



Customers' Intentions to Use Restaurants with Robot Waiters: An Extension of the Technology Acceptance Model

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Abstract

Service robots are growing to solve industrial labor shortages; however, how customers respond to robot waiters remains unclear. This study aims to better understand restaurant robot waiters' acceptance and continuous use. A survey was disseminated using social media networks and QR codes on location. From the 1070 responses received over 2 months, 415 were validated and proceeded with data analysis. Maximum likelihood estimation technique/CB-SEM was applied to assess the conceptual model. All underlying assumptions have been checked and successfully validated. The results show that only 52.6% of respondents visited a restaurant with robot waiters. The findings confirm that innovativeness, enjoyment, and hygienic handling positively influence the behavioral intention to continuous use. The positive influence of trust, risk, and willingness to pay more upon attitude were not supported. Applying an extended TAM produced novel and valuable insights on robot waiter acceptance. A new food safety construct under the TAM model was successfully added. Restaurant managers are suggested to increase the number of customers via an intensive and diversified advertising strategy and improve the dining experience by investing in more sophisticated robots in terms of the look and tasks performed.

Keywords Technology acceptance · Service robot · Customer behavior · Social influence · Food safety

Introduction

Along with the development of the modern digital age, currently under the fifth industrial revolution, innovative technologies are becoming increasingly popular (Schwab, 2017), and their improvement not only simplifies life routines but also saves valuable human resources. Artificial intelligence and automated and robotic services are now widely used in several sectors, such as industry, tourism, and

healthcare systems, among others (Fang et al., 2023; Roy et al., 2024; Zhang, 2022).

According to the International Federation of Robotics, a service robot refers to “a robot that performs useful tasks for humans or equipment” (International Federation of Robotics, n.d.). This creates a competitive advantage for service industry participants who have proactively adapted to a changing environment by differentiating themselves with the aid of new technologies (Roy et al., 2024; Santiago et al., 2024).

Service robots are designed to interact with humans in safe and useful modes. A “cobot,” or collaborative robot, is a service robot that works with humans to accomplish tasks. It can be controlled or autonomous and is already found in several industries, such as manufacturing, healthcare, tourism, and agriculture (Espí-Beltrán et al., 2017).

The use of robots in restaurants can provide benefits such as increased efficiency and productivity and improved safety and sanitation. However, a recent study highlighted the importance of continuously improving service quality to meet customer demands and reshape customer experiences (Ma et al., 2023). Therefore, understanding customer reactions is crucial, as they are influenced by factors such as acceptance, satisfaction, enjoyment, novelty, perceived relevance, humanoid appearance, and communication (Chen & Girish, 2023; El-Said & Al Hajri, 2022; Huang & Liu, 2022; Santiago et al., 2024).

Despite its potential, robotic restaurant service is still in its developmental stages (Wang & Wu, 2024), with studies pointing out some resistance from customers to being served by a robot instead of by a human being despite the service provided demonstrating an equivalent degree of quality, making it particularly important to examine the conditions that could lead to adverse customer reactions and how to surpass them. This study introduces an innovative focus on the concept of hygienic handling, a critical factor in shaping customer perceptions of robotic service systems. Inspired by social media controversies surrounding customers’ alleged misconduct towards robot-delivered food in Far Eastern restaurants, this research highlights how such interactions may influence customer satisfaction and overall experience in robotic service environments. The scope of this problem is particularly relevant in contexts where the use of robots is intended to enhance service efficiency, hygiene, and novelty (Kim et al., 2022). Customer satisfaction in robotic service contexts is intricately tied to the trustworthiness and perceived reliability of the robotic systems (Choi et al., 2021). Negative incidents, such as contamination or perceived mishandling of food by customers, can undermine the intended benefits of robotic services, leading to a deterioration in customer trust and a reduced likelihood of repeat patronage. Moreover, customer experience is not only limited to the functional aspects of service but also extends to the emotional and social dynamics involved, particularly in scenarios where robots interact with customers directly or indirectly (Wirtz et al., 2018). By addressing hygienic handling as a central theme, this study emphasizes the dual importance of ensuring proper protocols in robot-human-food interactions and fostering a positive emotional response from customers.

To maximize the potential of robotic restaurant services, marketing strategies should highlight their innovative and unique dining experiences to attract customers

and enhance acceptance. Accordingly, the current study addresses the following research questions (RQ):

- RQ1—What factors most influence customer perceptions of robotic waiters in restaurants?
- RQ2—How does the perceived hygienic handling of restaurant robotic waiters impact customers' behavioral intentions?
- RQ3—What marketing strategies can robotic restaurant managers implement to enhance customer acceptance?

This work has been structured in six major parts: the introduction explains the context of the study, and it puts forward the research questions. The “[Theoretical Background](#)” section presents the literature review describing the conceptual TAM-based model and the constructs added to the extended form of this model, which encompasses handling hygiene as a new construct. The “[Method](#)” section presents the methodology, including the empirical research model, the participants, procedures, and data analysis. The “[Results](#)” section conveys the results, followed by the discussion of results in the “[Discussion](#)” section. Lastly, the conclusions illustrate meaningful theoretical and practical limitations, and suggestions for future research in the area are provided in the “[Conclusions](#)” section.

Theoretical Background

Robot Services in Restaurants

Since the beginning of the 1970s, technological devices have been used to improve the performance of restaurants. This trend started in Japan, where food was served by vending machines, with customers ordering it directly from them. A few years later, robotic services were introduced in the restaurant business, handling online queries and consumer questions. In 2011, there were approximately 7000 restaurants all over Europe with screens meant to order (Ivanov & Berezina, 2017). More recently, restaurants have fully or partially automated services. The current study is focused on restaurants that use robots to replace human beings in the distribution and delivery of meals—they are called robot waiters or waiter robots (Garcia-Haro et al., 2021).

Although the adoption of robot waiters in restaurants is still a relatively new trend in the world, many businesses have already recognized the benefits of this technology in terms of productivity, customer satisfaction, and cost-effectiveness (Mene-gaki & Tiwari, 2023). One of the most significant benefits is that robot waiters can execute repetitive tasks with high reliability and quality, besides enhancing food safety and sanitary management (Grobbelaar et al., 2021) while lowering manpower and training expenses in restaurants. Additionally, they aid businesses in countries with severe labor shortages (Sawadwuthikul et al., 2022). The physical environment inside a restaurant is continuously changing, so a robot waiter must identify and avoid obstacles, including tables, chairs, customers, and other robots. Consequently,

a robot waiter must possess basic abilities for movement, manipulation, environmental sensing, and social interaction (Grobelaar et al., 2021; Sawadwuthikul et al., 2022). Some of these new social robot waiters are quite like personal robots, meant to move around the house (dynamic environments for humans) and verbally or even physically interact with humans (Garcia-Haro et al., 2021).

The global restaurant service robot market is expected to expand between 2021 and 2026 at a (compound) annual growth rate of 12.7%. This trend is anticipated to continue rising in the upcoming years, thanks to trailblazers who invest in technology and innovation and thus help transform how consumers view food and restaurants worldwide (Chinese Academy of Cyberspace, 2023). According to market research data, the Asia–Pacific region is anticipated to dominate the restaurant robots market expansion, driven by a rising demand for efficiency and automation in nations like China and Japan. Other regions of the world, namely Europe and Latin America, are starting to use robots in restaurants (Mordor Intelligence, 2021). In Portugal, there are currently only nine restaurants with robot waiters; the first one opened in 2018, and most of them use the type of model shown in Fig. 1.

Although robotic services have been introduced successfully at restaurants, several drawbacks have arisen. Together with keeping the machinery in top shape, it is essential to invest in the infrastructure and train staff members in charge of the robots. Another crucial element is preserving a healthy balance between automation and human experience to make sure that the presence of robots does not adversely affect a significant component of the whole dining experience. Despite the rise of interest in robot waiters, there is still scarce research on this topic, as no study with direct implications for Portuguese restaurants and their customers was found.

Theoretical Framework and Hypothesis Development

Technology Acceptance Model

The technology acceptance model (TAM) is an information systems theory that explains users' acceptance of technology (Davis, 1985, 1989). Davis (1985) states that the user's attitude toward technology is one of the main determinants of whether they will use or reject the system. User attitude, in turn, is influenced by two human perceptions: perceived usefulness and perceived ease of use. The author hypothesized that the characteristics of technology directly influence both perceptions and that the behavioral intention to use a system or application always precedes its actual use.

TAM has been used to explain how attitude toward robot use influences behavior intention when exploring information technology usage behaviors (Hwang et al., 2019; Park & del Pobal, 2013). Attitude was defined by Ajzen (p.188) as "the degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior" (Ajzen & Fishbein, 1977). From this point of view, it is a positive or negative feeling that an individual has when he or she behaves in a particular way (Ajzen, 1991). Therefore, behavioral intention can be considered a consequence of the attitudes that consumers develop through information processing and the perceptions



Fig. 1 Robotic waiter used in Portuguese restaurant

of the benefits they derive from using robots, which can mitigate their objections to eventual use (Alghamdi et al., 2018; Hwang et al., 2020; Oliver, 2014). For Oliver (p.28), behavioral intention refers to “a stated likelihood to engage in a behavior” (Oliver, 2014) and is a key concept in the TAM model denoting the degree to which an individual intends to use a particular technology (Alharbi & Drew, 2014; Chao, 2019).

Besides the attitude affecting behavioral intention, it is necessary to understand whether it influences the actual use of a system. The influence of behavioral intention on the whole process that stems from the attitude regarding going to the robotic restaurant is an important issue. To comply with previous research, in this study, the construct of *actual use* was changed to continuous use (Lawkobkit & Speece, 2012). The corresponding “continuous use” is the user’s intention to continue using or stop using the product or service. It is understood that consumers are willing to continue using robotic restaurants if the previous service expectation matches the experience performance.

The TAM’s perceived usefulness construct portrays how much individuals believe a given technology can improve productivity or performance in some work tasks or how much they will benefit when performing a task (Davis, 1989). Previous studies have shown that the greater the perceived usefulness of a technology, the greater the intention to use the technology (Xia et al., 2018). It is also assumed that the greater the perceived usefulness, the greater the attitude toward the intention to adopt a specific behavior (Kurtz et al., 2015).

The other construct in the TAM model is perceived ease of use. Perceived ease of use was defined by Davis (p.82) as “the degree to which an individual believes that using a system will be free of physical and mental effort” (Davis, 1989). It involves the individual’s belief about how easy or effortless the task of learning to use technology is, and it has been shown to be important in innovation diffusion in general. Since effort is a finite resource that a person can allocate diversely, technology that is easier to use among the available options is more likely to be accepted and adopted by consumers (Chien et al., 2019; Davis, 1989). Several studies showed that while difficulty of use may discourage the use of technology, no ease of use can compensate for a technology that does not perform a proper function. For instance, Davis (1989) highlighted that perceived ease of use is a critical determinant of perceived usefulness in the TAM model, as users are more likely to recognize the benefits of technology if they find it intuitive and easy to operate.

Based on the facts discussed, the following hypotheses regarding the core TAM model are proposed:

- H1:** Perceived ease of use positively influences consumers’ perceived usefulness of robot waiters.
- H2:** Perceived ease of use positively influences consumers’ attitudes toward using restaurants with robot waiters.
- H3:** Perceived usefulness positively influences consumers’ attitudes toward using restaurants with robot waiters.
- H4:** Perceived usefulness positively influences consumers’ behavioral intention to use restaurants with robot waiters.

H5: Attitude positively influences consumers' behavioral intention to use restaurants with robot waiters.

H6: Behavioral intention positively influences consumers' continuous use of restaurants with robot waiters.

Extended Technology Acceptance Model

Over time, distinct extended TAM models have been developed to enhance the original TAM's explanatory power and contextual relevance by incorporating additional constructs. The extended models allowed researchers to better understand technology acceptance and usage in various domains and provided a more comprehensive framework for studying user behavior towards technology (Alalwan et al., 2018; Chung & Kwon, 2009; El-Said & Al Hajri, 2022; Hwang et al., 2019, 2020; Lee et al., 2018; Sujood et al., 2022; Teo & Noyes, 2011; Tseng & Wang, 2016). As explained below, the current study also considers some of those constructs, such as perceived innovativeness, enjoyment, trust, risk, and willingness to pay more.

Prior empirical studies unfolded the effect of perceived innovativeness on attitude and behavioral intention. This study considers perceived innovativeness, as defined by Hwang et al. (p. 95), as "the degree to which the consumers believe that a product has important attributes of innovation, such as newness and uniqueness" (Hwang et al., 2019). The perception of innovation is a reward for the effort made by the company to meet the needs of consumers, who are always eager to have new technology-based services. When consumers perceive a high level of innovation from a new product/service, they tend to be more prompt to use the new product/service. Along with the original variables of the TAM, perceived innovativeness plays a positive role in forming attitudes and behavioral intentions regarding using new technology (Hwang et al., 2019). Cha (2020) and Rasheed et al. (2023) recently showed that perceived innovativeness could enhance consumers' attitudes toward technology, increasing their willingness to interact with restaurant robots.

Regarding perceived enjoyment, several studies on technology acceptance revealed that enjoyment determines the acceptance of a new information technology, highlighting also its relationship to the positive attitude of a user (Ajzen & Fishbein, 1977; Fishbein & Ajzen, 1972). Recently, Hwang et al. (2019) found that perceived enjoyment significantly impacted consumers' attitudes towards robot service, while Cha (2020) showed that perceived enjoyment plays a significant role in shaping individuals' behavioral intentions. When individuals perceive an activity or system as enjoyable, they are more likely to have a positive intention to use it. Understanding the relationship between perceived enjoyment and behavioral intention can help design and promote systems and services that are simultaneously engaging and enjoyable for users. For the context of the current study, we resorted to the definition by Zhou and Feng (2017), who have admitted that perceived enjoyment refers to the degree of enjoyment perceived while using video calling in leisure, independent of any expected outcome.

The relationship of trust built between the consumer and the restaurant is an important factor in predicting consumer behavior in the context of restaurant service robots. The current study adopted the definition of perceived trust by Liu et al. (p.6),

which is “the extent to which one believes the technology usage will be reliable and credible” (Liu et al., 2021). It is based on reliability metrics and conveys information to the consumer about the new technology that is to be used, thus reducing information asymmetry and acting as a sign of service quality (Lee et al., 2018; Seo & Lee, 2021; Shaker et al., 2021). Liu et al. (2021) indicated that trustful relationships with service providers are vital to increasing technology adoption because this construct reflects a person’s belief that the use of technology is secure and absent of privacy threats. Further research shows a positive relationship between customers’ perceived trust and attitude toward emerging technology products (Martin et al., 2015; Slade et al., 2015).

The perceived risk significantly influences consumers’ adoption of technologies encompassing new services (Seo & Lee, 2021). Consumers who face a new technology may perceive high levels of psycho-physiological risks, such as fear, hesitation, and even some negative feelings (Morosan, 2012). The definition of risk has a multi-dimensional context (Sohn et al., 2016). In the current study, perceived risk refers to “consumers’ perceptions of the uncertainty involved when the seriousness of undesirable consequences is a result of their behaviors,” as Seo and Lee (p. 5, 2021).

According to Hwang et al. (p. 4, 2020), willingness to pay more refers to “the maximum price a customer intends to pay for a product/service.” Indeed, it is acknowledged that small price adjustments can profoundly impact consumers’ attitudes, especially when exceeding the maximum price accepted by the consumer. Hence, understanding how much more consumers are willing to pay for bespoke services is crucial for pricing decisions, marketing communication, and new product development (Sarlay & Neuhofer, 2020).

Accepting the previous theoretical evidence related to the extended TAM model, the following hypotheses are put forward:

- H7:** Perceived innovativeness positively influences consumers’ attitudes toward using a restaurant with robot waiters.
- H8:** Perceived innovativeness positively influences consumers’ behavioral intention to use a restaurant with robot waiters.
- H9:** Perceived enjoyment positively influences consumers’ attitudes toward using a restaurant with robot waiters.
- H10:** Perceived enjoyment positively influences consumers’ behavioral intention to use a restaurant with robot waiters.
- H11:** Perceived trust positively influences consumers’ attitudes toward using a restaurant with robot waiters
- H12:** Perceived risk negatively influences the consumers’ attitudes toward using a restaurant with robot waiters
- H13:** Willingness to pay more positively influences consumers’ attitudes toward using a restaurant with robot waiters

Handling Hygiene as a New Construct in the Extended TAM

Although food safety plays an important role in the restaurant industry, little research focuses on the impact on food handling issues from human beings

being replaced by robots (Wang et al., 2022). Traditionally, hygienic handling knowledge has been seen as an important factor in improving food safety behavior (Moreb et al., 2017; Osaili et al., 2021; Rifat et al., 2022). The relationship between food safety knowledge, attitude, and practice is complex and varies depending on the context. While knowledge and attitude are important factors in reducing the incidence of foodborne diseases, they do not always translate into good food handling practices. Consumers in Europe and North America have greater knowledge about food safety risks than in other countries (Marklinder et al., 2020; Nesbitt et al., 2014; Samapundo et al., 2016; Tomaszewska et al., 2018). The construct of hygienic handling comprises the control of contamination, covering actions aimed at improving hygiene, such as environmental and personal hygiene practices, based on some studies made for human employees (Baş et al., 2006; Madaki & Mirosława, 2021; Zanin et al., 2021). Considering the little evidence available, we venture to propose that:

H14: Hygienic handling positively influences consumers' attitudes toward using a restaurant with robot waiters.

H15: Hygienic handling positively influences consumers' behavioral intention to use a restaurant with robot waiters.

Research Model

Based on the above rationale, the conceptual framework guiding the study is presented in Fig. 2.

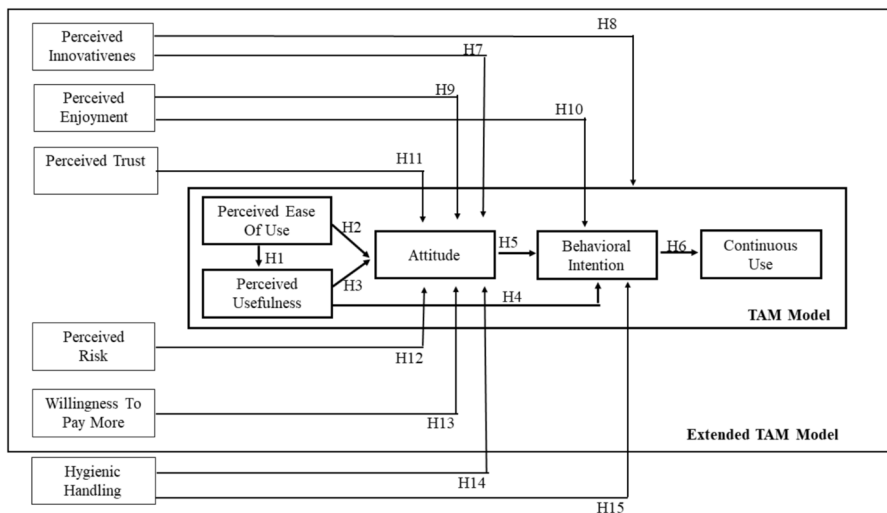


Fig. 2 Conceptual model and hypotheses

Methods

Research Instrument

The questionnaire used to collect data consisted of four sections. Section A explained the context of the study, approval by the University Ethic Committee (No. 140/2023), and a consent question (yes/no) for the use of data for research purposes only. Section B presented three questions about participants' compliance with new technologies and robot waiters. The survey had 35 statements measured on a 7-point Likert scale (from "totally disagree" to "totally agree") to evaluate the items applied to the context of the use of robot services by extended TAM, previously validated in several studies (Alalwan et al., 2018; Baş et al., 2006; Biswas, 2022; Cha, 2020; Huang et al., 2021; Hwang et al., 2020; Madaki & Miroslava, 2021; Sujood et al., 2022; Yan et al., 2022). Translation to Portuguese and back-translation were performed according to the best practice (Durán-Muñoz, 2010; Jansen et al., 2006). The statements were presented to all participants in the same order, and three questions were added to reduce acquiescence biases (Podsakoff et al., 2003). The socio-demographic characteristics of participants (e.g., age, gender, educational level, and income) were finally ascertained in section D.

Data Collection

The data collection took place from May to July of 2023 via a web survey conducted using the LimeSurvey software v.2.57.1. Invitation links for the survey were sent by social and professional networks (Facebook, WhatsApp, Instagram, and LinkedIn) and by email to all Portuguese universities. Additionally, QR codes were made available in two restaurants in Porto with robot waiters. The answers obtained were exported from the LimeSurvey platform to Microsoft Excel 365.

Participants

Of the 1070 responses received, only 415 were validated for data analysis. The remaining data was dismissed due to several reasons: (i) did not authorize their participation in the study ($n=75$); (ii) had never been to a restaurant with robot waiters ($n=444$); did not respond well to the three acquiescence questions ($n=85$); and did not complete the full questionnaire ($n=51$). The database had no missing value. The descriptive analysis of participant profiles was performed using IBM SPSS software (v. 29 Armonk, NY: IBM Corp). The characteristics of the sample are depicted in Table 1.

Measurement Model Validation

The fit of the measurement model was evaluated by Confirmatory Factor Analysis (CFA) with the IBM AMOS software (v. 28.0 Armonk, NY: IBM Corp) via the application of Maximum Likelihood Estimation to estimate the model parameters

Table 1 Descriptive statistics ($N = 415$)

Demographic characteristics	Frequency	%
Age		
[18, 19]	43	10.4
[20, 29]	171	41.2
[30, 39]	95	22.9
[40, 49]	56	13.5
[50, 59]	37	8.9
[60, 69]	11	2.7
[70, 79]	2	0.5
Gender		
Male	195	47.0
Female	217	52.3
Other	3	0.7
Education		
Basic school	1	0.2
High school	60	14.5
Bachelor's degree	247	59.5
Master's degree	89	21.4
Ph.D.'s degree	18	4.3
Annual income (€)		
None	115	27.7
≤ 7479	81	19.5
[7479; 11,284]	63	15.2
[11,284; 15,992]	50	12.0
[15,992; 20,700]	39	9.4
[20,700; 26,355]	31	7.5
[26,355; 38,632]	16	3.9
[38,632; 50,483]	15	3.6
[50,486; 78,384]	5	1.2
$> 78,384$	0	0.0
Frequency of use of technological equipment		
Rarely a year	5	1.2
At least once every month	7	1.7
At least once a week	29	7.0
Daily	374	90.1
How long the use of restaurants with service robots		
Less than 1 year	239	57.6
Between 1 and 3 years	115	27.7
More than 3 years	61	14.7

(Arbuckle, 2016; Marôco, 2021). All factor loadings were found to be greater than 0.707. No multivariate outliers were identified using the squared Mahalanobis distance (D2) (Fornell & Larcker, 1981), and the normality of the variables was not violated using criteria $l_{skl} < 2$ and $l_{kul} < 5$ (Collier, 2020; Marôco, 2021). Finally, the fit quality was increased by the correlation between errors within each construct with the highest Modification Indices (Arbuckle, 2016; Marôco, 2021). The model was therefore examined for construct reliability (Cronbach's alpha and composite reliability) and convergent and discriminant validity.

Structural Model Assessment

After assessing the reflective measurement, multicollinearity was verified within all independent constructs using the variance inflation factor (VIF) within IBM SPSS. The data analysis was followed by correlational relationships among constructs using structure equation modeling (SEM) and AMOS software. The statistical significance of the structural coefficients was evaluated with a Z test (Critical Ratio and p -value). Parameter estimates with $p < 0.05$ were considered statistically significant.

Results

Measurement Model Assessment

No items were removed since all values presented adequate loading values (> 0.707) according to Collier (2020) and Marôco (2021) guidelines (see Table 2). This table also shows that the constructs were reliable according to Cronbach's α and composite reliability (CR) values, with values above 0.7 (Collier, 2020; Marôco, 2021). It was also found that there was discriminant validity (see Table 3) when checking that almost all correlation values between constructs lie below the root of average variance extracted (AVE) proposed in the Fornell-Larcker criterion (Fornell & Larcker, 1981), although small non-conformities were associated with the usefulness (U) construct. However, further analysis of the cross-loadings matrix (available from the author on request) revealed that the indicators loadings on the construct are higher than the loadings on all other constructs. Furthermore, the analysis of the residuals covariance matrix also revealed that the items are much more related to the usefulness construct than any other construct in the model. Based on this additional information, we conclude that discriminant validity was not severely hampered so that the structural model analysis may be conducted.

According to several authors (Arbuckle, 2016; Collier, 2020; Hair et al., 2019; Marôco, 2021), a good fit of the measurement model was obtained based on the overall index $\chi^2/df = 2.457$ (acceptable if within [2,5]), the goodness of fit index (GFI) = 0.850 (sufficient if within [0.8, 0.9]), comparative fit index (CFI) = 0.952 (very good if ≥ 0.95), normed fit index (NFI) = 0.923 (good if within [0.90, 0.95]), parsimony-corrected fit index (PCFI) = 0.802 (very good if ≥ 0.8); and root mean square error of approximation (RMSEA) = 0.066 (acceptable if within [0.05, 0.08]).

Table 2 Results from the validation of the fit of the measurement model

Construct	Measurement Item	Code	Loadings	Cronbach's α	CR	AVE
Perceived innovativeness	The restaurant service robot seems new	I1	0.816	0.871	0.868	0.701
	The restaurant service robot seems original	I2	0.838			
	The restaurant service robot seems unique	I3	0.858			
Perceived enjoyment	The interaction with the service robots in the restaurant is fun	E1	0.827	0.856	0.895	0.666
	The interaction with the service robots in the restaurant makes me happier	E2	0.832			
	The interaction with the service robots in the restaurant seems to make my life pleasant	E3	0.788			
Perceived Trust	I trust in the service robot in restaurants	T1	0.935	0.914	0.917	0.822
	The service robot in restaurants is reliable	T2	0.918			
	The robot serves food/drinks without mistakes (error-free)	T3	0.865			
Perceived ease of use	Using the service robot does not require a lot of mental effort	EU1	0.733	0.856	0.842	0.665
	My interaction with the service robot was understandable	EU2	0.826			
	It was easy to learn how to use the service robot	EU3	0.739			
Attitude	I have a favorable attitude toward the restaurant service robot	A1	0.928	0.957	0.952	0.855
	I have a good feeling about the restaurant service robot	A2	0.914			
	I have a positive attitude about the restaurant service robot	A3	0.927			
	It is a good idea to use the restaurant service robot	A4	0.929			
Behavioral intention	I will recommend a service robot for other people	BI1	0.931	0.945	0.917	0.853
	I will say positive things about a service robot to other people	BI2	0.945			
	I will encourage friends and relatives to visit a service robot	BI3	0.894			
Continuous use	I am open to using the restaurant service robot in the near future	USE1	0.929	0.954	0.937	0.874
	I am likely to use the restaurant service robot in the near future	USE2	0.949			
	I will use the service robot when ordering food in the restaurant	USE3	0.927			
Construct	Measurement Item	Item Code	Item loading	Cronbach's α	CR	AVE
Perceived	Service robot is useful in a restaurant	U1	0.888	0.823	0.787	0.689

Table 2 (continued)

Construct	Measurement Item	Code	Loadings	Cronbach's α	CR	AVE
Usefulness	Service robot is likely to shorten delivery times in a restaurant	U2	0.790			
	Service robot is able to perform the same function as a regular employee	U3	0.811			
Perceived risk	A robotic restaurant does not seem to perform well	R1	0.920	0.960	0.851	0.890
	I think that making an order with the restaurant service robot is risky	R2	0.971			
	The probability that something's wrong with the performance of a robotic restaurant is high	R3	0.939			
Willing to pay more	I am likely to pay more for a robotic restaurant	WPM1	0.907	0.945	0.816	0.855
	It is acceptable to pay more for a robotic restaurant	WPM2	0.926			
Handling hygiene	I am likely to spend extra in order to use a robotic restaurant	WPM3	0.941			
	The probability of food contamination with the performance of a service robot is low	HH1	0.821	0.813	0.757	0.562
	The hygienic handling of dishes is the same whether served by a service robot or by an employee	HH2	0.799			
	Table service is related to food hygiene	HH3	0.818			
The service robot appears to carry the food hygienically		HH4	0.751			

CR composite reliability, AVE average variance extracted

Table 3 Discriminant validity

	I	E	T	EU	A	BI	USE	U	R	WPM	HH
I	0.837 ^a										
E	0.231	0.816									
T	0.794	0.245	0.907								
EU	0.791	0.305	0.899	0.815							
A	0.814	0.182	0.856	0.827	0.925						
BI	0.842	0.109	0.803	0.783	0.839	0.924					
USE	0.770	0.124	0.770	0.696	0.771	0.872	0.935				
U	0.819	0.218	0.915	0.863	0.890	0.871	0.843	0.830			
R	0.299	0.026	0.295	0.271	0.280	0.279	0.271	0.255	0.943		
WPM	0.468	0.057	0.485	0.455	0.530	0.529	0.535	0.599	0.012	0.925	
HH	0.731	0.185	0.751	0.713	0.733	0.778	0.752	0.825	0.200	0.716	0.750

^aSquare root of AVE (along the diagonal); *I*, innovativeness; *E*, enjoyment; *T*, trust; *EU*, ease of use; *A*, attitude; *BI*, behavioral intention; *USE*, continuous use; *U*, usefulness; *R*, risk; *WPM*, willing to pay more; *HH*, handling hygiene

Finally, the common method bias (CMB) was assessed using the post hoc Harman single-factor approach to determine if the data variance was not predominantly explained by a single factor (Babin et al., 2016). The Assessment of the unrotated factor solution revealed that a one-factor solution explained 46.16% of the variance, close but yet below the 50% threshold suggested by Podsakoff et al. (2003). This outcome suggests that CMB is not a major concern for the current study (Conway & Lance, 2010; Gopalan et al., 2022; Howard et al., 2024).

Multicollinearity was checked before evaluating the structural model, as shown in Table 4. The results show that only two VIF values were higher than five, although

Table 4 Multicollinearity assessment (VIFs)

	I	E	T	EU	A	BI	USE	U	R	WPM
I										
E	1.056									
T	2.706	1.064								
EU	2.672	1.103	5.214							
A	2.964	1.034	3.742	3.164						
BI	3.436	1.012	2.815	2.585	3.377					
USE	2.456	1.016	2.456	1.940	2.466	4.173				
U	3.037	1.050	6.143	3.918	4.810	4.143	3.456			
R	1.098	1.001	1.095	1.079	1.085	1.084	1.079	1.070		
WPM	1.280	1.003	1.308	1.261	1.391	1.389	1.401	1.560	1.000	
HH	2.148	1.035	2.294	2.034	2.161	2.533	2.302	3.131	1.042	2.052

I, innovativeness; *E*, enjoyment; *T*, trust; *EU*, ease of use; *A*, attitude; *BI*, behavioral intention; *USE*, continuous use; *U*, usefulness; *R*, risk; *WPM*, willing to pay more; *HH*, handling hygiene

close to the cut-off threshold. The cut-off value for VIF is not precisely defined. Some authors mentioned that VIF must be lower than 5 (Collier, 2020; Marôco, 2021), but others assumed that lower than 10 can also be accepted (Cameron & James, 1987; Hair et al., 2019). Since no severe multicollinearity problems were identified, we proceeded with the structural model analysis.

Considering these results for the measurement model, we conclude that it complies with the standard requirements for proceeding to the structural model analysis.

Structural Model Evaluation

The structural model analysis validated nine (60%) of the fifteen proposed hypotheses, considering the 0.05 significance level. The results show that innovativeness, enjoyment, hygiene, and attitude significantly impact behavioral intention, which is crucial for explaining continuous use. The R^2 values indicate that the model fitted the data well: (i) 90.2% of the variance of the perceived usefulness is explained by the perceived ease of use; (ii) 82.5% of the variance of attitude is explained by the perceived usefulness and the perceived enjoyment; (iii) 84.3% of the variance of the behavioral intention of use is explained by the perceived usefulness, attitude, perceived innovativeness, perceived enjoyment, and perceived hygienic handling; and (iv) 78.2% of the variance of the continuous use is explained by the behavioral intention of use.

The fit of the model was assessed based on the overall index $\chi^2/df=2.604$, GFI=0.838, CFI=0.945, NFI=0.915, GFI=0.838; PCFI=0.826, RMSEA=0.062 showing that the model adequately fits the data (Arbuckle, 2016; Collier, 2020; Hair et al., 2019; Marôco, 2021).

The model coefficient estimates, statistical inference, and Amos structural model output are shown in Table 5 and Fig. 3, respectively.

Discussion

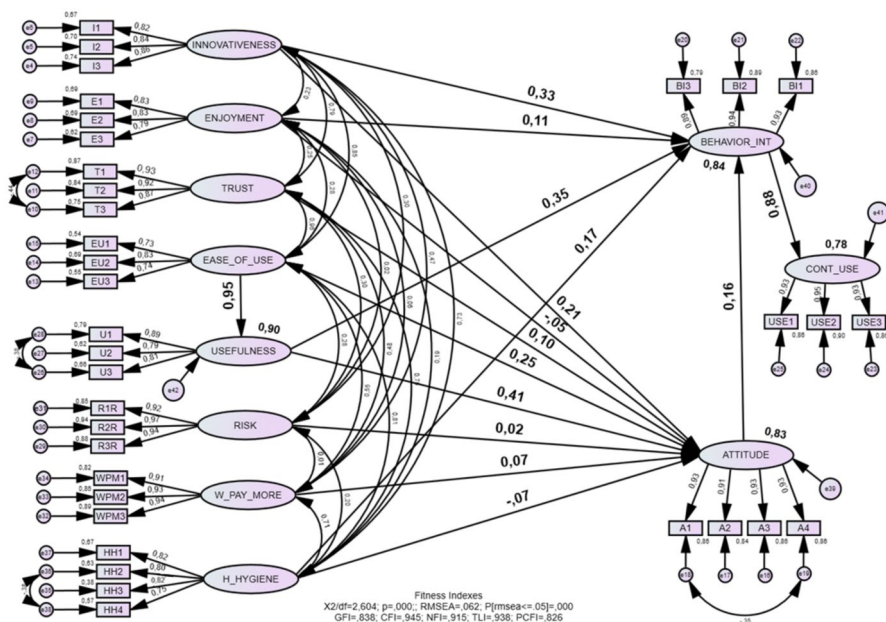
Understanding the factors determining the acceptance and continued use of robotic waiters in Portuguese restaurants is crucial for restaurants and the hospitality industry. Since Portugal depends heavily on tourism revenues, from a financial and economic point of view, studying ways of improving the profitability of this industry is very important, as tourism accounted for 19.1% of the wealth produced in the country last year, according to the World Travel & Tourism Council report (Presstur, 2022).

Our results revealed that all hypotheses for the original TAM model were supported except for H2. Hence, no perceived influence of ease of use on attitude was detected ($p=0.515$). This was an unexpected result, considering the importance of this construct on attitude in other studies (Kao & Huang, 2023; Sung & Jeon, 2020). One possible explanation for this result relates to the high degree of familiarity individuals have with technology nowadays due to constant interaction with technological devices and machines such as smartphones, ATMs, and other types of digital

Table 5 Path coefficients unstandardized estimates

Hypothesis	Path	β	S.E	Z	p-value
H1	Ease of use $\rightarrow$ usefulness	1.805	0.111	16.252	< 0.001
H2	Ease of use $\rightarrow$ attitude	0.342	0.525	0.652	0.515
H3	Usefulness $\rightarrow$ attitude	0.296	0.119	2.496	0.013
H4	Usefulness $\rightarrow$ intention	0.279	0.063	4.408	< 0.001
H5	Attitude $\rightarrow$ behavioral intention	0.173	0.074	2.340	0.019
H6	Behavioral intention $\rightarrow$ continuous use	0.909	0.039	23.375	< 0.001
H7	Innovativeness $\rightarrow$ attitude	0.207	0.076	2.725	0.006
H8	Innovativeness $\rightarrow$ behavioral intention	0.358	0.063	5.690	< 0.001
H9	Enjoyment $\rightarrow$ attitude	-0.080	0.046	1.741	0.082
H10	Enjoyment $\rightarrow$ behavioral intention	0.184	0.047	3.939	< 0.001
H11	Trust $\rightarrow$ attitude	0.097	0.189	0.512	0.609
H12	Risk $\rightarrow$ attitude	0.013	0.014	0.926	0.354
H13	Willing pay more $\rightarrow$ attitude	0.038	0.023	1.678	0.093
H14	Hygiene $\rightarrow$ attitude	-0.089	0.093	-0.948	0.343
H15	Hygiene $\rightarrow$ behavioral intention	0.245	0.070	3.509	< 0.001

Bold denotes statistically significant effects at the 0.05 level

**Fig. 3** Structural model output. Note: Values presented in the figure are the standardized estimates

kiosks. Nevertheless, perceived ease of use proves to be influential, as it displays a strong positive influence on perceived usefulness ($H1, p < 0.0001$), which is consistent with other studies (El-Said & Al Hajri, 2022; Seo & Lee, 2021). Perceived usefulness had the biggest positive influence on attitude ($H3, p = 0.013$) and behavioral intention to use robotic restaurants ($H4, p < 0.0001$). This finding was anticipated as consumers' privilege options that improve functionality and efficiency, especially when waits are expected. Several studies already supported these relationships (Hwang et al., 2020; Kao & Huang, 2023; Seo & Lee, 2021; Sung & Jeon, 2020). The attitude toward acceptance of a robot waiter positively influences the behavioral intention to use this (recent) type of restaurant ($H5, p = 0.019$), which, in turn, positively influences the customers to continue using this type of restaurant ($H6, p < 0.0001$). These findings align with evidence by Sung and Jeon (2020) that showed that attitude positively influences the acceptance intention to use barista robots, and a subsequent study in 2024 further demonstrated the effectiveness of RAISA in improving restaurant customer experience (Santiago et al., 2024).

From all constructs added in the extended TAM model, perceived innovativeness ($H8, p < 0.0001$), perceived enjoyment ($H10, p < 0.0001$), and perceived hygienic handling ($H15, p < 0.0001$) play significant roles in the intentional behavior of use of restaurants with robot waiters. Among them, only perceived innovativeness ($H7, p = 0.006$) positively influences the attitude. Similar findings were reported by Sung and Jeon (2020) regarding customers' intention to accept barista robots in coffee shops. Furthermore, Hwang et al. (2020) also reported the importance of perceived innovativeness in robotic restaurant marketing strategies in the current era of the fourth industrial revolution.

These findings align with and contribute to the evolving market trend of increasing automation in hospitality services. The global trajectory toward robotic integration in restaurants, characterized by advancements in AI, reductions in robot production costs, and shifting consumer expectations for contactless experiences, underscores the timeliness and strategic relevance of this research. According to recent industry forecasts, the deployment of service robots is expected to accelerate, particularly in urban and tourism-heavy regions where labor shortages are more critical and operational efficiency is prioritized. The robot waiter market is projected to reach USD 1.97 billion by 2028, growing at a compound annual growth rate (CAGR) of 35.14% (Arizton Advisory & Intelligence, 2024). As such, the proposed model not only captures current influences on customer attitudes but also anticipates future consumer behavior patterns in a progressively automated dining environment. By positioning robot waiters as both efficient and hygienic, restaurants can align with macro-level trends while differentiating themselves in an increasingly competitive and tech-driven market landscape.

The hypotheses involving the constructs of perceived trust, perceived risk, and willingness to pay more were not supported in this study ($p > 0.05$). These findings contradict those of Seo and Lee (2021) but are like those of Sung and Jeon (2020) regarding risk perception. It is important to stress that the hypothesized positive influences of perceived enjoyment ($H9, p = 0.082$) and willingness to pay more ($H13, p = 0.093$) fail to achieve statistical significance despite our initial expectations. These are interesting and relevant findings since they point out that consumers

are not willing to pay more for efficiency and the enjoyment of being served by robot waiters, so companies must carefully evaluate the cost/benefit ratio before investing in this technology.

As mentioned, studies on robot waiters' use in restaurants and using TAM as the supporting theoretical framework are scarce. Even though several constructs mimicked those used in other studies, current findings did not necessarily follow similar trends in the literature. Even though one could expect to confirm the findings drawn from other studies, we admit that differences linked to cultural aspects, socioeconomic development, level of development of technologies, and other factors linked to the country's social, economic, technological, and demographic reality may have interfered with the hypotheses' support.

Conclusions

The increasing adoption of robotic services in the restaurant industry reflects a broader global trend in which consumers and businesses alike show a growing preference for technology-driven solutions (Hautala & Jauhiainen, 2022). Today's younger and tech-savvy consumers value efficiency, novelty, and hygienic handling, all of which robotic systems can enhance. For companies, these solutions offer operational advantages such as labor cost reduction, consistency in service delivery, and resilience against labor shortages. The convergence of these interests is creating a favorable environment for the proliferation of robot waiters in the food service sector. This pattern mirrors developments in other industries, such as retail and transportation, where automation is already widely adopted. For example, autonomous checkout systems in supermarkets and the widespread use of digital kiosks in fast-food chains highlight how customers increasingly welcome machine-assisted experiences.

Furthermore, the rapid evolution of artificial intelligence (AI) and machine learning technologies is expected to elevate the capabilities of service robots significantly. As AI systems become more sophisticated in areas such as natural language processing, environmental awareness, and adaptive learning, robotic waiters can evolve from simple food delivery tools to interactive agents capable of understanding and responding to customer needs in real time. These parallels innovations are seen in the automotive industry, where autonomous driving technologies are redefining mobility. Just as self-driving cars are transitioning from experimental models to commercial applications, robot waiters are poised to become mainstream elements of smart dining environments. Embracing AI-enhanced robotics today may secure a competitive edge in a market that increasingly values technological integration.

Users of Portuguese restaurants perceive that the service provided by a robot is something that is easy to use and, therefore, useful; they also think it is innovative, enjoyable, and hygienic. Together, these factors guarantee a positive behavioral intention and a preference for continuing to attend this type of restaurant. Trust, risk, and eventually having to pay more for this service do not seem to be determinants for defining their attitudes and intentional behaviors.

Theoretical Implications

From a theoretical point of view, our study provides insights into the formation of attitudes and behavioral intentions to accept and use robot waiters in restaurants by introducing the never-before-explored concept of perceived hygienic handling in the context of restaurants with robot waiters. The perceived hygienic handling of the food served by robot waiters as a construct exhibited statistical validity, which is relevant for future research as it positively influenced the customers' behavioral intention to use robotic restaurants; still, it did not affect the customers' attitude towards the service provided by the robot. From a theoretical perspective, the current results reinforced the robustness of the TAM model for assessing novel additions to the technological landscape since it proves that it continues to be able to predict the acceptance of new technologies by users accurately. Finally, this study confirmed that applying extended TAM models to different contexts may produce novel and valuable insights guiding advanced research.

Managerial Implications

This study revealed two major practical implications in response to the original research questions. Firstly, it will be necessary to improve customer experience and satisfaction because (i) experience is poor, considering that 41.5% of respondents never had a meal in this type of restaurant, and (ii) satisfaction (based on attitude) comes only from perceptions about usefulness and innovation. At this time, the simplicity of the robot used in these restaurants (as shown in Fig. 1) and table service, simultaneously made by robotic and human waiters, turned the role of enjoyment, trust, and risk to be insignificant in terms of customers' attitudes and behaviors. Secondly, robotic restaurant managers can promote the use of robots in restaurants and attract more customers by (i) investing in upgraded robots (more human-like in format and bearing more functions, e.g., ordering) to turn the overall experience more enjoyable, gaining trust, and reducing the perception of risk; and (ii) promoting more extensive advertising, via social networks, media, and outdoor devices.

Recent advances in artificial intelligence offer critical managerial opportunities for leveraging service robots beyond simple task automation. From an organizational perspective, AI-powered robot waiters can be positioned not merely as novelty devices but as knowledge-intensive assets capable of learning customer preferences, optimizing service flows, and dynamically adapting to different operational contexts (Hautala & Jauhiainen, 2022). Their integration into service environments can contribute to data-driven decision-making, allowing managers to gain real-time insights into customer behavior and operational efficiency. At the macro-level, widespread adoption of such technologies aligns with broader economic imperatives, including improving productivity and fostering technological innovation as a strategic response to societal shifts toward digitalization.

Consumers like to experience novel things; thus, investing in this technology may provide pioneers competitive advantages, at least in the short term. In the long term, as waiter robot technology becomes common, affordable, and commonly accepted by customers, the benefits could come from the increased profitability of these systems. Nevertheless, the consequences of workforce replacement should be accounted for as it may produce resistance from the public. Strategies to deal with more aggressive actions should be anticipated.

In practical terms, the findings offer concrete guidance for service and operations managers seeking to integrate robotic waiters into restaurant settings. Specifically, the significance of perceived innovativeness, enjoyment, and hygienic handling as drivers of behavioral intention suggest that restaurant operators should not only invest in cutting-edge robotic technology but also emphasize its novelty and hygiene-enhancing attributes in consumer-facing communications. For example, food safety certification labels displayed on the robots or digital screens highlighting hygiene protocols may serve to increase perceived trustworthiness and reinforce positive behavioral intentions. Furthermore, given the strong predictive power of behavioral intention for continuous use, customer retention strategies should focus on reinforcing these positive perceptions during post-experience stages through loyalty programs, digital feedback channels, or exclusive promotions for repeat users. Thus, AI-enabled robotic services represent a technological upgrade but also a platform for knowledge creation, diffusion, and application. Managers who strategically implement these technologies stand to benefit from increased operational agility and the capacity to address complex service challenges with scalable, intelligent solutions. These efforts are vital for maximizing customer lifetime value.

Limitations and Future Research

One limitation of this study was to convince restaurant managers to allow the distribution of QR codes, which reduced the number of restaurants to just two (out of ten possible). Another limitation was not having added a question to identify the source of respondents to know who responded via social networks and who responded *in loco* at the restaurant. Future research should consider comparing the results from people answering inside and outside the restaurant, people who have never experienced using a robot waiter, and those familiar with them. Building on the limitations identified in the current sampling approach, future research should adopt more rigorous and diversified sampling strategies to enhance the generalizability of the findings and reinforce the model's validity. Incorporating participants from varied geographic regions, demographic segments, and dining environments will be crucial for verifying the consistency of the observed relationships and assessing the broader applicability of the results within dynamic, knowledge-driven service economies. A deeper exploration of customers' challenges, such as privacy concerns and the potential depersonalization of the dining experience and other variables, is also necessary. However, these issues were not considered and must be considered a limitation. Another possible limitation arose from the Ethics Committee's demand that the questionnaire be answered only by adults (aged 18 or above). Complying with this

requisite limited the population and may have affected the results because young people are more open to adhering to novel technologies. Future studies may try to include this population to validate the agreement with the current findings.

Author Contribution Ivo G. Figueiredo: formal analysis, investigation, writing original draft. Paula F. Moutinho: conceptualization, formal analysis, methodology, supervision, writing—review and editing. Paulo O. Duarte: formal analysis, funding acquisition, writing—review and editing. Angela C. Macedo: conceptualization, data curation, formal analysis, funding acquisition, methodology, supervision, visualization, writing original draft, writing—review and editing.

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Data Availability Data available on request.

Declarations

Competing Interests The authors declared no competing interests.

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