentions found in the context of full-service restaurants (Marinkovic et al., 2014; Jani & Han, 2011). Full-service customers tend to place a greater emphasis on the enjoyment of interactions with service providers (Kim & Qu, 2020; Wang & Lang, 2019). On the other hand, as limited-service customers tend to be more price sensitive and rely more on price when evaluation a service situation, they are less likely to rely on non-price related attributes (e.g., the quality of service interaction) when evaluating a service situation (Tanford et al., 2012). Based on the above rationale, we expect that the impact of interaction quality on customers' evaluations of a service robot will be stronger in a full-service context than in a limited-service context. Thus, the hypotheses are proposed as follows:

Hypothesis 1 (H1b). The positive effect of customers' perceived interaction quality with a service robot on their perceived usefulness of the service robot is stronger in a full-service context than in a limited-service context.

Hypothesis 2 (H2b). : The positive effect of customers' perceived interaction quality with a service robot exerts on their perceived ease of use toward the service robot is stronger in a full-service context than in a limited-service context.

3.2. Customer perceptions and attitudes

According to the technology acceptance model (Davis et a., 1992), individuals' attitudes toward a technology is a function of perceived usefulness and ease of use of the technology (Bagozzi et al., 1992; Davis et al., 1989). People tend to hold positive attitudes toward adopting a technology when they believe it is useful and when they believe they can easily and quickly learn how to use the technology. Specifically, in the hospitality and restaurant setting, customers' perceived usefulness and ease of use toward service robots have been shown to positively influence their attitudes toward the robots (Fuentes-Moraleda et al., 2020; Parvez et al., 2022). In line with this logic, we expect that customers' perceptions of a service robot's usefulness and ease of use will exert positive effects on their attitudes toward using a service robot. Therefore, we propose:

Hypothesis 3 (H3a). Customers' perceived usefulness of a service robot exerts a positive impact on their attitudes toward the service robot.

Hypothesis 4 (H4a):. Customers' perceived ease of use of a service robot exerts a positive impact on their attitudes toward the service robot.

We also expect these relationships will vary based on the types of service context involved (i.e., full vs. limited services). Tanford et al. (2012) have found that limited-service customers view price as the key determinant of purchase decisions whereas full-service customers consider utility to be the most important factor when it comes to making purchase decisions. This is because limited-service customers are usually driven by value consideration in the form of pricing whereas full-service customers tend to value non-price related attributes (Tanford et al., 2012), such as the usefulness of service technologies. In line with this logic, we contend that customers' usefulness perceptions are even more likely to generate positive attitudes towards a service robot in a full-service context as opposed to a limited-service context. Thus, we hypothesize:

Hypothesis 3 (H3b). The positive effect of customers' perceived usefulness of a service robot on their attitudes toward the service robot is stronger in a full-service context than a limited-service context.

While full-service customers can enjoy services provided by frontline agents (Kim & Qu, 2020; Wang & Lang, 2019), limited-service customers are often expected to serve themselves. When engaging in self-services, such as using self-service technology, customers tend to place greater weight on the convenience aspect of service Park, Letho, & Lehto, 2021; Xu, Jeong, & Baiomy, 2021), such as the ease of use. Therefore, we argue that customers' perceived ease of use exerts a greater effect to their attitudes towards a service robot in a limited-service context as opposed to a full-service context:

Hypothesis 4 (H4b). The positive effect of customers' perceived ease of use of a service robot on their attitudes toward the service robot is stronger in a limited-service context than in a full-service context.

3.3. The outcome of adoption

As a model commonly used to understand how individuals accept a specific technology, technology acceptance model (Davis et a., 1992) argues that an individual's intentions toward using a new technology are determined by his/her attitudes derived from the considerations of the benefits associated with the technology. Since attitudes represent a critical determinant of users' technology adoption intention (Bagozzi et al., 1992; Davis et al., 1989), we expect that customers' positive attitudes toward using a service robot will increase their intention to interact with the service robot. In addition, the influence of positive attitudes on adoption intention is proposed to be stronger in a full-service situation because the positive attitudes are derived from values that are not price-related (i.e., usefulness and ease of use), given that limited-service customers tend to be driven by price-related attributes while full-service customers are more likely to value attributes that are not priced related (Tanford et al., 2012). Therefore, we hypothesize:

Hypothesis 5 (H5a). Customers' attitudes toward the service robot exerts a positive impact on their intention to adopt robotic services.

Hypothesis 5 (H5b). The positive effect of customers' attitudes toward a service robot on their intention to adopt robotic services is stronger in a full-service context than a limited-service context.

3.4. The outcome of customer-robot rapport

As a concept which indicates the relationship between customer and employee Hwang & Lee (2019), rapport has been identified as an important factor that influences customer's positive responses toward service providers (Chang et al., 2020; Kim, Ok, & Gwinner, 2010). It is critical to examine the role of rapport in a service encounter as it often increases customers' organization loyalty, positive attitudes toward and emotional attachment to a service provider, and intention to revisit (Choi & Jo, 2021; Hyun & Kim, 2012). Given the importance of rapport and rapid growth in the adoption of service robots, an increasing number of scholars begin to investigate the nature of human-robot interaction (; Lee et al., 2012;Kim, Kim, & Lyons, 2020; Nomura & Kanda, 2014, 2016; Qiu et al., 2019). Building on Gremler and Gwinner's (2000) work, we define customer-robot rapport as the degree to which a customer perceives he/she has an enjoyable interaction experience with a service robot that is characterized by the two interactants' personal connection.

Extant literature has examined factors that improve the rapport between humans and robots. For example, users were found to perceive rapport with a robot when the robot is capable of displaying deictic gestures (Huang & Mutlu, 2013) and providing personalized services (Lee et al., 2012). Because the gestures can serve as a communication mechanism to help users better comprehend the information communicated by a robot (Huang & Mutlu, 2013), it can arguably help improve the ease of use of a robot. On the other hand, as adding personalized services can highlight the additional benefits that a robot can provide, the additional services can arguably help improve the usefulness of a robot. Building on the past work suggesting that attitudes toward robotic services plays a key role in affecting customer-robot rapport (Deborah et al., 2020; Qiu et al., 2019; Nomura, 2014), we extend this literature by contend that the positive attitudes derived by the usefulness and ease of use perceptions are key to driving the rapport building between customers and service robots.

Furthermore, existing literature has also examined rapport building in different service contexts. For instance, in the full-service restaurant setting, rapport has been associated with the factors of customer satisfaction, affective commitment, and server–patron mutual disclosure (Ali et al., 2021; Hwang et al., 2013; Kim & Ok, 2010). On the other hand, in the limited-service context setting, rapport has been shown to relate to a different set of factors, such as service quality (Mathe et al., 2014), perceived external prestige (Mathe & Scott-Halsell, 2012), and age of the employee (Rocco & Thijssen, 2006). Because rapport building can vary in full and limited services, we expect that customers' response to perceived rapport can be different in these service contexts. As compared to limited-service restaurants, full-service restaurants involve offering a wider range of services (Parsa et al., 2020) and, thereby, involve more interactions during the service encounters (Liang & Zhang, 2011), which is a key element to facilitate rapport building. Based on this rationale, we expect that the relationship between customers' positive attitudes towards a service robot and their perceived customer-robot rapport will be stronger in the full-service situation as compared to the limited-service situation. Thus, we propose:

Hypothesis 6 (H6a). Customers' attitudes toward robotic services generate higher levels of perceived customer-robot rapport.

Hypothesis 6 (H6b). The positive effect of customers' attitudes toward robotic services on customer-robot rapport is stronger in a full-service context than in a limited-service context.

All the hypotheses proposed in our theoretical model are visually presented in Fig. 1.

4. Methodology

4.1. Sample

To examine our hypothesized relationships, participants were recruited in exchange for the compensation of $1 USD using an online

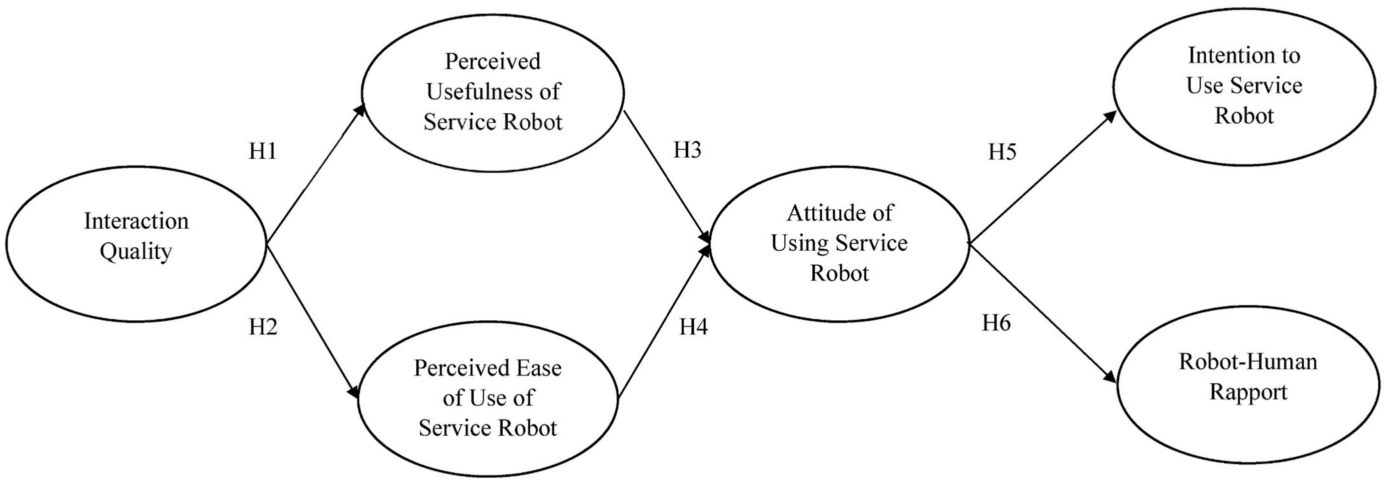

Fig. 1. Proposed model: Full-vs. limited-service contexts.

research panel (M-Turk) in the United States. Based on the recommended ratio of observations to estimated parameters (*N*:q), we recruited 507 subjects in our study (Kline, 2015). We deployed a between-subjects experimental design to manipulate full and limited-service contexts using a scenario-based approach, a widely adopted approach to better control for treatment effects (e.g., Bendapudi & Leone, 2003).

We randomly assigned participants to one of the two manipulated scenarios: full-service scenario (n = 252) and limited-service scenario (n = 257). In the full-service group, participants were 65.1% male and their ages ranged from 20 to 66 years old with 37 years old as the average age. In the limited-service group, participants were 60.7% male. The average age was 36.3 years old, ranging from 21 to 63 years old.

4.2. Procedure

Participants were first asked to answer questions regarding their demographic information, such as age, gender, and their previous experience of using service robots. Next, they were randomly assigned to read either a full or a limited-service scenario with a picture of the service robot. We adopted "Nao" as the service robot (Appendix 2) in our scenario because it has been used in many different service industries and research, such as hotel services (IBM, 2018) and human-robot interaction studies (Filippini et al., 2021). After reading the scenario, they were instructed to respond to the measures of interaction quality, perceived usefulness, perceived ease of use, attitude toward using service robots, intention to use service robots and rapport with the service robot described in the scenario.

4.3. Manipulation of the service situations

We manipulated full- and limited-service situations in a restaurant setting, a context by which service providers commonly offer these two distinct types of services (Omland, 2020)that can also be provided by robots (Hwang et al., 2022). In the limited-service scenario, participants walked into the restaurant, approached the encounter to review the menu, and then interacted with the service robot "Nao" to place an order. In the full-service scenario, the service robot "Nao" seated the participants, provided a menu for participants to look over, and assisted them in placing orders. We presented the detailed scenarios in Appendix 1.

4.4. Measures

Unless otherwise indicated, all measurement items were assessed using a 7-point Likert scale (1 = strongly disagree; 7 = strongly agree). To measure interaction quality, we adapted the 2-item scale from Brady and Cronin (2001). Next, we assessed participants' perceived usefulness and ease of use of the service robot "Nao" using Lund's (2001) scale. Also, we assessed attitude toward using a service robot using Bagozzi et al.'s (1992) 4-item measure on a 7-point semantic differential scale. In addition, we measured intention to use service robots using MacKenzie, Lutz, and Belch's (1986) 3-item scale on a 7-point semantic differential scale. Lastly, we adapted Brady and Cronin's (2001) 4-item scale to assess customer rapport. Detailed measurement items are reported in Table 1.

5. Result

5.1. Measurement quality assessment

A confirmatory factor analysis was performed using maximum likelihood estimation in R version 3.6.1 to examine the expected factor structure. The measurement model suggested a good fit ($X2 = 770.32$ $df = 207$, $p < 0.01$; root mean square error of approximation (RMSEA) = 0.07; comparative fit index (CFI) = 0.93; standardized root mean residual (SRMR) = 0.04; Bollen & Long, 1993). Factor loadings for all items were statistically significant ($0.66 \leq \lambda s \leq 0.82$, $p < 0.01$). The values of composite reliability and average variance extracted suggested adequate internal consistency and convergent validity of the measurement scales (Fornell & Larcker, 1981; Lam, 2012). Similarly, Cronbach's coefficient alphas provided support for the good internal reliabilities of the scales (Nunnally & Bernstein, 1994). In addition, discriminant validity was found to be accepted at both the construct level and the item level across all constructs. The details are reported in Table 1.

5.2. Manipulation check

We checked manipulation conditions by requesting participants to identify the type of restaurant that they were in based on the scenario (0 = a fast-food restaurant; 1 = a full-service restaurant). The results of our cross-tabulation analysis (Kendall's rank correlation tau = 0.35, $p < 0.001$) suggest that most participants in the full-service-restaurant condition (64%) indicated they were in a full-service restaurant and that the majority of participants in the fast-food-restaurant condition (71%) indicated they were in a fast-food restaurant. These findings suggest that the restaurant type manipulation was successful.

5.3. Hypotheses testing

The approach of structural equation modeling (SEM) was adapted to examine the proposed hypotheses. The SEM model showed an adequate

Table 1
Full measurement model.

Construct	Cronbach's alphas	Composite Reliability	Average Variance Extract	Standardized Loading
Adjusted Interaction Quality Scale	0.70	0.71	0.53	
Overall, I'd say the quality of my interaction with this firm's robotic assistant is excellent.				0.72*
I would say that the quality of my interaction with this firm's robotic assistant is high.				0.74*
Perceived usefulness	0.88	0.77	0.58	
The robotic assistant helped me be more effective.				0.76*
The robotic assistant helped me be more productive.				0.78*
The robotic assistant saved me time to use it.				0.73*
The robotic assistant required the fewest steps to accomplish what I wanted to do with it.				0.79*
The robotic assistant made the task I wanted to accomplish easier to get done.				0.76*
Perceived ease of use	0.85	0.72	0.54	
The robotic assistant was easy to use.				0.67*
I learned to use the robotic assistant quickly.				0.78*
The robotic assistant was simple to use.				0.74*
I easily remember how to use the robotic assistant.				0.74*
The robotic assistant was easy to learn to use it.				0.73*
Attitude toward using service robot	0.86	0.80	0.61	
Overall, how would you describe your experience? For me, using the robotic assistant to take order is: bad/good				0.75*
Overall, how would you describe your experience? For me, using the robotic assistant to take order is: negative/positive				0.76*
Overall, how would you describe your experience? For me, using the robotic assistant to take order is: unfavorable/favorable				0.80*
Overall, how would you describe your experience? For me, using the robotic assistant to take order is: unpleasant/pleasant				0.81*
Intention to use service robot	0.86	0.82	0.62	
Assuming you have access to the robotic assistant in the future, what is the probability that you would use it? -unlikely/likely				0.81*
Assuming you have access to the robotic assistant in the future, what is the probability that you would use it? -improbable/probable				0.81*
Assuming you have access to the robotic assistant in the future, what is the probability that you would use it? -impossible/possible				0.82*
Customer employee rapport	0.81	0.70	0.53	
In thinking about my relationship with this firm's robotic assistant, I enjoyed interacting with these assistants.				0.73*
This firm's robotic assistant created a feeling of "warmth" in our relationship.				0.77*
This firm's robotic assistant related well to me.				0.71*
I was comfortable interacting with this firm's robotic assistant.				0.69*

**All values significant at 0.01 level.
Model Fit: $X^2 = 770.32$, $df = 207$, $p < 0.01$; CFI = 0.93; RMSEA = 0.07; SRMR = 0.04.

fit ($\chi 2$ (214) = 795.02, $p < 0.01$, CFI = 0.91, RMSEA = 0.07, SRMR = 0.04) and thus indicated empirical support of our hypothetical model. Consistent with our theoretical predictions, the results suggested that customers' perceived interaction quality with the service robot positively influenced their positive perceived usefulness of the service robot ($\beta = 1.08$, $SE = 0.07$, $p < 0.01$) and their perceived ease of use toward the service robot ($\beta = 0.77$, $SE = 0.05$, $p < 0.01$), which supported H1a and H2a. Second, we found that customers' perceived usefulness ($\beta = 0.67$, $SE = 0.07$, $p < 0.01$) and ease of use toward the service robot ($\beta = 0.19$, $SE = 0.09$, $p < 0.01$) showed significant influence on their attitude of using robotic services. Therefore, H3a and H4a were confirmed. The model also indicated that customers' attitudes toward robotic services exerted a positive impact on both their intention to use service robots ($\beta = 1.13$, $SE = 0.06$, $p < 0.01$) and perceived human-robot rapport ($\beta = 1.11$, $SE = 0.08$, $p < 0.01$), which provided evidence to support H5a and H6a. We presented the model results in Fig. 2.

Next, to examine how the causation relationships vary depending on the manipulated conditions (full- and limited-service contexts), a multi-group structural equation modeling analysis was performed (Bollen, 1989). Multi-group SEM is one of the better approaches in studying measurement invariance in group comparison (Yuan & Chan, 2016). The process of multi-group modeling testing began with the estimation of two models: The first model allowed target paths to differ between groups while the others were constrained; The second model served as the baseline control model that fixed all regression paths. If the two model showed no significant difference, it suggested that there is no variation in the path coefficient across groups. On the other hand, if the significance is found, the difference of regression path between groups can then be confirmed (Schermelleh-Engel et al., 2003). The overall model was first established by studying the regression coefficients in two service conditions. The fit of this configural model appeared to adequate, suggesting that the factor structure was well represented as a six-factor model in both groups ($\chi 2$ (428) = 527.40 and 656.17, $p < 0.01$, CFI = 0.91, RMSEA = 0.08 SRMR = 0.05). The result details were presented in Fig. 3. The model suggested that in between the two conditions, some factors provided stronger impacts to their corresponding outcome factors, while others were not.

After comparing the two SEM models, the Chi-Squared difference test suggested that there was a significant difference ($p < 0.01$) with respect to regression coefficients in two conditions. The result indicated that the impact from customers' perceived interaction quality with the service robot to their perceived usefulness of the service robot was significantly stronger in the full-service group ($\beta = 1.21$, $SE = 0.09$, $p < 0.01$) than in the limited-service group ($\beta = 0.91$, $SE = 0.08$, $p < 0.01$). Therefore, H1b was supported.

With respect to H2b, no support was found because the Chi-Squared difference test suggested there was no significant difference ($p = 0.71$) between full ($\beta = 0.76$, $SE = 0.06$, $p < 0.01$) and limited-service ($\beta = 0.79$, $SE = 0.08$, $p < 0.01$) conditions regarding the path from customers' perceived interaction quality with the service robot to their perceived ease of use toward the service robot.

We made another model comparison to examine the effect of customers' perceived usefulness of the service robot on their attitude toward adopting robotic services in the two conditions. The result indicated that this effect was significantly higher ($p < 0.01$) in the full-service group ($\beta = 0.75$, $SE = 0.07$, $p < 0.01$) than the limited group ($\beta = 0.58$, $SE = 0.07$, $p < 0.01$). Thus, H3b was supported accordingly.

In terms of H4b, we found that the effect of customers' perceived ease of use on their attitude toward adopting robotic services did not show a significant difference ($p = 0.10$) between full ($\beta = 0.23$, $SE = 0.10$, $p < 0.01$) and limited ($\beta = 0.14$, $SE = 0.08$, $p < 0.01$) groups.

In addition, the results revealed that customers' attitude toward using the service robot did not exert a significantly higher impact on intention to use ($p = 0.52$) in the full-service group ($\beta = 1.15$, $SE = 0.07$, $p < 0.01$) than in the limited-service condition ($\beta = 1.09$, $SE = 0.08$, $p < 0.01$). Thus, H5b was not supported.

Lastly, customers' attitudes toward interacting with the service robot generated a significantly higher level of human-robot rapport ($p < 0.01$) in the full-service condition ($\beta = 1.21$, $SE = 0.09$, $p < 0.01$) than in the limited-service group ($\beta = 0.96$, $SE = 0.09$, $p < 0.01$). The results provided support for H6b.

6. General discussion

In the past decade, AI technologies have revolutionized service encounters by enabling robotic assistants to deliver services (Wirtz et al., 2018). In response to the increasing usage of service robots across different service industries, many researchers (Go et al., 2020; Park & del Pobil, 2013) draw on the technology acceptance model to study service robot adoption among customers. Yet, it remains unclear how customers' intention of using robotic services can vary across different contexts. In the current research, we aim to provide additional insights into this issue by considering the boundary condition of full- and limited-service contexts.

Our results reveal that as customers perceive a higher level of interaction quality with a service robot, they perceive the robotic to be easy to use and useful, resulting in an increase in their attitudes toward the robot. In turn, customers perceive a stronger rapport between the customers and the robot and have a greater intention to adopt robotic services. In addition, as expected, when the context involves a full-service restaurant instead of a limited-service restaurant, these relationships are stronger, except for the following relationships: 1) The

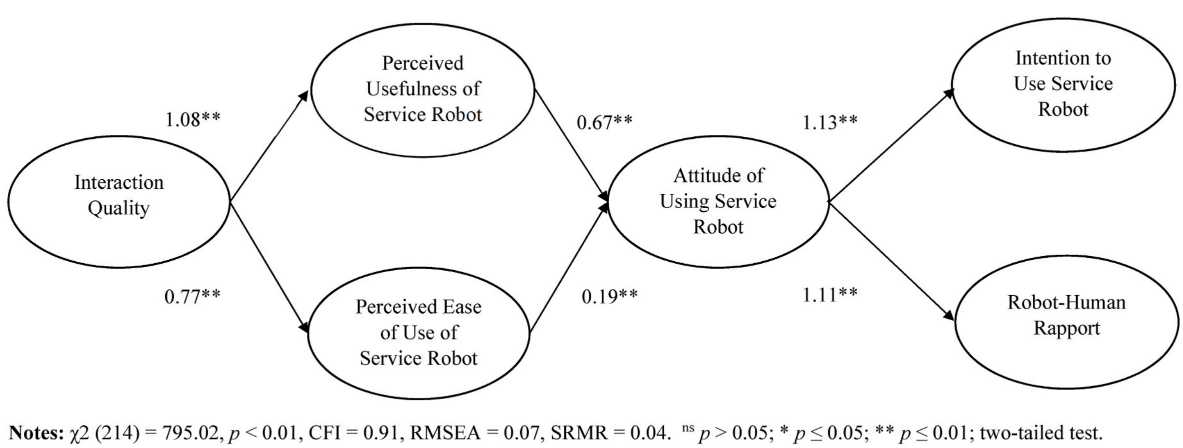

Fig. 2. Overall model
Notes: $\chi 2$ (214) = 795.02, $p < 0.01$, CFI = 0.91, RMSEA = 0.07, SRMR = 0.04. [ns] $p > 0.05$; *$p \leq 0.05$; **$p \leq 0.01$; two-tailed test.

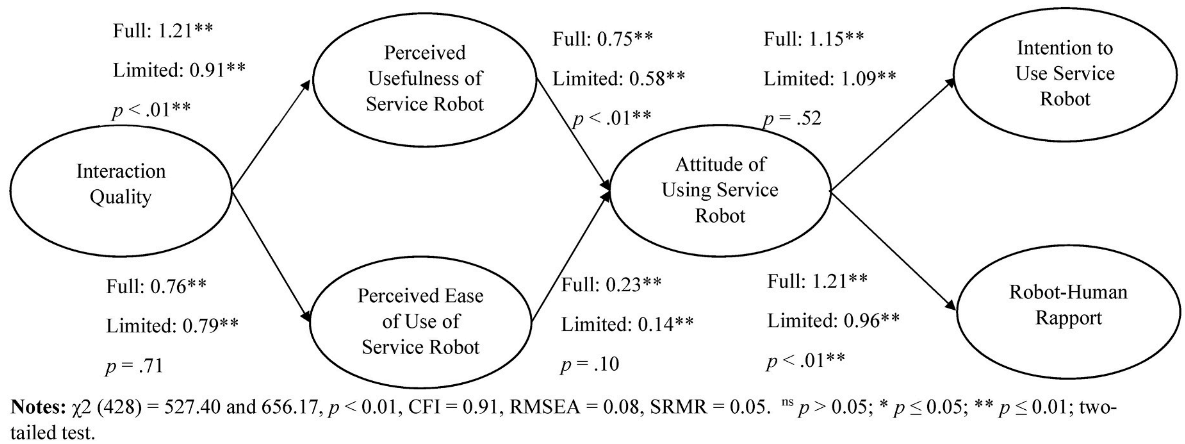

Fig. 3. Model results in two manipulated service contexts
Notes: $\chi 2$ (428) = 527.40 and 656.17, $p < 0.01$, CFI = 0.91, RMSEA = 0.08, SRMR = 0.05. ^{ns} $p > 0.05$; $^{*}p \leq 0.05$; $^{**}p \leq 0.01$; two-tailed test.

perception of interactional quality with a robot leads customers to view the robot as easy to use regardless the restaurant contexts; 2) The relationship between customers' perceived ease of use of the robot and their attitudes toward adopting robotic services is absent in a full-service-restaurant context; 3) These attitudes exert a similar influence on customers' intention to adopt robotic services in both restaurant contexts.

One possible explanation why the relationship between interactional quality and ease of use does not vary depending on the restaurant service types could be that a service robot is perceived to be easy to use once a threshold of interaction quality level has been achieved such that similar perceptions regarding the service robot's ease of use are observed because the interaction quality in both restaurant situations passes the threshold level. With respect to the absence of a relationship between ease of use and attitudes in the full-service restaurant context, it could be possible that the service robot's ease of use serves as a necessary but not sufficient factor for attitude formation. In other words, the ease of use might do little to increase attitudes but could undermine the attitudes when it is absent. In addition, we may not have support for a stronger relationship between attitudes and intention on using service robots in a full-service restaurant condition because the attitudes represent a robust and critical determinant of intention as suggested by the technology acceptance model and, thereby, the relationship is unlikely to be affected by boundary conditions.

6.1. *Theoretical contributions*

First, we extend the literature on the technology acceptance model by identifying interaction quality as an additional antecedent. An enduring criticism of the technology acceptance model is its failure to identify antecedents to the perceptions of usefulness and ease of use (Autry et al., 2010; Venkatesh et al., 2007). Extant literature that explores this issue has identified the antecedent role of technical quality, such as the quality of an e-procurement system (Brandon-Jones & Kauppi, 2018) and the quality of an e-shopping site (Ha & Stoel, 2009). Because customers also play a key role in co-creating service experiences with organizations, our study contributes by further considering the interaction between customers and robotic technology. In particular, we draw upon the stimulus–organism–response paradigm (Mehrabian & Russell, 1974) to explain that stimuli in a technology service environment (i.e., customer-robot interaction quality) can influence customers' assessment of the service technology (i.e., perceptions and attitudes towards a service robot) and, thereby, their subsequent responses (i.e., intention to use the service robot and rapport with the robot). Our research adds a fresh perspective to the literature by integrating stimulus–organism–response paradigm and the technology acceptance model to identify environmental cues in a technology-service encounter as additional antecedents that can trigger customers' internal responses and subsequent behavioral reactions to the service technology.

In addition, we contribute to the service robot literature. Prior research has primarily focused on examining the influence of robotic design, such as gender (Rogers et al., 2020) and physical features (Martini et al., 2015), as well as robotic functions, such as task performance (Park, Lee, & Cho, 2012) and communication skills (Saunderson & Nejat., 2019), on customers' acceptance of service robots. Little attention has been paid to the impact of service contexts on how customers respond to frontline agents enabled by AI technology, except for a few recent studies (e.g., Huang & Kao, 2021; Longoni & Cian, 2022) that primarily examine the hedonic and utilitarian nature of service situations. Although Lin et al. (2020) have attempted to study the moderating role of limited and full hotel services, they only focused on hotel service contexts and the role of customers' overall positive emotions towards service robots in driving their evaluations of the robots. This research adds to this literature by exploring the moderating role of limited and full services in a different context (i.e., restaurant service context) and further examining the moderating effect on the relationship between customers' cognitions of a service robot, as opposed to their emotions, and their willingness to use the robot.

In this research, we found that the positive effects of the customer-robot interaction quality on customers' cognitions and behavioral intentions are stronger in a full-service context. As full-service customers have previously been found to be more likely than limited-service customers to associate robotic services with hedonic motivations and perceive that the benefits received from the services outweigh the cost of using services (Lin et al., 2020), our findings expand this literature by further showing that customers can respond to service robots more positively in full-service contexts than limited-service contexts. Also, while full-service customers are more likely than limit-service customers to demand high levels of social interactions during robotic service delivery (Lin et al., 2020), our findings broaden the service robot literature by implying that service robots capable of having quality interaction with customers can sufficiently satisfy customers' need for social interactions.

Lastly, we broaden the stream of research that studies the rapport between robots and human beings. Because of the importance of rapport in driving positive outcomes, an increasing number of researchers begin to identify factors that facilitate human-robot rapport, such as enabling the robots to display deictic gestures (Huang & Mutlu, 2013) and to provide personalized services (Lee et al., 2012). Our findings extend this literature by identifying the interaction quality between a user and a robot as an additional factor that can drive human-robot rapport through facilitating positive perceptions and favorable attitudes towards a robot.

6.2. Practical implications

This research holds important implications for marketing practitioners. First, our findings suggest that service organizations should make an effort to improve the quality of the interaction between a customer and a service robot. Organizations can proactively conduct market research to better understand customers' expectations in terms of the role that a service robot should play. For example, service organizations can conduct in-depth interviews to request frontline employees to report different types of customer expectations observed. In addition to conducting market research, organizations can analyze existing customer information (e.g., behavioral cues observed in their surveillance records and comments from customer feedback surveys) to gauge customer expectations with respect to robotic services. With an understanding of the expectations, service providers can enhance the interaction quality by designing a service process and a service script for their robotic services accordingly to facilitate customers' positive responses to service robots.

Second, service providers would benefit from recognizing that customers' responses to robotic services can vary depending on service types. Robots are generally perceived to be suitable for performing pragmatic tasks rather than personal tasks (Ray et al., 2008), which may discourage full-service providers from adopting service robots because full services often involve intense interpersonal interaction between customers and service providers (Parsa et al., 2020). Interestingly, as shown in our study, customers can respond to robotic services more positively in a full-restaurant-service context than in a limited-restaurant-service context. Our findings provide organizations that offer full services with an understanding of how they can benefit from incorporating robotic technology into service encounters. In order to facilitate the rapport between customers and the service robot, full-service organizations are recommended to identify different types of service interactions performed by service robots that are perceived to be useful and viewed favorably by their customers, such as paying close attention to the relevant keywords used in customer feedback and comments.

6.3. Limitations and directions for future research

In spite of the contributions, our research has a few limitations that need to be taken into consideration. First, our study was limited in that we tested the hypotheses using a scenario-based experiment that involves restaurant service scenarios. It is possible that the observed relationships can change as the contexts and study methods vary. Future studies may consider conducting field experiments with live robot-customer interactions to capture customers' real-time responses as well as examining the research issue in other service industries, such as full-service vs. limited-service hotels, to expand the investigation scope.

In addition, our data were also limited in that "Nao" was the only type of service robot considered. Another avenue for future research is to investigate how factors related to the robotic design could affect customers' responses to the service robots in different service contexts. For example, it may be possible that customers respond to humanoid service robots more positively in a full-service context and view non-humanoid service robots more favorably in a limited-service context.

Also, this research focused on the situation that service robots are capable of providing quality services. Because it is not uncommon for service robots to fall short of the expectations of customers (Huang & Philp, 2021), future research would benefit from taking robotic service failures into consideration. For example, it could be possible that when robotic service failures occur, participants would respond more negatively to a full-service provider than a limited-service provider, given the differences in service expectations.

Finally, the presence of human employees in robotic service encounters was not in the scope of the current research. One emerging challenge that many service organizations encounter is how to strike a balance between frontline agents enabled by AI technologies (e.g., service robots) and human employees (Flavián & Casaló, 2021). An additional avenue for future studies is to examine the degree to which the appropriate balance between service robots and human employees can change in full- and limited-service contexts.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

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Appendix 1

Manipulated Scenarios

Limited service

Service Robot: Hello, welcome to Taylor. You can take your order whenever you are ready.

Full service

Service Robot: Hello, welcome to Taylor. How many do you have?
You: Only one.
Service Robot: No problem. I will take you to a seat, please follow me.
You: Thank you.
Service Robot: Would you like to anything to drink before taking your order?
You: Water, please?
Service Robot: Of course, here is your menu and I will be right with you.

Continue with manipulation

Service Robot: Hello. Are you ready to take your order?
You: No, I am not. Do you have any 'special of the day' or like at this place?
Service Robot: Yes, we do provide grilled salmon sandwich and Philly cheese steak burger as today's special.
You: Hmm … I don't like salmon. Tell me about the burger?

Service Robot: Absolutely. It is one of our most popular items. It serves with a 14 oz grilled philly steak with garlic and mushroom topping. You will also have four sides including butter corn, curly fries, backed potato and fresh broccoli.

You: Sounds good. I will take it.

Service Robot: How would you like that cooked?

You: Median please?

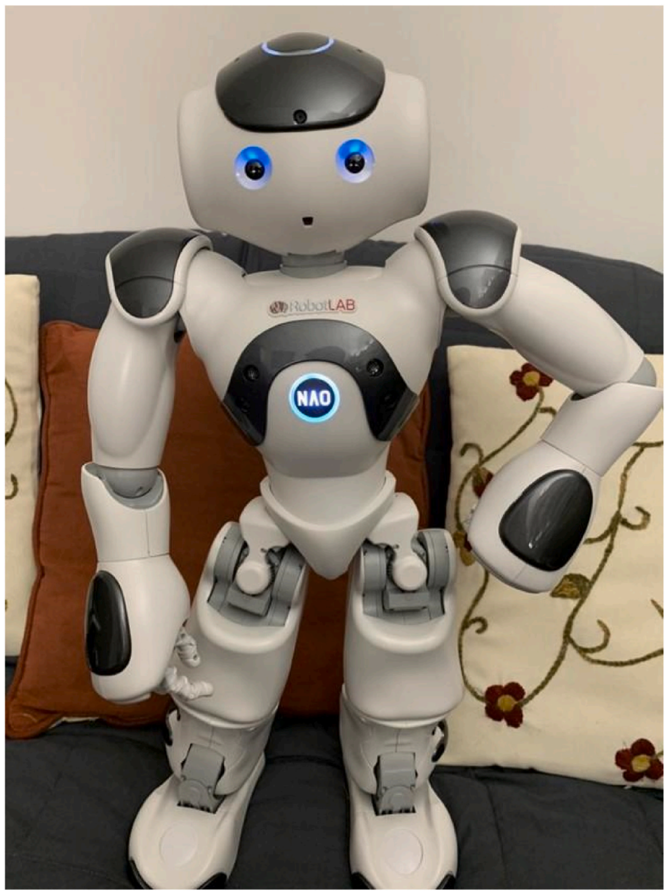
Service Robot: Of course. Anything else?

You: I think that's it for now.

Service Robot: No problem. Your meal will be ready soon.

Appendix 2

Photo of the Service Robot Nao



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