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Being Served by Humanoid Service Robots: Antecedents of Individuals' Willingness to Use in Restaurant Settings

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Matthias Dendooven

Abstract

In this study, we explored the antecedents (social influence, performance expectancy, anthropomorphism, perceived intelligence, perceived safety, hedonic motivation) of 170 individuals' willingness to use humanoid service robots in both quick service and traditional restaurants. Grounded on technology acceptance and Human-Robot Interaction (HRI) literature, separate Structural Equation Modelling (SEM) were conducted for 2 different types of robots : one type concerning Low Human-like service robots (LH) and the other type for High Human-like service robots (HH). Both models show that the level of anthropomorphism perceived by the individual has a relatively low effect on its evaluation of safety; Results also show that individuals with a high level of hedonic motivation are more likely to accept service robots restaurants. Compared to the HH model, the LH model suggests that individuals might be more socially influenced when it comes to evaluating robot's capacities; their performance expectancy will determine their enjoyment to interact with the service robot. The insights provided by the study might be valuable for researchers seeking to develop the literature on HRI but also for business owners who are interested in implementing humanoid service robots in restaurants.

Keywords

Service Robots; technology acceptance; High-Humanlike (HH); Low-Humanlike (LH); Human-Robot Interaction (HRI); quick service restaurants; traditional restaurants; Willingness to Use.

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1. Introduction

The word "robot" comes from a drama scenarized by Karel Čapek (1920). It originates from the Czech term *robota*, meaning forced labour. Recently, research on Human–Robot Interaction (HRI) has described a shift in the role of robots from 'tools' to 'partners' or 'teammates' (Bankins & Formosa, 2020). The continuous progress in social robotics and artificial intelligence is empowering robots to a greater potential of collaboration with humans. The number of "service robots" is getting higher every year, the International Federation of Robotics (2022) reports that the use of robots in the hospitality sector has increased by 85% in 2021, with an additional 20,000 units deployed worldwide.

Service Robots are characterized as autonomous agents with the primary objective of delivering services to customers through the execution of both physical and nonphysical tasks (Joerling et al. 2019). Compared to the industrial robot, the service robot has to adapt to its users (Sprenger & Mettler 2015). The appearance of a robot might also differ, it can take the form of robotic arms, wheeled robots or a humanoid robot characterized by a certain degree of human likeliness. One of the oldest example to illustrate this category is from the saga Star Wars. C-3PO appears more human-like with his humanoid structure and refined speech, while R2-D2 has a more mechanical and compact design but still possesses advanced cognitive capabilities and emotions (David and Maja, 2009).

Based on the uncanny valley theory of Mori (1970), Kim et al. (2022) showed that perceptual mismatches between humanlike features might lead to different reactions from humans. For example, a service robot with high humanlike face but a low humanlike body has a higher probability to create *bukimi* (negative emotions in Japanese) or a feeling of unsafety. Certain service robots are designed in order to contain some human-like features such as voice, appearance or even a level of sense of humour similar to humans (Zhang et al., 2021). As the level of human-likeness can vary from one service robot to another, this difference may also have an impact on their acceptance and willingness to use.

In order to understand more deeply consumer's acceptance of service robots in general, Bartneck et al. (2009) developed a set of scales used to measure human perceptions of robots and among them : anthropomorphism, perceived intelligence, and perceived safety. In the domain of the hospitality industry, Qiu et al. (2019) discovered that incorporating human-like characteristics, such as anthropomorphism and intelligence, into robots resulted in improved rapport-building between customers and robots, leading to a more positive overall hospitality experience. Consumer's acceptance is also depending on technology-likeliness factors as performance expectancy (Chua et al., 2022). Zhang et al. (2021) found that High human-like robots are perceived as being more performant. Concerning the hedonic motivation of individuals, the expectancy value theory has been used in order to understand individuals' intention to use service robots (Lin, 2022).

Concerning the influence of socio demographic factors, Ivanov et al. (2018) suggested that young individuals are evaluating differently the usefulness of service robots depending on their geographical location. The study also found that women were less positive towards service robots and their adoption in hotels. Another significant factor that is used to explain consumer's acceptance is social influence. For example, the adoption of JoMoPay, a service payment system, was found to be influenced by social pressure (Alkhwaldi et al., 2023).

To develop a set of factors that are shaping consumer's acceptance of a particular technology, the study will adopt a three-stage process inspired by Lazarus' cognitive appraisal theory (1991). Firstly, individuals evaluate the relevance of using service robots in restaurants (primary appraisal). Secondly, They will generate (or not) potential utilitarian benefits that they might get by using service robots (secondary appraisal). Finally, the positive (negative) emotions experienced from the last stage will influence their willingness to use service robots in restaurants (outcome stage) (Pande et al., 2022; Lin et al., 2020).

Studying the acceptance of robots is context dependant and given this reason, I will look at the consumer's acceptance of service robots in the context of both quick service and traditional restaurants (Knutson et al., 1996). The aim of the study will be to investigate and analyse potential factors influencing consumers' willingness to use humanoid service robots (with different degrees of human-likeliness) in these 2 different types of restaurants. To do so, I will use the common way by conduction Structural equations modelling models, often used in the technology acceptance literature. The findings of this study may contribute to advancing hospitality research on customers' acceptance of service robots by identifying relevant antecedents and the impact mechanism. Additionally, these findings may also be beneficial to managers as they will provide valuable suggestions to improve customers' positive attitudes toward service robots in restaurants.

2. Literature Review

Even before the implementation of robots in services, Different theories have try to explain direct and indirect factors that lead to the willingness to use of a particular technology. Venkatesh et al. (2003) developed a more global model with the Unified Theory of Acceptance and Use of Technology (UTAUT), it is composed of factors like performance expectancy and social influence. Considered as a more precise and adapted for particular contexts, TAM (Technology acceptance model) is focusing on the perceived usefulness of a particular technology for both employees and consumers. Concerning employees, it is mainly related to which extent the particular technology will enhance the job performance. On the consumer 'side TAM has been studied through for example mobile banking applications (Lule et al., 2012), the perceived ease of use along the perceived usefulness were keys to predict usage intention.

The Theory of Planned Behaviour (TPB) has been widely acknowledged as a suitable framework for explaining volitional behaviours, including the adoption of novel technologies (de Graaf et al., 2019). Choe et al. (2022) used both TAM and TPB to explain the behavioural intentions of consumers to use robots in a Korean restaurant. Concerning the Service Robot Acceptance Model (sRAM), Wirtz et al. (2018) took also into account the functional elements of the TAM (Davis et al., 1989) model but also the socio-emotional elements and the relational elements. This theory was developed to make a comparison between the front line employee and the robot in the hospitality sector. One of the key difference is that the service provided by an employee will be heterogeneous and the service provided by the robot will be homogeneous. The service employee has the ability to think sometimes out of the box and being creative and on the other hand, the service robot can only engage in surface acting (Lu et al., 2020).

Service robots have gained extensive popularity in diverse professional and personal domains due to their numerous advantages, including improved user-friendliness, the ability to provide precise and high-quality services, reliability, and decreased operational expenses and human mistakes (Malani and Lanjudkar, 2016). In the food and beverage industry, robots are increasingly being employed for a range of tasks including customer greeting, cooking, and meal service. Cooking robots ensure food is prepared to a consistent standard, while greeting robots warmly welcome and guide customers to their designated seating areas, acquainting them with the restaurant. Service robots in food and beverage establishments take on the role of waiters, attending to customer orders and delivering meals (Li et al., 2012).

In the late 20th century and early 21st century, the concept of social robotics gained prominence. Researchers began developing robots with the ability to engage in social interactions with humans (Breazeal et al., 2016). The Human-Robot Interaction (HRI) is a field that is been exponentially explored and studied through the years as robots an given the growth of service robots in the tourism and hospitality services, some studies are interested in exploring this particular interaction between robots and humans (Choi et al., 2020). One key aspect while studying the quality of the interaction between humans and robots is the level of human-likeliness exhibited by the service robot. As robots or virtual characters become more human-like, people feel more connected until a critical point where discomfort arises, known as the "Uncanny Valley" (Mori, 1970). Beyond this point, as realism increases, negative emotions decrease, leading to a rise in positive feelings with further resemblance to humans. Kim et al. (2022) investigates the uncanny valley phenomenon in the context of various human-like robots. The authors analysed the emotional responses elicited by these robots based on their level of human-likeness. DI/DreamWorks' Lucia Modesto noted that her team had to pull back a little on Princess Fiona: "She was beginning to look too real, and the effect was getting distinctly unpleasant" (Brenton et al., 2005).

While some studies suggest a positive relationship between anthropomorphism and perceived safety, some studies present opposing findings. Studies focussing on industrial HRI indicate that using human-like design features may not always be beneficial. In fact, such design features can potentially diminish the perceived reliability of robots and give rise to apprehensions regarding their self-safety (Roesler et al., 2021). Concerning the HRI for service robots, Schepers et al. (2022) found that highly anthropomorphic robots raised concerns about physical safety due to their perceived unpredictability. Participants perceived highly human like robots as potentially having hidden intentions or being prone to unpredictable malfunctions, reducing perceived safety. These studies demonstrate that concerns about individuals self-safety can arise when robots are perceived as too human-like.

The notion of safety not explored the safety of the consumer but also safety of the robot itself. Waytz et al. (2014) found that higher levels of anthropomorphism in an autonomous vehicle increased participants' trust in its safety. Van Pinxteren et al. (2019) conducted a study that confirmed the relationship between anthropomorphism and perceived trust in humanoid service robots. In other words, the more anthropomorphic the robot appeared, the higher the level of trust people placed in it. However, Some studies didn't find a relationship of anthropomorphism on trust (Erebak & Turgut, 2019; Hancock et al., 2011). Waytz et al. (2014) found an anthropomorphic and highly intelligent robot is being perceived as possessing greater animacy and potentially evoking a higher degree of likability.

Evidence suggests that perceived intelligence is also one of the key factor that the consumer will use in order to determine its willingness to use robots. As defined within the Godspeed Scale (Bartneck et al., 2009), the level of perceived intelligence encompasses five dimensions: incompetent-competent, ignorant-knowledgeable, irresponsible-responsible, unintelligent-intelligent, and foolish-sensible. Further research indicates that human-like avatars exhibit higher levels of intelligence (Koda & Maes, 1996) and credibility (Nowak & Rauh, 2005) compared to non-human-like avatars. The presence of human-likeliness in a robotic chef has a direct impact on the prediction of food quality (Zhu et al. 2020), which is mediated by the sequential factors of warmth and competence. The consumer may perceive the humanoid service robot as being emotional and capable of reasoning, which can lead as perceiving the robot as more intelligent. While research has consistently demonstrated the significant influence of anthropomorphic attributes on the connection between consumers and AI devices (Wan et al. 2015).

Knutson et al. (1996) worked on the consumer satisfaction in restaurants, they did a segmentation of the restaurants in 3 different parts : quick service, casual theme and fine dining restaurant. SERVQUAL (Service Quality) is a widely recognized framework developed by Parasuraman et al. (1988) It is a general tool used to assess service quality in various industries beyond just restaurants, such as retail, banking, healthcare, and more. SERVQUAL is based on reliability, empathy, tangibles, responsiveness, and assurance. Concerning robots, factors like perceived usefulness and reliability were the most relevant related to the reusing of chatbots.

In order to attain a hedonic value for the consumer, Moriuchi (2022) reported that companies of smart AI devices should firstly concentrate on the level of safety experienced by the consumer before focussing the hedonic aspect. The relationship between safety and hedonic motivation can be understood through the concept of Maslow's hierarchy of needs (Scheepers et al., 2022). Once a certain degree of safety is attained, individuals will be more likely to engage and have positive emotions about the service robot. The explanations for hedonic motivation can be both intrinsic and extrinsic. The intrinsic value is representing the internal drive and enjoyment that individuals experience when engaging with the service robot (Lu et al., 2019). Moreover, Customers' performance expectancy regarding the service robots directly influences their expectations about the robot's ability to provide a positive and enjoyable experience (Ho et al., 2020). Based on the Expectancy value theory (Wigfield et al., 2009), an increase of their expectations will lead to a more pleasant interaction and, therefore, their hedonic motivation.

On the other hand, from the Cognitive dissonance theory (Festinger, 1962), a technology that is inconsistent with beliefs of an individual, is more likely to lead to discomfort. Additionally, according to Yu's (2020) observations, the utilization of humanoid robots in hotels has the potential to elicit unsettling and undesirable emotions, including feelings of discomfort and insecurity. Note that People tend to develop negative opinions faster and find them harder to change compared to positive opinions, even if the information supporting both opinions is equally strong (Baumeister et al., 2001).

Some factors of acceptance might be external like the socio demographic factors and cultural factors. The degree of uncertainty avoidance within different countries also play a significant role in the impact of social influence on willingness to use service robots. A study conducted by Chi et al. (2023) demonstrated that the effect of social influence on acceptance is amplified when considering cultural dimensions such as collectivist versus individualist cultures. Additionally, countries with varying levels of uncertainty avoidance exhibited differences in the influence of social factors on consumer behaviour regarding service robots. Lin et al. (2020) showed that the amount of services provided by service robots (full service-limited service) in a hotel might change some consumers responses. Consumers that are using robotic devices in a limited service context, are more likely to rely on their social group than in full service context. Evidence suggests also that consumer perceptions of robots in the hospitality industry vary based on sociodemographic characteristics, such as gender and urban-rural location. For example, a study conducted in Russia (Ivanov et al., 2018) explored young people's perceptions of robots and the hotel services they would accept being delivered by robots, while other studies have examined the significance of a robot's gender type. Findings have shown that women are generally less receptive to the introduction of robots than men.

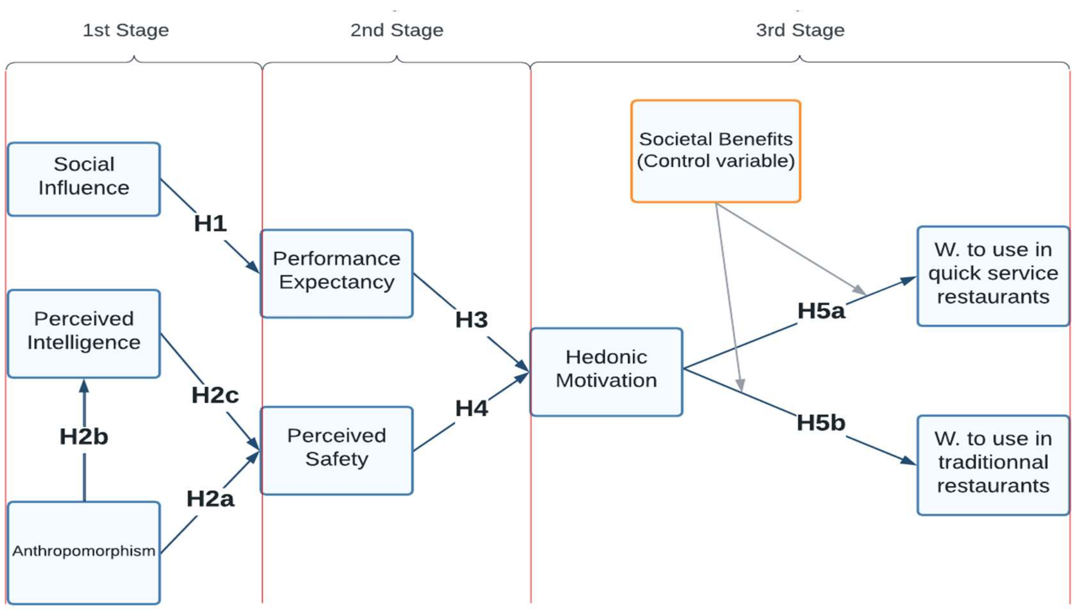
Inspired by the cognitive appraisal theory of Lazarus (1991), Lin et al. (2020) studied the consumer's acceptance of AI devices with their AIDUA model (Artificially Intelligent Device Use Acceptance) through three stages of acceptance. The three stages are primary appraisal, secondary appraisal, and outcome stage. In the primary appraisal stage, customers evaluate the relevance and importance of using AI devices in service encounters. The secondary appraisal stage involves assessing the feasibility and capability of AI devices to fulfil their needs. Finally, the outcome stage considers the perceived benefits and outcomes of using AI devices. The six antecedents of the willingness to use social devices are social influence, hedonic motivation, anthropomorphism (attributing human-like qualities to AI devices), performance expectancy (expectations of AI device performance), effort expectancy, and emotion. Pande et al. (2022) conducted empirical experiences in a Indian restaurant in order to determine the factors of consumer's acceptance, they also assumed that the customer is going through a three stages process, which determines their willingness to tolerate robot waiters in a restaurant.

3. Proposed model and hypothesises

3.1 Model Overview

I decided to base the model (Figure 1) on the theory of the three stages process (Lazarus, 1991) in order to explain the willingness to use service robots in restaurants. The model contains 5 hypotheses (H1, H2, H3, H4 and H5) in total. The second hypothesis is divided into 3 different sub hypothesises (H2a, H2b and H2c) and the fifth hypothesis, which defines two 2 different contexts (H5a and H5b) : the willingness to use in quick service and in traditional restaurants. This division is justified as the consumer's satisfaction differs from the type of restaurants and the acceptance of a technology is context dependent (Knutson et al., 1996).

Figure 1. Proposed model : antecedents of willingness to use



3.2 1st stage (primary appraisal)

During this first stage, customers form their initial impressions of service robots based on *anthropomorphism* (attributing human-like characteristics) and *social influence* (perceptions influenced by others). These factors will create some expectations on the perceived safety and the performance of the service robot in restaurants as outcomes.

First hypothesis

H1 : Social Influence is positively related to the Performance Expectancy of the service robot.

Social influence represents the measure of how much consumers perceive that important people in their lives (such as family and friends) believe they should accept and experience service robots in a restaurants (Venkatesh et al., 2012). Previous studies (Alkhwaldi et al., 2023) showed positive relations between these two variables. Lin et al. (2020) found an impact of social influence on performance expectancy while service robots provided a limited amount of services. We will test if this hold also in our context of service robots in restaurants.

Second hypothesis

H2a : The direct effect of anthropomorphism on Perceived Safety is negative.

H2b : The direct effect of anthropomorphism on perceived intelligence is positive.

H2c: The direct effect of perceived intelligence on perceived safety is positive.

H2 : The total effect of anthropomorphism on perceived safety is positive (mediated by perceived intelligence)*.

*Hint : The pathway H2b + H2c in Figure 1 represents the indirect effect of anthropomorphism on perceived safety, which we hypothesize to be positive. On the other hand, H2a represents the direct effect of anthropomorphism on perceived safety, which we hypothesize to be negative. Therefore, The total effect is represented is by H2a + H2b + H2c that formed H2 together and we think that the total will be positive.

Epley (2018) defines *anthropomorphism* as "perceiving human-like traits in nonhuman Agents". This second hypothesis is a bit more complex because the relationship between anthropomorphism and people's perceptions of safety is still unclear (Belanche et al., 2020). We saw in the literature that Some researchers have acknowledged the existence of an effect, while others have not. Nevertheless, there is evidence suggesting that anthropomorphism has a positive impact on perceived intelligence (Moussawi, 2021) , which itself has a positive impact on perceived safety. As a result, even if the direct effect of anthropomorphism on safety might be negative (Roesler et al., 2021), the total effect would be mediated by perceived intelligence and lead to a positive overall impact of anthropomorphism on perceived safety.

3.3 2nd stage (Secondary appraisal)

Once individuals have formed their initial impressions, they move on to the secondary appraisal stage, where they evaluate the *performance expectancy* and the level of *perceived safety* associated by using service robots. People that are feeling comfortable and that are expecting the service robot to perform, will express their hedonic motivation by interacting with it.

Third hypothesis

H3 : Performance expectancy and hedonic motivation are positively related

Performance expectancy refers to the degree to which individuals believe that using a particular technology will help them enhance their job performance or achieve desired outcomes (Venkatesh et al. 2003). In the context of restaurants, the performance expectancy refers to consumers' perceptions of how well the robot can perform tasks and deliver quality service (Pande et al., 2022). Based on the expectancy value theory (Wigfield et al., 2009), if individuals believe the robot will perform well, it increases their expectations of a pleasant interaction and, therefore, their hedonic motivation.

Fourth hypothesis

H4 : Safety and hedonic motivation are positively related

In this particular context, the level of *perceived safety* describes "the user's perception of the level of danger when interacting with a robot, and the user's level of comfort during the interaction" (Bartneck et al., 2009). Based on the concept of Maslow's hierarchy of needs (Schepers et al, 2022), we are making the hypothesis that the consumer has to feel comfortable before he enjoys the interaction with the service robot.

3.4 3rd stage (outcome stage)

3rd stage : the level of *hedonic motivation* generated by the consumer in the 2nd stage will finally determine the final *willingness to use service* robots in quick service restaurants or in traditional restaurants.

Fifth hypothesis

H5a : Hedonic Motivation is positively related to the willingness of use service robots in quick service restaurants (Controlled by the variable "Societal Benefits")

H5b : Hedonic Motivation is positively related to the willingness of use service robots in traditional restaurants (Controlled by the variable "Societal Benefits")

The *hedonic motivation* reflects consumer's perceptions of fun, entertainment and enjoyment. (Lin et al., 2020) This internal drive might be completed by an external drive concerning the personal ideology of individuals about robots. In other words, we'll look at which extent individuals view robots as a good thing for society as a whole. These societal benefits, along hedonic motivation, might incentivize consumers to use service robots in restaurants (Lu et al., 2020; Gretzel, & Murphy, 2019).

4. Methodology

4.1 Survey design and structure

I utilized Microsoft Forms to create my questionnaire, which provided me with the option to share a link and a QR code for collecting data through online social networks like Facebook, Instagram, and LinkedIn. As an incentive, all participants received a chance to win a restaurant experience for one person. These different data collection techniques allowed me to collect a total of 170 individuals who completed the questionnaire. It was opened from the 20th of June till the 15th of July.

At the beginning, the survey was composed of socio-demographic questions (characteristics are shown in Table 2), these questions were the same for everyone. Afterwards, I designed 4 similar situations, each respondent got one situation out of four. The only difference is that each situation was composed by a different service robot: Cruzr, Pepper, Sophia or Erica (Table 1). Then, individuals had to evaluate the service robot that he got through a Likert scale of 1 to 5, ranging from Strongly Disagree to Strongly Agree (Appendix 1). The total survey was composed of 57 different items defining 16 latent variables, I had to remove some items as they were either not significant or not adapted to our hypothesises or the general literature/theoretical background. In the end, after the selection process, we were left with a total of 29 items and 9 latent variables (Table 2) that were the core of our proposed model (Figure 1).

4.2 Service robots and the degree of human likeliness

As explained, I focused on four different robots for the study: Cruzr, Pepper, Sophia, and Erica. Among them, Cruzr and Pepper fall into the category of humanoid robots with a low to moderate degree of human likeliness, while Sophia and Erica represent humanoid robots with a high degree of human likeliness. Concerning our analysis, we decided to simplify our approach by merging robots 1 and 2 (Cruzr and Pepper) into the LH (Low humanlike) category, and robots 3 and 4 (Sophia and Erica) into the HH (High humanlike) category (Table 1). This classification allows us to examine how human-likeness influences people's willingness to use robots in our model.

Cruzr and Pepper (Figure 2) are real humanoid service robots that are currently commercialized and widely applicable in industries such as hospitality, retail, healthcare, education, and public services. It is important to note that while Pepper has received positive feedback, it has also faced some criticisms from consumers. These robots, being part of the LH category, will be compared to the HH category represented by Sophia and Erica, which have a more realistic human-like appearance. Sophia and Erica (Figure 3), on the other hand, are humanoid robots in the HH category with highly lifelike appearances. However, they are currently in the experimental phase and are mainly designed to advance the field of human-robot interaction (HRI). They are not yet commercialized for providing services in the hospitality industry. Despite this, I am interested in exploring whether consumers would be open to engaging with these types of robots in the context of restaurants.

Figure 2. Low humanlike category (LH) : Presentation of robots Cruzr (left) and Pepper (right)

Figure 3. High humanlike category (HH) : Presentation of robots Sophia (left) and Erica (right)

Table 1. : degree of human likeliness, confidence interval and developers.

Robots	*Human likeliness category*	*Year added to the database*	*Degree of human likeliness*	*Confidence interval (95%)*	*Name of the developer*
Cruzr	Low Human-like category (LH)	2019	32,15	[25.52, 38.80]	Ubtech Robotics
Pepper		2018	42,17	[30.79, 49.42]	Softbank Robotics
Sophia	High Human-like category (HH)	2018	78,88	[67.73, 83.39]	Hanson Robotics
Erica		2018	89,6	[85.60, 93.12]	HIL

Source : Phillips, E., Zhao, X., Ullman, D., & Malle, B. F. (2018). What is human-like?: Decomposing robots' human-like appearance using the Anthropomorphic roBOT (ABOT) Database.

Table 2. Design of the Likert scale and means of the different items (1-5)

Constructs		Items	Mean (LH Scenario)	Mean (HH Scenario)
Social Influence [Venkatesh et al., 2003]			**3**	**2.98**
	SOI1	I would be willing to go to a restaurant which employs service robots if my friends are interested in doing so.	3.66	3.73
	SOI2	Going to restaurants that employ service robots will be a status symbol within my social networks.	2.40	2.31
	SOI3	People who are important to me may encourage me to visit a restaurant which employs service robots.	2.96	2.91
Anthropomorphism [Golossenko et al., 2020]			**2.21**	**2.22**
	ANT1	The service robot has a mind of its own.	2.43	2.51
	ANT2	The service robot is capable of reasoning.	2.57	2.50
	ANT3	The service robot might experience emotions.	1.90	1.90
	ANT4	The service robot has its own free will.	1.94	1.98
Perceived Intelligence [Bartneck, 2009]			**3.31**	**3.3**
	INT1	The service robot seems to be competent.	3.43	3.36
	INT2	The service robot seems to be intelligent.	3.22	3.30
	INT3	The service robot seems to be responsible.	3.29	3.25
Performance Expectancy (compared to humans) [Lin et al., 2020]			**3.34**	**3.38**
	PEF1	The service robot is more accurate than human beings.	3.06	3.19
	PEF2	The service robot would make fewer mistakes than human beings.	3.52	3.45
	PEF3	The service robot is more consistent than human beings.	3.44	3.5
Perceived Safety [Jia et al., 2021]			**3.64**	**3.37**
	SAF1	The service robot is safe (the design of the robot is safe to prevent accidents).	3.69	3.41
	SAF2	The service robot makes me personally safe.	3.72	3.38
	SAF3	The service robot does not bring me a safety hazard when I use it.	3.51	3.31
Hedonic Motivation [Lin et al., 2020]			**3.49**	**3.26**
	HEM1	I think that interacting with the service robot would be fun.	3.60	3.51
	HEM2	I think that interacting with the service robot would be entertaining.	3.77	3.69
	HEM3	I think that interacting with the service robot would be pleasant.	3.27	2.84
	HEM4	I think that interacting with the service robot would be enjoyable.	3.33	3.00
Societal Benefits [Gretzel, & Murphy, 2019]			**3.06**	**3.16**
	SOC1	Service robots will be profitable to society as a whole.	2.96	3.04
	SOC2	Service robots can contribute to sustainable development.	3.01	2.96
	SOC3	Service robots can contribute to the growth of the economy.	3.22	3.49
Willingness to use in quick service restaurants [Pande et al., 2022; Knutson et al., 1996]			**3.49**	**3.28**
	WIQ1	I am likely to interact with this service robot in a quick service restaurant.	3.57	3.46
	WIQ2	I will feel happy to interact with this of service robot in a quick service restaurant.	3.37	3.05
	WIQ3	I am willing to receive services from this service robot in a quick service restaurant.	3.54	3.34
Willingness to use in traditional restaurants [Pande et al., 2022; Knutson et al., 1996]			**2.52**	**2.52**
	WIT1	I am likely to interact with this service robots in a traditional restaurant.	2.60	2.66
	WIT2	I will feel happy to interact with this service robot in a traditional restaurant.	2.44	2.38
	WIT3	I am willing to receive services from this service robot in a traditional restaurant.	2.52	2.53

4.3 Data analysis and methodology

Concerning the data analysis, I used R studio software and the lavaan package, which helped me to conduct the Confirmatory Factor Analysis (CFA) and the Structural Equation Modeling (SEM). Our measurement model was composed on the basis of the 29 items and 9 latent variables (Table 2). To assess the validity of this measurement model, a Confirmatory Factor Analysis (CFA) was conducted. This step aimed to establish the reliability, convergent and discriminant validity of the measurement model. In other words, we analysed the validity of our items and if they were predicting well their particular latent variable. Afterwards, we were able to conduct the different Structural Equation Models (SEM) based on the hypothetical model. A first SEM (Figure 4) model utilized the full sample without taking into account the degree of human likeness of the robot (LH and HH scenario together). The second model (Figure 5) divided the sample between the people who were assigned the LH scenario and the others the HH scenario. After assessing different SEMs, I studied the effects of socio demographic constructs and added them to the model in order to evaluate their influence.

5. Results

5.1 Socio demographic representation

Table 3. Socio demographic characteristics of the 170 individuals and their distribution over the 2 scenarios

Variables	*Category*	*Full sample (n=170)*	*Sample for Scenario LH (n=90)*	*Sample for Scenario HH (n=80)*
Gender	Woman	48.2%	54.4%	41.3%
	Man	51.8%	45.6%	58.7%
Age	18-25	66.5%	62.22%	71.2%
	>25	33.5%	37.8%	28.8%
Nationality	Belgian	41.2%	48.9%	32.5%
	Other EU	42.9%	33.3%	53.7%
	Outside EU	15.9%	17.8%	13.8%
Social status	Student	64.7%	58.9%	71.3%
	Employee	27.1%	33.3%	20%
	Others	8.2%	7.8%	8.7%
Personal experience	Novice	79.4%	78.9%	80%
	Experienced	20.6%	21.1%	20%
Personality type	Introvert	45.3%	50%	40%
	Extrovert	54.7%	50%	60%

In relation to the sociodemographic distribution outlined in Table 3, the survey comprises a wide range of individuals. Women constitute a slightly lower percentage in the full sample (48.2%) than men (51.8%). However, women were more represented in LH scenario (41.3%) and men more represented in HH scenario (58.7%). Regarding age, the majority of participants in the full sample (66.5%) were between 18 and 25 years old. In HH scenario, this age range dominates even more significantly, accounting for 71.2% of the sample.

Nationality exhibits notable variations within the samples. While the largest proportion in the full sample is Belgian (41.2%), the most prominent group among the nationalities is actually the "Other EU countries" category (42.9%) mainly composed of people coming from Germany, Italy France, Netherlands and Lithuania. "Outside EU" participants account for 15.9% of the full sample and these are the people coming mainly from the Asian continent with countries like India and Thailand in majority. In LH scenario, the proportion of Belgians was the largest group (48.9%) and in HH scenario, the "Other EU" group became the largest group (53.7%).

The majority of participants across all scenarios are students (ranging from 58.9% to 71.3%), while employees represent a smaller proportion. Novices are the dominant group in terms of personal experience, accounting for approximately 80% in all scenarios. Extroverts have a slightly higher representation in the full sample and in HH scenario but they are perfectly distributed in LH scenario.

5.2 Measurement model

Table 4. Different indexes assessing the validity of the measurement model

Constructs/Items	*Standardized loadings*	*Cronbach's Alpha*	*AVE*	*Composite Reliability*
Social Influence (SOI)		0.7	0.447	0.716
SOI1	0.623			
SOI2	0.630			
SOI3	0.746			
Anthropomorphism (ANT)		0.84	0.578	0.842
ANT1	0.809			
ANT2	0.696			
ANT3	0.733			
ANT4	0.796			
Perceived Intelligence (INT)		0.8	0.597	0.817
INT1	0.824			

INT2	0.849			
INT3	0.625			
Performance Expectancy (PEF)		0.83	0.615	0.826
PEF1	0.765			
PEF2	0.778			
PEF3	0.809			
Safety (SAF)		0.83	0.64	0.832
SAF1	0.849			
SAF2	0.923			
SAF3	0.589			
Hedonic Motivation (HEM)		0.9	0.68	0.896
HEM1	0.850			
HEM2	0.736			
HEM3	0.830			
HEM4	0.883			
Societal Benefits (SOC)		0.77	0.53	0.773
SOC1	0.760			
SOC2	0.751			
SOC3	0.675			
Willingness to use in Quick Service Restaurants (WIQ)		0.91	0.78	0.913
WIQ1	0.876			
WIQ2	0.900			
WIQ3	0.868			
Willingness to use in Traditional restaurants (WIT)		0.92	0.81	0.924
WIT1	0.878			
WIT2	0.941			
WIT3	0.873			

Notes : Observations (n) = 170; Chi-Square = 570.294; Degrees of freedom = 406; RMSEA = 0.063; CFI = 0.923; TLI = 0.908; SRMR = 0.06.

The CFA (Confirmatory factor analysis) yielded a reliable measurement scale. Standardized factor loadings (Table 4) of the different items exceeded 0.60, suggesting a reliable measurement scale except for "SAF3" which had a slightly lower value of 0.589. Despite this, we opted to retain the item in the analysis because removing it would have resulted in lowering the power of our structural model.

Furthermore, both the values of Cronbach's alpha and composite reliability are higher than or equal to the threshold of 0.70, indicating satisfactory measurement item reliability (Hair et al., 2014). Moreover, the average variance extracted (AVE) values for all factors exceed 0.5, providing evidence of convergent validity at the factor level, as per the criteria established by

Fornell and Larcker (1981). The only exception is the Social Influence factor, where the AVE value falls below 0.5. Nevertheless, given that the standardized items surpass the 0.6 threshold and both Cronbach's alpha and composite reliability demonstrate significant results, it indicates that the latent variable of social influence is evenly distributed across the three items. Consequently, we decided to retain all items and include them in the analysis.

The chi-square statistic is 570.29 and the degrees of freedom are 341. Therefore, the ratio of the chi-square to the degrees of freedom is calculated as Ratio = chi-square / degrees of freedom (570.294 / 341 ≈ 1.673), which gave an answer of 1.673 was less than 3 (Kline, 2005). The model demonstrates a good fit based on various fit indices. The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) indicate favourable fits with values of 0.923 and 0.908 respectively. Additionally, the Root Mean Square Error of Approximation (RMSEA) of 0.063 and Standardized Root Mean Square Residual (SRMR) of 0.060 are both below the threshold value of 0.08 (Hu & Bentler, 1999). Overall, the measurement was assessed to be valid and ready to be used for our structural model. We also assessed the discriminant validity (Table 5) thanks to the matrix of correlation between the different latent variables. On the diagonal, we can find the squared roots of AVEs and the rule is that the values of AVEs of the respective constructs have to be strictly higher than the correlation between the constructs. Given the results, the rule is satisfied for all of the variables. In conclusion, the indicators of the measurement model are satisfactory and ready to use for the structural model.

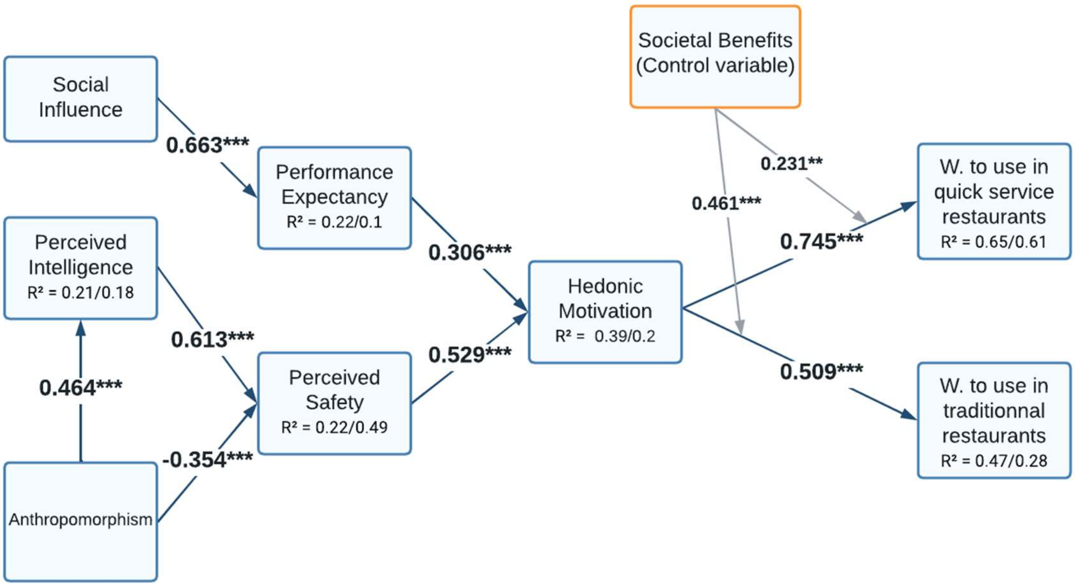
Table 5. Discriminant validity

Latent variables	SOC	ANT	INT	PEF	SAF	HEM	SOC	WIQ	WIT
Social	**0.669**								
Anthropomorphism	0.149	**0.760**							
Intelligence	0.195	0.278	**0.773**						
Performance Expectancy	0.199	-0.039	0.231	**0.784**					
Safety	0.120	-0.066	0.274	0.243	**0.800**				
Hedonic Motivation	0.377	0.208	0.458	0.312	0.344	**0.826**			
Societal benefits	0.277	0.062	0.239	0.264	0.252	0.407	**0.730**		
WU in Quick Service Restaurants	0.423	0.142	0.384	0.418	0.379	0.745	0.412	**0.881**	
WU in Traditional Restaurants	0.394	0.157	0.305	0.200	0.304	0.624	0.485	0.628	**0.898**

Notes: Diagonal elements are the squared roots of AVEs of the respective constructs.

5.3 Structural model

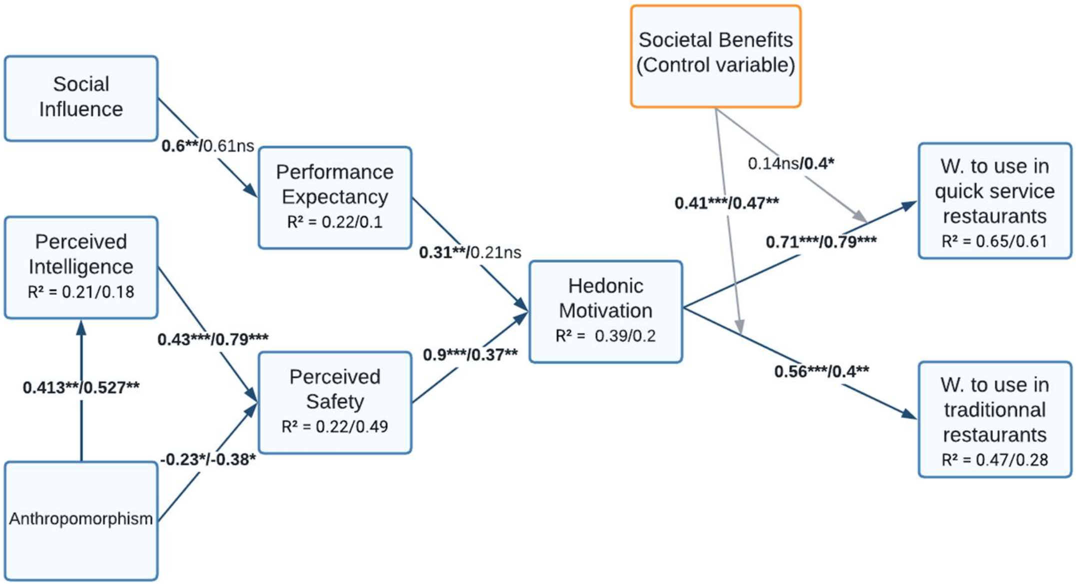
Figure 4. Results of the full model



Notes : Observations (n) = 170; Chi-Square = 715.37; Degrees of freedom = 363; RMSEA = 0.076; CFI = 0.882; TLI = 0.868; SRMR = 0.157; ****p-value < 0.001; **p-value < 0.01; *p-value < 0.05*

Overall, the indicators of the full model (Figure 4) provided a good fit. The Root Mean Square Error of Approximation (RMSEA) value of 0.076 indicates an acceptable fit, with values below 0.08 generally considered good. The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) values of 0.882 and 0.868, respectively, suggest an acceptable fit but may benefit from enhancement. The Standardized Root Mean Square Residual (SRMR) value of 0.157 indicates reasonable model fit. This structured model might give some insights to explain the willingness to use service robots in restaurants but it should be revised for further studies. In general, all the hypothesises were supported with a ρ value < 0.001 and had significant estimates. Among the relationships, the only negative relation is anthropomorphism to safety ($\beta = -0.354$, $\rho < 0.001$), the rest of the relationships were significantly positive. Among the stronger links, we can denote the significant impact of the exogeneous variable social influence on performance expectancy ($\beta = 0.663$, $\rho < 0.001$), the perceived intelligence has also a non negligeable impact on perceived safety ($\beta = 0.613$, $\rho < 0.001$). Finally it seems to be a higher relationship between the hedonic motivation and the willingness of use in quick services restaurants ($\beta = 0.745$, $\rho < 0.001$) than in traditional restaurants ($\beta = 0.509$, $\rho < 0.001$).

Figure 5. Results of Low Humanlike/High Humanlike (LH/HH) models



Notes on Low Humanlike scenario (LH) : Observations (n) = 90; Chi-Square = 736.779; Degrees of freedom = 363; RMSEA = 0.107; CFI = 0.819; TLI = 0.798; SRMR = 0.196; ****p-value < 0.001; **p-value < 0.01; *p-value < 0.05.*

Notes on High Humanlike scenario (HH) : Observations (n) = 80; Chi-Square = 585.471; Degrees of freedom = 363; RMSEA = 0.088; CFI = 0.817; TLI = 0.796; SRMR = 0.147; ****p-value < 0.001; **p-value < 0.01; *p-value < 0.05.*

Non significant (ns) *p-value* > 0.05

The Figure 5 represents the SEM of the 2 categories of human likeliness (LH and HH). HH outperformed LH in terms of RMSEA (LH = HH = 0.088) and SRMR (0.147), indicating slightly a better fit but both are higher than the threshold of 0.08, suggesting suboptimal fit. While both models did not meet the recommended threshold of 0.8 for TLI, indicating suboptimal fit, CFI reached this threshold of 0.8, suggesting a relatively better fit for the models in terms of overall comparative fit. Although the ratio of chi-square to degrees of freedom indicated reasonable fit, both models would benefit from refinement to achieve a more accurate representation of the observed data. Overall, the 2 different models have some weaknesses and provides a moderate fit.

Mostly all hypotheses are supported in the model (H1, H2a, H2b, H2c, H3, H4, H5a and H5b). However, There are some unsignificant relationships among the SEM in HH scenario. The social influence failed to explain the performance expectancy (H1) in HH scenario while it significantly explained it in LH scenario. Similarly, the performance expectancy (H2) failed also to explain the level of hedonic motivation (β = 0.31, ns) and it significantly explained it in

LH scenario ($\beta = 0.31$, $\rho < 0.01$). Given the indicators, HH scenario seems to explain a bit better the antecedents of willingness to use robots in restaurants than in LH scenario. There is a significant change in the relationship perceived safety to hedonic motivation in HH scenario ($\beta = 0.9$, $\rho < 0.001$) than in LH scenario ($\beta = 0.37$, $\rho < 0.01$). The control variable was assessed being not reliable in the LH model ($\beta = 0.14$, ns). In terms of willingness to use service robots in restaurants, the hedonic motivation predicts better the willingness to use in quick service restaurants in HH context ($\beta = 0.79$, $\rho = 0.001$) than in LH restaurants ($\beta = 0.71$ $\rho < 0.001$). On the other hand the variation of the hedonic motivation explains a higher proportion of the willingness to use in traditional restaurants in LH scenario ($\beta = 0.56$, $\rho < 0.001$) than in HH scenario ($\beta = 0.4$, $\rho < 0.01$). Among the other relationships, anthropomorphism is negatively related to the level of perceived safety ($\beta = -0.23$, $\rho < 0.05$) in LH and the relationship is even stronger in HH scenario ($\beta = -0.38$, $\rho < 0.05$). By computing the direct and indirect effects (Table 6), we can assess that social influence, anthropomorphism and performance expectancy all failed to explain the willingness to use service robots in restaurants (HH scenario), due to unsignificant indirect effects. Although, all of the variables in LH scenario have a significant indirect impact on the willingness to use robots in both traditional and quick service restaurants. Among the stronger indirect relationship, the perceived safety is indirectly highly linked with the willingness to use in quick service ($\beta = 0.62$, $\rho = 0.001$) and in traditional restaurants ($\beta = 0.51$, $\rho < 0.001$) in LH scenario. On the other hand, even if the Table 6 shows that we can assess that H2 is supported in both scenarios, anthropomorphism has a low total positive effect on safety ($\beta = 0.05$, $\rho < 0.05$). It suggests that overall, anthropomorphism has a low total effect on safety.

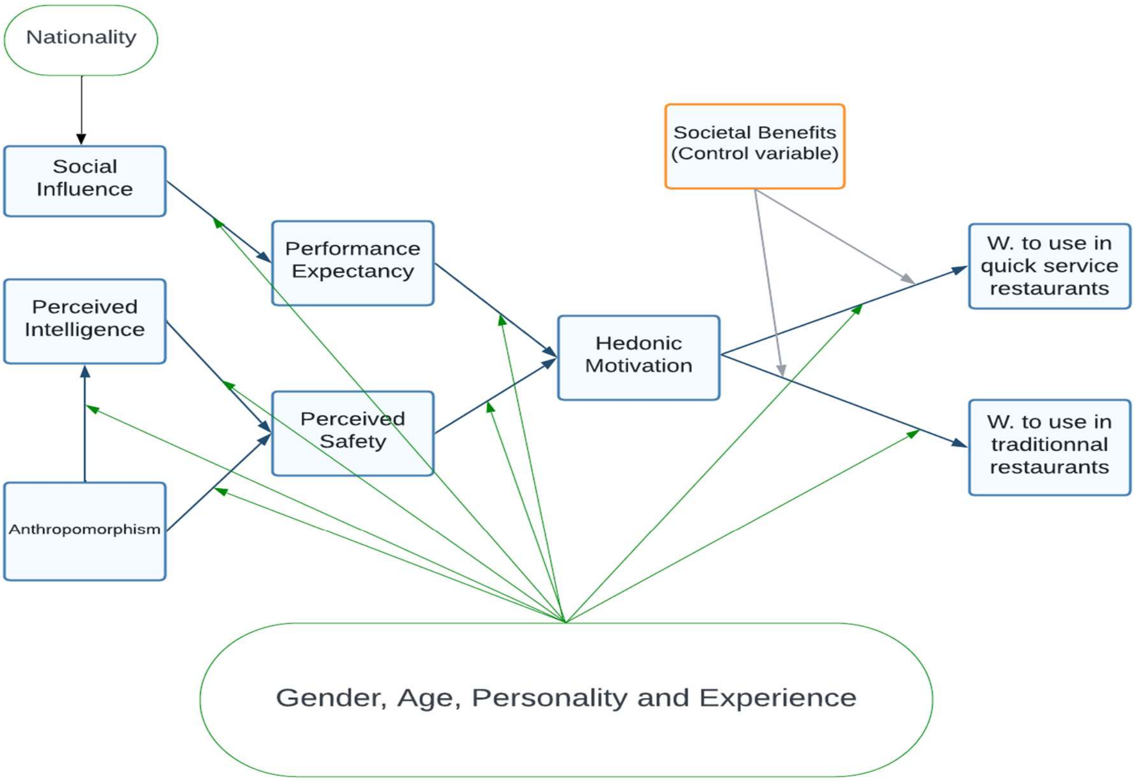
Table 6. Direct, indirect and total effects of the structural model

Pathways	LH Scenario			HH Scenario		
	Direct effects	Indirect effects	Total effect	Direct effects	Indirect effects	Total effect
Social Influence (SOI)						
SOI → PEF	0.6**		0.6**	0.61ns		0.61ns
SOI → HEM		0.18*	0.18*		0.13ns	0.13ns
SOI → WIQ		0.13*	0.13*		0.10ns	0.10ns
SOI → WIT		0.11*	0.11*		0.05ns	0.05ns
Anthropomorphism (ANT)						
ANT → SAF	-0.23*	0.28** (0.18)	0.05*	-0.38*	0.42**	0.04*
ANT → HEM		0.16*	0.16*		0.15*	0.15*
ANT → WIQ		0.11*	0.11*		0.12*	0.12*
ANT → WIT		0.09*	0.09*		0.06ns	0.06ns
Perceived Intelligence (INT)						
INT → HEM	0.43***		0.43***	0.79***		0.79***
INT → HEM		0.38**	0.38**		0.29**	0.29**
INT → WIQ		0.27**	0.27**		0.23**	0.23**
INT → WIT		0.22**	0.22**		0.12*	0.12*
Performance expectancy (PEF)						
PEF → HEM	0.31**		0.31**	0.21ns		0.21ns
PEF → WIQ		0.22**	0.22**		0.17ns	0.17ns
PEF → WIT		0.18*	0.18*		0.08ns	0.08ns
Perceived Safety (SAF)						
SAF → HEM	0.9***		0.9***	0.37**		0.37**
SAF → WIQ		0.62***	0.62***		0.29**	0.29**
SAF → WIT		0.51***	0.51***		0.15*	0.15*
Hedonic Motivation (HEM)						
HEM → WIQ	0.71**		0.71**	0.79***		0.79***
HEM → WIT	0.56**		0.56**	0.4**		0.4**

****p-value < 0.001; **p-value < 0.01; *p-value < 0.05*

5.4 Moderation effects

Figure 6. Structural model composed with socio-demographic constructs



We saw in the literature the importance of socio demographic constructs on the willingness to use robots. We want to check the effects of socio demographic constructs (Figure 6, Table 7) and how it affects our model. In order to do so, we added control variables like age, nationality, gender, experience and personality.

However, across all the different models, socio-demographic constructs failed to serve as control variables in the relationship between hedonic motivation and the willingness to use robots, in both quick service and traditional restaurants. The variable Nationality represents the people that have the Belgian nationality (=1) and the people from abroad (=0). The role of this variable is a bit different than the other socio demographic constructs because we set it as an exploratory variable and as a successful negative predictor of the level of social influence in LH scenario ($\beta = -0.67$, $\rho < 0.001$) and in full model ($\beta = -0.48$, $\rho < 0.001$) but it was not significant in HH scenario ($\beta = -0.19$, ns). This result means that Belgians are less socially influenced than the other nationalities. In HH scenario, we found a significant negative relationship between personality (Introvert =0 and Extrovert =1) and the perceived safety ($\beta =$

−0.4, ρ = 0.05), suggesting that the more introvert a person is, the more it will feel at ease with the service robot in HH scenario. It seems that the young generation is expecting less performance from the service robot in LH scenario (β = 0.6, ρ < 0.01) and they are also perceiving the service robot as less intelligent than the older generation in both LH scenario (β = 0.55, ρ < 0.001) and HH scenario (β = 0.55, ρ < 0.001). Women are also expecting robots from the first scenario to be less intelligent (β = −0.3, ρ < 0.05). In the end, we can't conclude that socio demographic constructs have a direct or indirect impact on the willingness to use robots, as coefficients were too low and unsignificant to find a reliable relation.

Table 7. Significant relationships of socio demographic constructs on latent variables

Significant relationships	*LH Scenario*	*HH Scenario*	*Full model*
Personality → Safety	0.22	**-0.4***	0.04
Nationality → Social influence	**-0.67*****	-0.19	**-0.48*****
Age → Performance Expectancy	**0.6****	0.06	0.29
Age → Intelligence	**0.55*****	**0.25***	**0.46*****
Gender → Intelligence	**-0.3***	0.07	-0.13

****p-value < 0.001; **p-value < 0.01; *p-value < 0.05*

6. Discussion

After analysing our different models, we can assess that both models of human-likeliness showed significant different results. Main observations are that anthropomorphism has a significant direct negative impact on the level of perceived safety, confirming some studies of the literature (Roesler et al., 2021; Schepers et al., 2022) . However, this impact appears to be mitigated by the perceived level of intelligence. This suggests that consumers who perceive the robot as intelligent are more likely to feel comfortable with the idea of interacting with it. This result aligns with the study of (Zhang et al., 2021) that found that a high sense of humour might diminish some negative emotions related to the service robot. Despite constituting a core factor within the UTAUT model (Venkatesh et al., 2003), the level of performance expectancy does not seem to create a level of hedonic motivation in the context of high human-like robots compared to the low-human-like context. It suggests that even if individuals think that the robot might perform, it does not necessarily mean that they will enjoy to interact with this robot that has a human appearance. From the Cognitive Dissonance Theory (Festinger, 1962), we can deduce that customers with a strong hedonic motivation for utilizing service robots are more likely to engage in a deliberate evaluation that favours the use of these robots. Concerning demography effects, we didn't find major effects of socio demographic constructs on willingness to use and its antecedents. Although, results of the socio demographic showed that on average, Belgians are less likely to be socially influenced than the rest of the world. We have to be careful with this interpretation because the people from abroad are coming from different countries and continents. Therefore it is likely to be a heterogeneous sample with a lot of different cultures. In Appendix 3, there is the evaluation from individuals of the strangeness exhibited by every robot. This might give us insights on the degree of likeability across the 2 groups of robots. The level of negative emotions is significantly higher for HH robots than LH robots. Despite this negative feeling, it does not seem influence too much the willingness to use robots in restaurants.

7. Contribution of the research and limitations

7.1 Theoretical contribution, limitations and suggestions

The study can contribute theoretically to the literature of technology acceptance and the Human-Robot interaction. It proposes a new structural model based on the 3 stages appraisal from Lazarus (1991), composed of factors carefully chosen and new hypothesises which were tested in order to determine the willingness to use in different contexts. It showed different results and different relations given the degree of human likeliness (LH and HH scenario). I focused on the appearance side but there are other aspects of human likeness. Robots might also be designed with other human likeliness features like languages, the voice or even the sense of humour similar to humans. Finally, technology acceptance can be examined from the perspective of consumers but also from employees. Further studies might investigate the acceptance of robots on the side of employees, if they think that robots might be beneficial for them.

7.2 Managerial implications, limitations and suggestions

The exploration of the antecedents of the willingness to use service robots in restaurants is also valuable for managers of restaurants that are planning to invest in it. We saw that the hedonic motivation is strongly positively related to the willingness to use service robots in quick service restaurants, more than in traditional restaurants, suggesting that owners of this kind of quick service restaurants should focus more on the entertainment side of consumers. In LH scenario, factors like social influence, performance expectancy, anthropomorphism, perceived safety and perceived intelligence are all indirectly positively related to the willingness to use service robots in both traditional and quick service restaurants. However in HH scenario, the findings didn't show significant results for the relations between social influence, anthropomorphism and performance expectancy to the willingness to use service robots in quick service restaurants and traditional restaurants. Further studies should investigate more deeply on HH service robots acceptance to see if it confirms our results or not. However, safety is also related to the willingness to use robots in restaurants, making this factor as a key factor in both contexts.

Further studies might also explore more the managerial aera and trade-offs faced by owners of businesses between engaging a robot with a high human aspect or low human aspect. It is crucial for managers to know which degree of human likeliness is optimal because the price of a service robot generally more expensive when it has human likeliness features. Investing in a robot with a high degree of human likeliness might be an optimal choice if managers want to get consumers that are willing to use the robot. However, it is always important that the appearance of the service robot does not fall into the uncanny valley, as it will be no longer accepted.

7.3 Survey and design limitations

The main limitation is that I didn't do a real experience in a restaurant. Respondents of the survey had to evaluate the given service robot through pictures but they didn't have the opportunity to interact with the robot. Moreover, while it is possible to rate some of our emotions based on pictures, I think it is quite challenging to judge the performance expectancy only given the appearance. I divided the two types of restaurants into quick service restaurants and traditional restaurants. However, every respondent has a broad and subjective view about the type of these 2 restaurants. It would be better for future researchs to conduct an experimental research in 2 concrete restaurants that are part of these categories. Similarly, I compared Belgians to the rest of the nationalities but it would be more relevant to compare Belgium with an another country to reduce heterogeneity.

8. Conclusion

In conclusion, our study provides insights for the willingness to use service robots in restaurants, it helps to understand the emotions and the reactions of consumers through a 3 stages appraisal. It showed that some factors are non-significant in HH scenario, suggesting that there is more work to be done on the real effect of the high level of human likeliness. In conclusion, this study delved into the factors influencing individuals' inclination to utilize humanoid service robots within quick service and traditional restaurant settings. Through a survey capturing insights from 170 respondents across nine latent variables and 29 items, we investigated the antecedents driving this willingness, encompassing social influence, performance expectancy, anthropomorphism, perceived intelligence, perceived safety, and hedonic motivation.

Drawing on a foundation of technology acceptance and Human-Robot Interaction (HRI) literature, we employed distinct Structural Equation Models (SEM) to analyse two categories of robots: Low Human-like service robots (LH) and High Human-like service robots (HH). The findings underscored intriguing nuances within the relationships among variables. The impact of anthropomorphism on perceived safety emerged as relatively limited across both robot types and restaurant scenarios. This challenges previous assumptions regarding the significance of anthropomorphism in fostering safety perceptions. Importantly, our study revealed a robust connection between hedonic motivation and the readiness to engage with service robots across both quick service and traditional restaurant contexts. This suggests that the pleasure derived from interacting with these robots plays a pivotal role in shaping individuals' acceptance and willingness to adopt this technology.

Comparatively, the LH model accentuated the role of social influence in evaluating robot capabilities, hinting that individuals may lean more heavily on social cues when assessing these robots' functionalities. Furthermore, the LH model emphasized the influence of performance expectancy on individuals' enjoyment of interacting with the service robot, underlining its role as a key determinant in shaping user experience.

The implications of these insights extend beyond academia, offering valuable guidance for researchers interested in advancing the Human-Robot Interaction field. Equally significant, these findings hold pragmatic relevance for business proprietors contemplating the integration of humanoid service robots within restaurant settings. Armed with this knowledge, stakeholders can make informed decisions that align with customer preferences and optimize the implementation of this innovative technology.

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10. Appendices

Appendix 1 : whole survey

Constructs	**Items**	**Mean (LH Scenario)**	**Mean (HH Scenario)**
Social Influence		3	2.98
SOI1	I would be willing to go to a restaurant which employs service robots if my friends are interested in doing so	3.66	3.73
SOI2	Going to restaurants that employ service robots will be a status symbol within my social networks	2.40	2.31
SOI3	People who are important to me may encourage me to visit a restaurant which employs service robots	2.96	2.91
Anthropomorphism		2.21	2.22
ANT1	The service robot has a mind of its own.	2.43	2.51
ANT2	The service robot is capable of reasoning.	2.57	2.50
ANT3	The service robot might experience emotions.	1.90	1.90
ANT4	The service robot has its own free will.	1.94	1.98
Perceived Intelligence		3.13	3.12
INT1	The service robot seems to be competent.	3.43	3.36
INT2	The service robot seems to be intelligent.	3.22	3.30
INT3	The service robot seems to be responsible.	3.29	3.25
INT4	The service robot seems to be sensible.	2.56	2.56
Performance Expectancy (compared to humans)		3.18	3.24
PEF1	The service robot is more accurate than human beings.	3.06	3.19
PEF2	The service robot would make fewer mistakes than human beings.	3.52	3.45
PEF3	The service robot is more consistent than human beings.	3.44	3.5
PEF4	The service robot can provide me better information than human beings.	2.68	2.83
Perceived Safety		3.64	3.37
SAF1	The service robot itself is safe (the design of the robot is safe to prevent accidents).	3.69	3.41
SAF2	The service robot makes me personally safe.	3.72	3.38
SAF3	The service robot does not bring me a safety hazard when I use it.	3.51	3.31
Hedonic Motivation		3.49	3.26
HEM1	I think that interacting with the service robot would be fun.	3.60	3.51
HEM2	I think that interacting with the service robot would be entertaining.	3.77	3.69
HEM3	I think that interacting with the service robot would be pleasant.	3.27	2.84
HEM4	I think that interacting with the service robot would be enjoyable.	3.33	3.00
Extrinsic Motivation		3.26	3.34

EXM1	Service robots might be profitable to the owner of the restaurant.	3.83	3.88
EXM2	Service robots will be profitable to society as a whole.	2.96	3.04
EXM3	Service robots can contribute to sustainable development.	3.01	2.96
EXM4	Service robots can contribute to the growth of the economy.	3.22	3.49
Willingness to use in quick service restaurants		3.49	3.28
WIQ1	I am likely to interact with this kind of service robots in a quick service restaurant.	3.57	3.46
WIQ2	I will feel happy to interact with this kind of service robots in a quick service restaurant.	3.37	3.05
WIQ3	I am willing to receive services from this kind of service robot in a quick service restaurant.	3.54	3.34
Willingness to use in traditional restaurants		2.52	2.52
WIT1	I am likely to interact with this kind of service robots in a traditional restaurant.	2.60	2.66
WIT2	I will feel happy to interact with this kind of service robots in a traditional restaurant.	2.44	2.38
WIT3	I am willing to receive services from this kind of service robot in a traditional restaurant.	2.52	2.53
Uncanny Valley construct		2.54	3.56
UNV1	The service robot looks creepy.	2.76	3.93
UNV2	The service robot looks uncanny (strange or mysterious, especially in an unsettling way).	2.70	3.49
UNV3	The service robot looks scary.	2.18	3.28
Empathy		2.75	2.87
EMP1	The service robot seems to have the consumer's interest at heart.	2.83	2.78
EMP2	The service robot seems sensitive to my individual needs.	2.98	3.21
EMP3	The service robot makes me feel special.	2.74	2.98
EMP4	The service robot looks sympathetic.	2.46	2.51
Reliability		3.73	3.65
REL1	The service robot will serve you in the time promised.	3.83	3.75
REL2	The service robot has the ability to correct quickly anything that is wrong.	3.41	3.39
REL3	The service robot will serve you food exactly as you ordered it.	3.93	3.83
Performance Expectancy		3.58	3.52
PE1	The service robot is accurate.	3.57	3.54
PE2	The service robot does not make mistakes.	3.21	3.08
PE3	The service robot is consistent.	3.77	3.63
PE4	The service robot can provide me accurate information.	3.79	3.83
Willingness to use in High Standard Restaurants		2.26	2.05
WIH1	I am likely to interact with this kind of service robots in a high standard restaurant.	2.34	2.15

WIH2	I will feel happy to interact with this kind of service robots in a high standard restaurant.	2.17	1.99
WIH3	I am willing to receive services from this kind of service robot in a high standard restaurant.	2.27	2.03
Expertise in AI		2.7	2.75
EXP1	I have studied or worked on AI devices such as service robots.	2.22	2.18
EXP2	I have had some experience with AI devices such as service robots.	3.39	3.58
EXP3	I am familiar with AI devices such as service robots.	2.48	2.51
Integration of service robots		3.44	3.65
INR1	Assigning routine tasks to robots lets people do more meaningful tasks.	3.64	3.93
INR2	Dangerous tasks should primarily be given to robots.	3.37	2.58
INR3	Robots are a natural product of our civilization.	3.08	3.07
INR4	Robots are necessary because they can do jobs that are too hard or too dangerous for people.	3.43	3.64
INR5	Robots can make my life easier.	3.67	4.05

Appendix 2 : Scenario

The scenario was the same for every service robot :

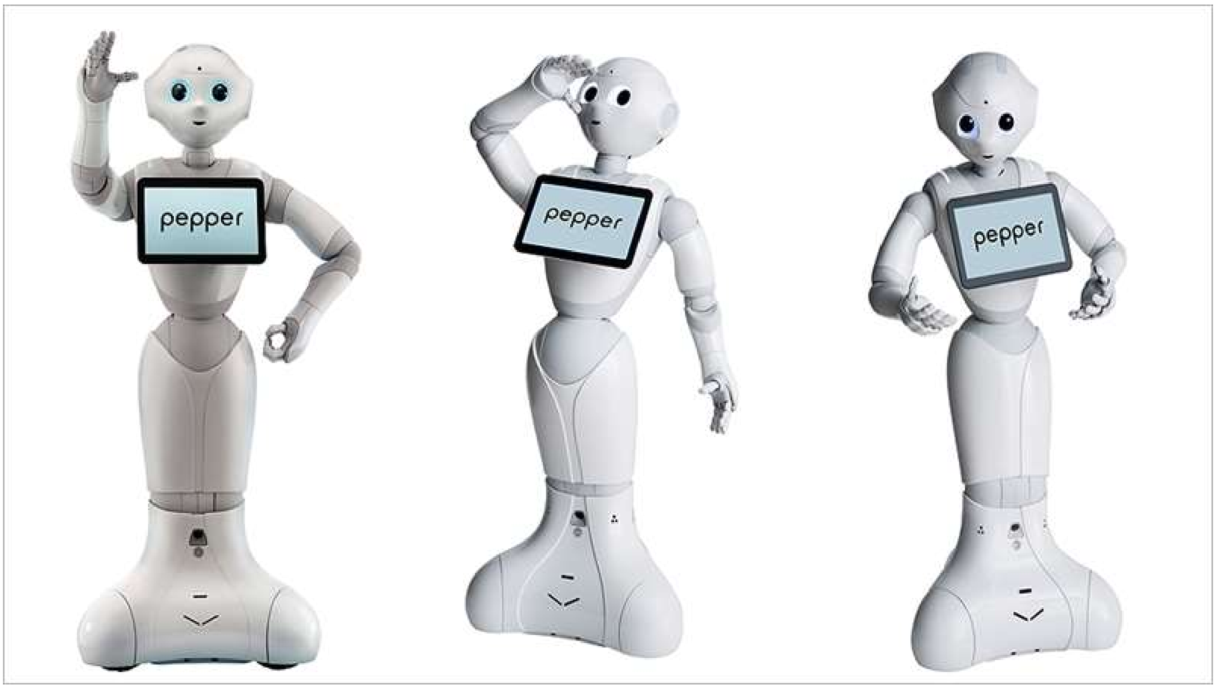
"SITUATION 1/2/3/4: Imagine that you booked a casual restaurant for dinner with your family or friends. As you enter the restaurant, you notice that the establishment has introduced a new service robot (name of the robot) as a waiter to enhance the dining experience.

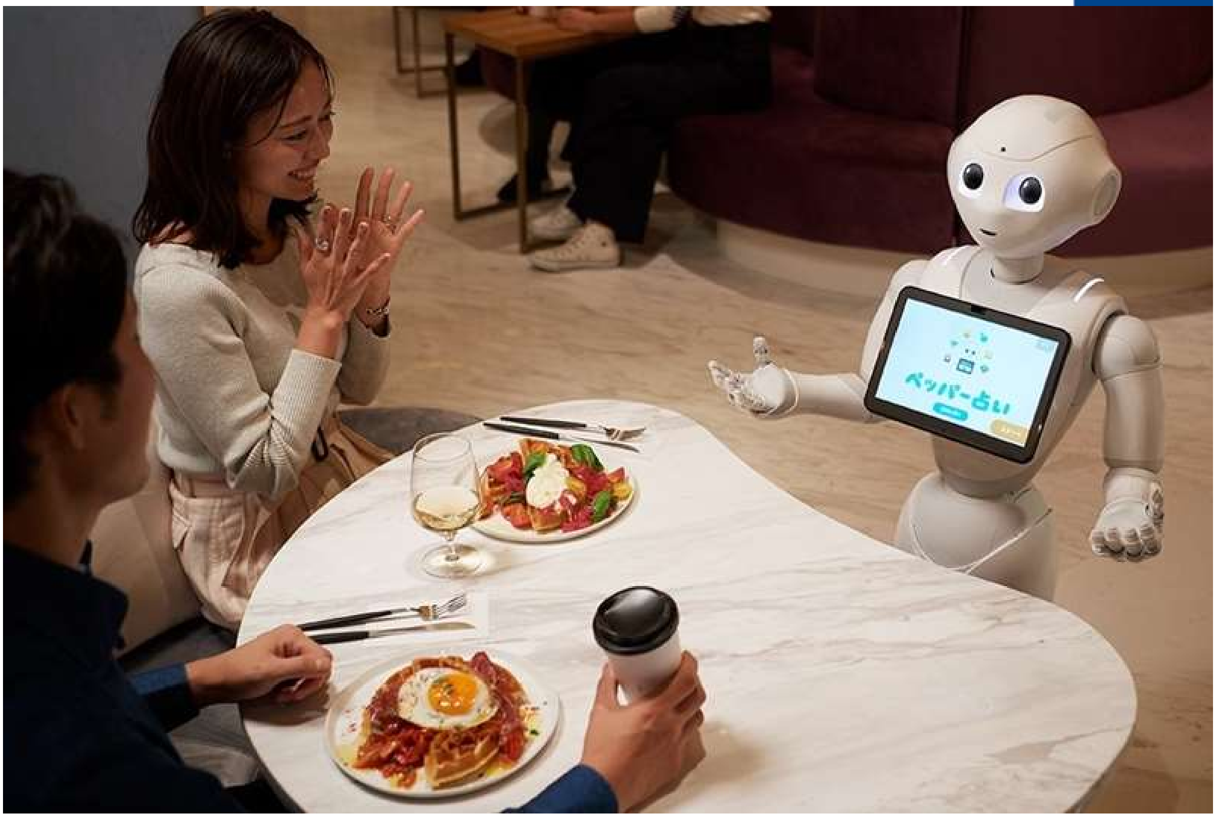
Note that you were not aware that this service robot would be working at the restaurant. We also showed a range of pictures of the different robots."

Along with this situation, we also gave some pictures of every robot (Cruzr, Pepper, Sophia and Erica) :

Pictures of Cruzr (Situation 1)

Pictures of Pepper (Situation 2)





Pictures of Sophia (Situation 3)

Pictures of Erica (Situation 4)

Appendix 3 : Uncanny valley

Given the degree of human likeliness of the four service robots in table 3, The emotional reactions should be negative for Erica and Sophia and it should be positive for Cruzr and Pepper.

Table

Uncanny Valley construct		**2.54**	**3.56**
UNV1	The service robot looks creepy.	2.76	3.93
UNV2	The service robot looks uncanny.	2.70	3.49
UNV3	The service robot looks scary.	2.18	3.28

Graph