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## Article

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## MARKETING | RESEARCH ARTICLE

# Robotic dining delight: Unravelling the key factors driving customer satisfaction in service robot restaurants using PLS-SEM and ML

Vinod Sharma<sup>1</sup>, Manohar Kapse<sup>1</sup>, Jeanne Poulouse<sup>2</sup> and Yogesh Mahajan<sup>1\*</sup>

**Abstract:** In the past few years there has been a remarkable surge in demand for robot service restaurants. However, as both the technology and the concept of such restaurants are relatively new, there is a limited understanding of how consumers would react to this new change in the service industry. This study focuses on the key factors influencing customer satisfaction and their intention to repeat the experience by using two staged hybrid PLS-SEM and Machine Learning approaches. The finding confirms that perceived enjoyment, speed, and novelty influence customer satisfaction, whereas perceived usefulness has no influence. Additionally, the study uncovers that customer satisfaction and trust positively mediate the relationship and establish the link with repeat experience. The machine learning models (Artificial Neural Network, Support Vector Machines, Random Forest, K-Nearest Neighbors, Elastic Net) predict the intention to repeat the experience of the service robot with an overall model fit of around 57%. We also discussed several new and useful theoretical and practical implications for enhancing the customer experience during the visit to the restaurants.

**Subjects:** Machine Learning; Consumer Behaviour; Hospitality;

**Keywords:** robotics; PLS-SEM; machine learning; repeat experience; trust; service restaurants

## 1. Introduction

According to Wirtz and Pitardi (2023) “a service robot is a self-contained, system-based machine with artificial intelligence that enables it to interact, communicate, and offer a variety of consumer services in a service environment”. In recent years, using service robots to replace human workers in front-line service positions has gained popularity in the hospitality industry (El-Said & Al Hajri, 2022; Kim et al., 2023). However, before the COVID-19 pandemic, most researchers agreed that humans were preferred for their personalized service (Choi et al., 2023; Gupta & Pande, 2023; Leung et al., 2023), sincere interactions, and experience enrichment, which robots cannot replicate (Roozen et al., 2023). However, with the pandemic, preferences changed (Becker et al., 2023; El-Said & Al Hajri, 2022) due to rising customers’ fear of viral infection, prompting them to prefer contactless restaurant services (El-Said & Al Hajri, 2022; Wirtz & Pitardi, 2023). This resulted in a surge in demand for establishments with robot services (Kim et al., 2023). As a result, more restaurants are expected to embrace robot services to meet the technology’s growing popularity (Choi et al., 2023; Meyer et al., 2023).

The use of service robots in restaurants has gained attention in India in recent years, especially in the wake of the COVID-19 pandemic. There are already a few examples of restaurants in India that have successfully implemented service robots. For instance, the robot “Ginger” is being used in a restaurant in Chennai to take orders and serve food to customers (Agrawal et al., 2023). Another restaurant in Bangalore has introduced robots to serve food (Kamran et al., 2021) and drinks, while yet a few more in Mumbai, Jaipur, and Delhi NCR have implemented robots for dine-in services (Shah et al., 2023). While the use of service robots in restaurants is still in its early stages in India, there is a growing interest among restaurant owners in exploring this technology further (Agrawal et al., 2023; Gupta & Pande, 2023). One of the key benefits of using robots in restaurants is the potential for reducing human-to-human contact (Choi et al., 2023; Meyer et al., 2023) and the risk of spreading infectious diseases. Additionally, robots can work around the clock without getting tired, which can help restaurants operate more efficiently and reduce labour costs in the long run (Wang & Wang, 2021; Xu et al., 2023).

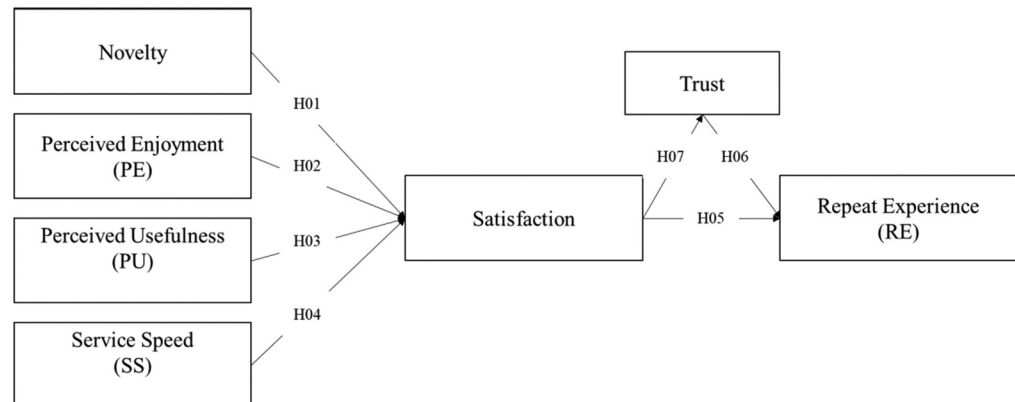
However, there are concerns regarding the impact of service robots on human employment in the hospitality industry (El-Said & Al Hajri, 2022; Seo & Lee, 2021). Some argue that using robots could lead to the displacement of human workers, while others believe that robots can complement human labour and enhance the overall customer experience (Choi et al., 2023; Jang & Lee, 2020). As with any new technology, service robots in restaurants have both advantages and disadvantages. It will be important for restaurant owners to carefully consider the potential benefits and drawbacks before implementing this technology in their establishments. Very few academic researchers have looked into whether or not diners are happy to have robots serve them (Leung et al., 2023) in restaurants. The following questions are addressed to fill this knowledge gap in this paper: What factors contribute to customer satisfaction with service robot restaurants during the pandemic? What factors contribute to customer intention to return to or suggest service robot restaurants?

This study has been conducted in India, which provides a useful opportunity to investigate the generalizability of previous research as most of the past studies on service robot restaurants were conducted USA, China, Japan, South Korea, UAE, Taiwan, India (Choi et al., 2023; El-Said & Al Hajri, 2022; Jang & Lee, 2020; Kim et al., 2023; Meyer et al., 2023; Wirtz & Pitardi, 2023). Even though service robot restaurants are still a relatively new concept in the region, there are currently a handful scattered throughout India. Therefore, a sizable sample may be gathered from guests of the various eateries, allowing for more precise testing of the suggested model. The study will also provide valuable insights into customer attitudes (Gaber et al., 2019) towards service robots in the new normal era.

## 2. Theoretical background

The Technology Acceptance Model (TAM), initially proposed by Davis (1985), offers insights into individuals’ new technology adoption based on three key factors: perceived ease of use, perceived enjoyment and perceived usefulness (Davis, 1989). Earlier studies on consumer acceptance of robots have found these three factors to be predominantly influential (de Graaf, 2016). However, in the context of the service robot restaurant, where customers are only experiencing the services offered by the restaurant rather than using the actual technology, perceived ease of use was dropped and other two additional factors, novelty and speed, were introduced to comprehensively understand the service robot technology adoption (El-Said & Al Hajri, 2022; Go et al., 2020). This would help fill the gap where faster service robots could leave a positive impression on customers. Likewise, the novelty associated with the service robot experience could increase customer satisfaction (Wang et al., 2022). Finally, we incorporated perceived usefulness (PU), perceived enjoyment (PE), novelty (Novel) and speed (Speed) leading to satisfaction (Sat). Experience of satisfaction results in building trust and customers’ willingness to have a repeat experience of the services. Figure 1 illustrates the theoretical framework employed in the study, which aims to measure customers’ and repeat experience (RE) in a service robot restaurant.

**Figure 1. Theoretical framework.**



### 3. Hypotheses development

#### 3.1. Novelty

The novelty of interacting with robots in a restaurant setting can contribute to satisfaction. Experience novelty refers to the sense of trying something new and different, which is associated with feelings of curiosity, adventure, and encountering the unfamiliar (Feng et al., 2019; Xie et al., 2023). Research suggests that individuals often find new technologies exciting and enjoyable, especially when they perceive them as useful and easy to use (Davis, 1989; El-Said & Al Hajri, 2022). Consequently, prior research has highlighted this as an important driver of both travel and technological adoption (Hwang et al., 2023) among the general public. Customers who seek out new adventures have a more favourable impression of new technologies (Xie et al., 2023).

The presence of robots in a restaurant can create a unique and engaging experience, leading to higher levels of satisfaction. In the context of hospitality, the introduction of robot service in restaurants has been found to enhance guest experiences by offering a novel technological element (Rasheed et al., 2023). The novelty factor associated with robots in service settings can intrigue and engage customers, contributing to a more enjoyable and satisfying experience. In this study, we propose that the novelty of the overall dining experience will positively influence satisfaction for customers at robot service restaurants in India. The novelty factor adds an extra dimension of enjoyment and satisfaction for patrons as they engage with the innovative technology (Correa et al., 2022) and embrace the unique experience the robot service offers.

**H01:** Novelty has a positive influence on satisfaction.

#### 3.2. Perceived Enjoyment (PE)

Perceived enjoyment is a psychological concept that has been extensively studied. In a robot service restaurant, perceived enjoyment refers to customers' subjective experience of pleasure and satisfaction derived from their interactions with the robots and the overall dining experience (El-Said & Al Hajri, 2022; Song et al., 2022). Perceived enjoyment refers to the level of enjoyment individuals experience when using a particular technology, irrespective of its performance (Won et al., 2023). It has been observed as a crucial factor in determining customer acceptance of new technologies across various service sectors. Consumers' opinions of drone food delivery services (Chen et al., 2023) were found to be affected by how much fun they were thought to be (Hwang et al., 2019, 2023). They also discovered that customers' perspectives on robot service were greatly affected by customers' perceptions of their satisfaction, a concept known as hedonic consumer innovation. Our research hypothesizes that diners who experience robot service in Indian restaurants are more satisfied than those who do not.

**H2:** Perceived enjoyment has a positive influence on satisfaction.

### **3.3. Perceived Usefulness (PU)**

Individuals' expectations of how much a new piece of technology will improve their efficiency on the job are what we call its "perceived usefulness" (Davis, 1989). Earlier studies in the hotel business on robot service have shown that customers' opinions of their experience greatly depend on how beneficial they found the robot to be (Shah et al., 2023).

Informational precision, transmission efficiency, and the availability of translation services are all variables that positively influence the adoption of robots and AI in hotels, according to research conducted by (Kim, 2023) and others. Similar findings were found by (Moon & Lee, 2022) and (Seo et al., 2022): customers' evaluations of the value of self-service kiosks influence their desire to reuse them.

For hotels, the introduction of robot service offers numerous significant advantages, including improved performance, efficiency, and productivity (Wirtz, 2020). We hypothesize that customers will be more satisfied with their meals at robot service restaurants in India if they believe that the robots can precisely and efficiently complete their orders. Customers who perceive robot service as beneficial and effective are likely to have a more satisfying dining experience due to the enhanced performance and efficiency provided by the robots.

**H3:** Perceived usefulness has a positive effect on satisfaction

### **3.4. Service Speed (SS)**

Robots generally outperform humans in terms of task speed. This advantage becomes particularly relevant in restaurants, where robots can significantly reduce waiting times for orders, which leads to potentially improved customer satisfaction (Lu et al., 2020; Wirtz & Pitardi, 2023). Customer attitudes toward online reservations and payments were studied (Ahmed et al., 2023) and shown to be positively correlated with faster service and increased satisfaction at restaurants. Furthermore, the introduction of robot service in restaurants allows human staff to allocate their efforts to more intricate tasks. By effectively distributing tasks between humans and robots, service time can be reduced, resulting in improved efficiency (El-Said & Al Hajri, 2022). Another study on service quality in robotic systems by (Wijesekera & Fernando, 2023; Zeithaml et al., 1988) highlights the importance of reliability, responsiveness, and accuracy in shaping user satisfaction.

Our research is based on the hypothesis that patrons of robot service restaurants in India report higher levels of satisfaction due to the faster service provided by the robots. The ability of robots to expedite service delivery contributes to a more streamlined dining experience, reducing waiting times and enhancing overall customer satisfaction.

**H4:** Service speed has a positive influence on satisfaction.

### **3.5. Repeat Experience (RE)**

The term "repeat experience" refers to the active efforts made by visitors to share the emotional and cognitive benefits they perceive from their experiences, often through word-of-mouth communication with their friends and acquaintances (Clarke & Bowen, 2021). Extensive research has revealed that customers are more inclined to share and prolong their experiences when their initial expectations are met (El-Said et al., 2021; Pai et al., 2022). In addition, the level of enjoyment derived from the experience plays a crucial role in determining the likelihood of individuals sharing and extending it with others (Dong & Siu, 2013; El-Said & Al Hajri, 2022). Similarly (Wang et al., 2023), demonstrated that pleasurable e-commerce experiences have a positive impact on electronic word-of-mouth. Consequently, it can be inferred that both satisfaction with the overall experience and the perceived enjoyment derived from it will positively influence the repeat experience

(Yang et al., 2023). These factors contribute to the tendency of individuals to actively share their experiences and prolong the benefits they have gained, thereby enhancing the overall impact and reach of the experience.

**H5:** Satisfaction has a positive effect on repeat experience.

### **3.6. Trust**

Song et al. (2022) define trust in their study of robot service as an individual's belief in the technology's potential to deliver on their needs and wants. Their research also shows that trust directly affects people's willingness to use and enjoy new technologies. The beneficial effect of trust on consumer inclinations to eat at these restaurants in India was also demonstrated by (Chi et al., 2023) researchers.

However, there is a dearth of research examining trust's mediating role in the context of experience satisfaction and experience repetition. Our research assumes that trust will play a mediator role in the relationship between satisfaction and repeat experience for customers at robot service restaurants in India. Trust in the technology and the establishment offering the service will likely influence customers' willingness to repeat their experience, such as returning for future visits or recommending the restaurant to others and spreading positive word of mouth. The level of trust in the robot service and the overall dining experience will shape customers' perceptions and decisions regarding the extension of their engagement with the restaurant.

**H6:** Trust has a positive effect on repeat experience.

**H7:** Satisfaction has a positive effect on trust.

**H8:** Trust mediates the relationship between satisfaction and repeat experience.

**H9:** Satisfaction mediates the relationship between perceived enjoyment, speed, novelty, perceived usefulness and repeat experience.

## **4. Research methodology**

### **4.1. Sample and sampling procedure**

Data from the robot service restaurants in four different cities—Chennai, Mumbai, Jaipur, and Delhi NCR—was manually gathered. In these restaurants, robots bring food to tables. The study employed the intercept technique, which was similar to (Leong et al., 2020a) the study applied the mall intercept technique. In order to reduce sample bias and obtain a diverse group of respondents, the interceptions were conducted near the restaurants' entrances and exits, as recommended by (Yani de Soriano et al., 2019). This intercept strategy has been extensively applied in studies of a similar nature since the interviewers were able to evaluate and filter out possible respondents to confirm their eligibility.

The respondents were explicitly informed that the study was solely conducted for academic purposes and had no commercial aspects. The consent to collect the data was secured from the restaurant owners before beginning the data collection process (Bonfanti et al., 2023). A total of 402 legitimate questionnaires were collected after discarding the incomplete, unengaged, and unreturned ones. With an effect size of 0.3, an alpha level of 0.05, and a power of 0.95, the sample size of 402 outperformed the recommended minimum sample size of 384 (Hair et al., 2019). As a result, the 402-sample size is adequate for the PLS-SEM-ML analysis. The entire data collection process took around 3 months to complete. Table 1 represents the sample characteristics.

#### 4.2. Materials and methods

The goal of the survey was to find out how happy customers were with different parts of the service robot eateries. The questionnaire was divided into two parts. The demographic characteristics of the respondents were the primary focus of the first section. The second half was divided into the following categories: perceived enjoyment, speed, novelty, perceived usefulness, satisfaction, repeat experience, and trust. Table 1 describes the source of the research instrument and also the scale used is given in annexure 1. A 5-point Likert scale was used to score the responses. 5-point Likert scales from “strongly disagree” to “strongly agree” were employed to reduce respondents’ degree of annoyance and increase response rates (Rodrigues et al., 2019).

The pilot test was carried out before the actual fieldwork. Similar to (Leong et al., 2020b), the face validity and content validity of the instrument were evaluated by speaking with five professors who have published in a similar area of study. We made some modest changes based on the feedback. Fifty respondents were surveyed for the pilot testing and we received Cronbach’s alpha values within the range (>0.70), which confirmed that the constructs employed in the study are reliable.

#### 5. Data analysis and results

SPSS version 25, Smart PLS version 4, and R-Studio for machine learning algorithms were used to analyse the data. Demographic details are given in Table 2. Figure 2 describes the procedure used in the study for data analysis.

##### 5.1. Common method bias

The measuring method used in an SEM study, not the network of causes and effects in the model being studied, causes common method bias. Principal Axis Factoring was used as the extraction method to run Harman’s Single Factor test and check for common method bias. When less than 40% of the variance could be explained by a single component with all the observed variables loaded, the results showed no shared method bias (Harman & Chomsky, 1967). In order to identify the common bias in the variance inflation factor (VIF) is also recommended (Kock & Lynn, 2012); a value of more than 3.3 is considered to be indicative of common method bias. As per the author (Podsakoff et al., 2012), if the Latent factors correlation is less than 0.90 indicates no CMB.

##### 5.2. Measurement model

The validity and reliability of the constructs were assessed using Smart-PLS output. The value of Cronbach’s alpha and composite reliability, according to Table 3, is greater than 0.70, which ascertains that the measurement model has a high level of construct reliability (Hair et al., 2019). Convergent validity is validated when the average variance extracted (AVE) is more than 0.50, which indicates that the items converge to the pertinent constructs (Hair et al., 2019; Leong et al., 2020a).

Notably, the AVE values presented in Table 3 are all greater than the minimum and average shared variances that correspond, proving that all AVEs are within the acceptable range. According

**Table 1. Research instrument**

Constructs	No of Items	Source
Perceived Enjoyment (PE)	4	Davis, (1989)
Service Speed (SS)	3	Lee, (2011)
Novelty	5	Bello & Etzel, (1985)
Perceived Usefulness (PU)	4	Davis, (1989)
Satisfaction	3	Tussyadiah et al. (2020)
Repeat Experience (RE)	4	Dong & Siu, (2013)
Trust	4	Mcknight et al. (2011)

**Table 2. Demographic profile of the respondents**

	<b>N</b>	<b>%</b>
<b>Gender</b>		
Male	233	58%
Female	169	42%
<b>Age</b>		
21–30 Years	121	30%
31–40 Years	138	34%
41–50 Years	89	22%
51–60 Years	32	8%
Above 60 Years	22	5%
<b>Marital Status</b>		
Single	241	60%
Married	140	35%
Other	21	5%
<b>How many times did you visit a robot service restaurant?</b>		
First Visit	178	44%
Second Visit	160	40%
More than two visits	64	16%
<b>Did you find the restaurant friendly?</b>		
Yes	366	91%
No	36	9%
<b>With whom did you visit the restaurant?</b>		
Alone	25	6%
With friends	208	52%
With family	169	42%

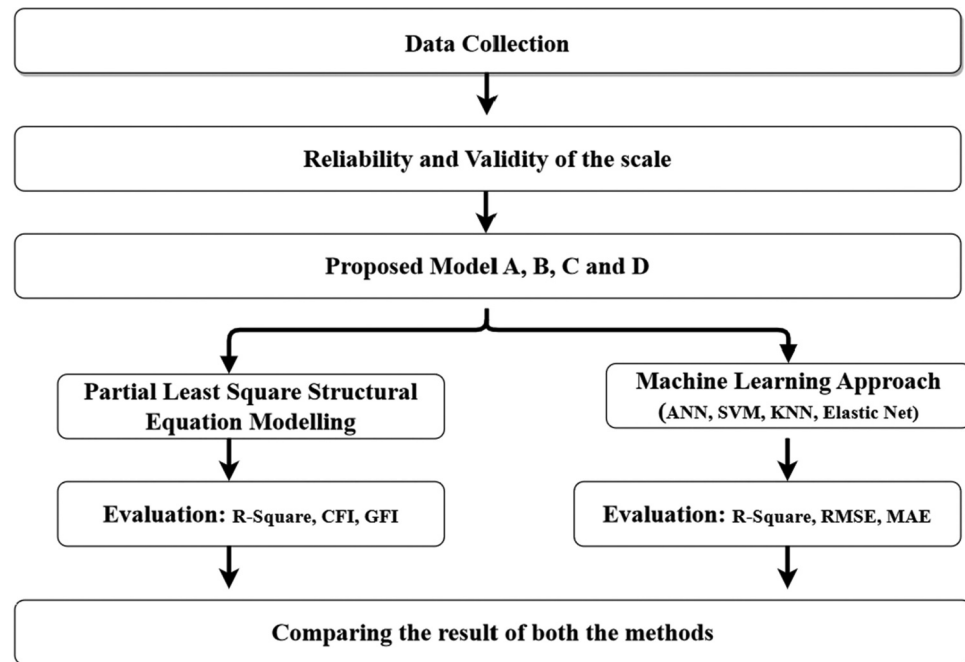
to the Fornell-Larcker criterion (Table 4), the square roots of AVEs are greater than the inter-correlation coefficients (Chin, 1998; Chin et al., 2003; Fornell & Larcker, 1981). In addition, discriminant validity was also evaluated using the Heterotrait- Monotrait (HTMT) criterion. The upper limit of the HTMT confidence interval for the HTMT ratio is above 0.90 and discovered that all of them are smaller than 1 (Henseler et al., 2015). The cross-loadings (Table 4) show that all items strongly load to the constructs, validating the discriminant validity.

### 5.3. Structure model

After obtaining satisfactory results for reliabilities, and validities analysis from the structural assessment of the study model, Figure 3 the study's hypotheses were tested. Using PLS-SEM analysis, we calculated the model fit indices. Notably, in PLS-SEM, numerous model fit statistics are typically used to assess the model's goodness of fit. To evaluate model fit in the absence of model specification errors, several academics have advocated the use of the normalised fit index (NFI) and the standardised root mean square residual (SRMR). close to 1), and the SRMR is less than 0.10 or 0.08, The SRMR value of 0.064 found here is within the range of what might be considered normal. In addition, the NFI was around 0.901, which means that the model used in the analysis matches the data.

The  $R^2$  and adjusted  $R^2$  values for the four exogenous constructs, i.e., (Novelty, PE, PU, and SS) elucidated 57.8% and 57.4 % of the change in the "Satisfaction", respectively. The predictive

**Figure 2. Illustrates the methodology adopted for the study.**



relevance ( $Q^2$ ) value for this part of the model was 0.563, demonstrating medium predictive relevance (Hair et al., 2019). Meanwhile, the  $R^2$  and adjusted  $R^2$  values for the “Trust” and “Satisfaction” to comply with the exogenous construct on RE explained 56.5% of the change as per R-square and 56.5% as per Adjusted R-Square. The predictive relevance ( $Q^2$ ) value for this part of the model was 0.449, signifying a large predictive relevance. Similarly, for model 3, with “Satisfaction” as the independent variable and “Trust” as the dependent variable, the model explained is 34.0% and 43.9 % as per  $R^2$  and adjusted  $R^2$ , respectively. The Q-Square is 0.439, signifying a large predictive relevance for all three models. Table 5 presents the results.

Using resampling methods like Bootstrap, we found that the partial least squares method was statistically significant. Using this method, you can get t-test data for all path coefficients. Path coefficients and t-statistics were employed to examine the strength of the association between the explanatory and response variables in the model. After determining the level of fit between the data and the model, we determined the significance of the coefficient.

As per Table 6, Novelty has a positive and significant impact on Satisfaction ( $\beta=0.359$ ,  $p < 0.05$ ), PE has a positive and significant impact on Satisfaction ( $\beta = 0.305$ ,  $p < 0.05$ ), PU has a positive and non-significant impact on Satisfaction ( $\beta = 0.095$ ,  $p > 0.05$ ), SS has a positive and significant impact on Satisfaction ( $\beta=0.139$ ,  $p < 0.05$ ), Satisfaction has a positive and significant impact on RE ( $\beta=0.268$ ,  $p < 0.05$ ), Trust has a positive and significant impact on RE ( $\beta=0.562$ ,  $p < 0.05$ ), and Satisfaction has a positive and significant impact on RE ( $\beta=0.590$ ,  $p < 0.05$ ). Therefore, the results confirmed that all other hypotheses are supported except hypothesis (H3).

The indirect effect quantifies the amount of change in the dependent variable (the outcome) that can be attributed to the mediating variable (the mediator) while controlling for the effect of other variables in the model. Table 7 presents the indirect effect, and the results confirmed that there is a strong and positive mediation effect on customer satisfaction and trust (Novelty -> Satisfaction -> Trust; Novelty -> Satisfaction -> Trust -> RE, and Satisfaction -> Trust -> RE) and, therefore hypotheses 8 and 9 are supported.

Table 3. Validity and reliability analysis

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	The average variance extracted (AVE)	Square root of AVE	Satisfaction	Novelty	PE	PU	RE	SS	Trust
Satisfaction	0.822	0.831	0.882	0.653	0.8081	1						
Novelty	0.932	0.933	0.951	0.830	0.911	0.70	1					
PE	0.882	0.884	0.919	0.740	0.860	0.68	0.71	1				
PU	0.932	0.946	0.956	0.879	0.9377	0.54	0.55	0.51	1			
RE	0.946	0.947	0.965	0.903	0.950	0.60	0.63	0.61	0.62	1		
SS	0.920	0.921	0.949	0.862	0.9285	0.51	0.47	0.47	0.62	0.57	1	
Trust	0.907	0.920	0.935	0.781	0.8839	0.59	0.59	0.55	0.75	0.72	0.66	1

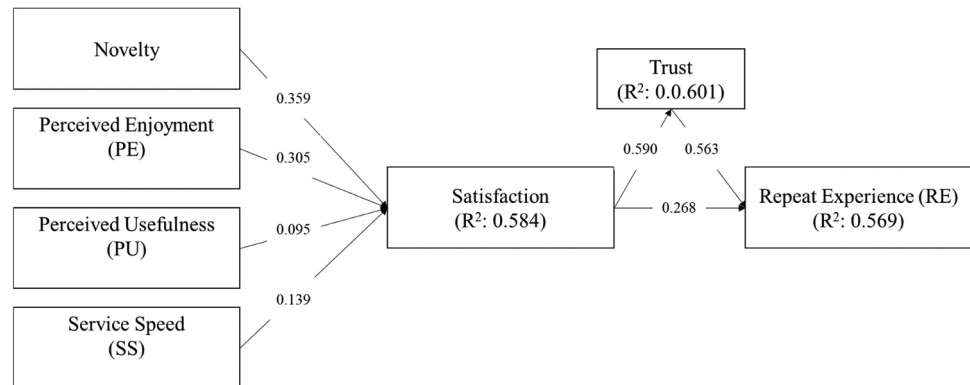
\*PE: Perceived Expectation; PU: Perceived Usefulness; SS: Service Speed; RE: Repeat Experience.

Table 4. HTMT and Fornell-Larcker criterion

Table 4. HTMT and Fornell-Larcker criterion														Fornell-Larcker Criterion									
HTMT-Ratio																							
Constructs	Satisfaction	Novelty	PE	PU	RE	SS	Satisfaction	Novelty	PE	PU	RE	SS	Satisfaction	Novelty	PE	PU	RE	SS	Trust				
Satisfaction							0.808																
Novelty	0.791						0.695	0.91															
PE	0.795	0.782					0.675	0.71	0.86														
PU	0.603	0.592	0.563				0.537	0.55	0.51	0.94													
RE	0.677	0.669	0.667	0.656			0.600	0.63	0.61	0.62	0.95												
SS	0.582	0.512	0.527	0.674	0.611		0.513	0.47	0.47	0.62	0.57	0.93											
Trust	0.671	0.638	0.613	0.816	0.768	0.715	0.590	0.59	0.55	0.75	0.72	0.66	0.88										

\*PE: Perceived Expectation; PU: Perceived Usefulness; SS: Service Speed; RE: Repeat Experience.

**Figure 3. Structured Model.**



**Table 5. Model fitness indicators**

Relation	F-square	R-square	R-square adjusted	Q-square predict	RMSE	MAE
Novelty → Satisfaction	0.135	0.578	0.574	0.563	0.665	0.488
PE → Satisfaction	0.103					
PU → Satisfaction	0.011					
SS → Satisfaction	0.027					
Satisfaction → RE	0.108	0.567	0.565	0.449	0.746	0.563
Trust → RE	0.476					
Satisfaction → Trust	0.535	0.349	0.347	0.439	0.754	0.592

\*PE: Perceived Expectation; PU: Perceived Usefulness; SS: Service Speed; RE: Repeat Experience.

**Table 6. Path coefficient- direct effect**

	Hypotheses	Relation	Path Coefficient	Sample Mean	Standard Deviation	t-statistics
<b>P-values</b>						
H01	Novelty → Satisfaction	0.359	0.361	0.06	6.021	0.000
H02	PE → Satisfaction	0.305	0.304	0.054	5.607	0.000
H03	PU → Satisfaction	0.095	0.099	0.062	1.552	0.121
H04	SS → Satisfaction	0.139	0.136	0.059	2.370	0.018
H05	Satisfaction → RE	0.268	0.269	0.057	4.723	0.000
H06	Trust → RE	0.563	0.562	0.051	10.989	0.000
H07	Satisfaction → Trust	0.590	0.591	0.041	14.27	0.000

\*PE: Perceived Expectation; PU: Perceived Usefulness; SS: Service Speed; RE: Repeat Experience.

#### 5.4. Machine learning approach

In contrast to ANN's ability to measure linear and non-linear correlations between the factors impacting the variable of interest, the SEM method is useful for measuring linear interrelationships. To assess and counterbalance the SEM results, we are employing a Machine Learning strategy. Since the SEM is well-suited for hypothesis testing of linear relationships but fails to capture the

**Table 7. Path coefficient- indirect effect**

Relation	Specific indirect effects	Conclusion
PE -> Satisfaction -> Trust	0.180	Strong Relation
PE -> Satisfaction -> RE	0.082	Weak Relation
PU -> Satisfaction -> RE	0.026	Weak Relation
SS -> Satisfaction -> RE	0.037	Weak Relation
PE -> Satisfaction -> Trust -> RE	0.101	Strong Relation
Novelty -> Satisfaction -> T	0.212	Strong Relation
Novelty -> Satisfaction -> RE	0.096	Weak Relation
PU -> Satisfaction -> Trust	0.056	Weak Relation
Novelty -> Satisfaction -> Trust -> RE	0.119	Strong Relation
Satisfaction -> Trust -> RE	0.332	Weak Relation
PU -> Satisfaction -> Trust -> RE	0.032	Weak Relation
SS -> Satisfaction -> Trust	0.082	Weak Relation
SS -> Satisfaction -> Trust -> RE	0.046	Weak Relation

\*PE: Perceived Expectation; PU: Perceived Usefulness; SS: Service Speed; RE: Repeat Experience.

nonlinearity of interactions, the SEM-ML strategy would be mutually supportive (Carrion et al., 2019; Ringle et al., 2022). At the same time, ML algorithms deal with non-linearity and linearity among the constructs. Many researchers have used the SEM-ANN approach for the same in the past (Das & Panja, 2022; Tiwari, 2022, 2023). In this study, we are using the SEM-ML approach, using R Programming.

The machine learning approach is applied to the construct to find the significance of the relation between the construct and verify them with the output of the SEM models. This study used R Programming net (Venables & Ripley, 2002), neuralnet (Fritsch et al., 2019) and caret package (Kuhn, 2021) to perform Machine Learning analysis. This study included Novelty, PE, PU, SS, Satisfaction, and Trust as independent variables and RE as the dependent variable for ML. We employed one hidden layer for the ANN model since one hidden layer is enough to portray any continuous function (Negnevitsky, 2011). A 10-fold cross-validation process was used to rule out the possibility of over-fitting. We calculated the root mean square of errors (RMSE), R-Square, and Mean absolute error (MAE) to evaluate the performance of the ML models in making predictions.

Four models were created to measure the goodness of fit of the model created using PLS-SEM. Model A had Novelty, PE, PU, and SS as the independent variable and Satisfaction as the dependent variable. In model B, they considered Satisfaction and Trust, as independent variables and RE as the dependent variable. Model C employed Satisfaction as the independent variable and Trust as the dependent variable, and the last model D had all the variables, Novelty, PE, PU, SS, Satisfaction, and Trust, as independent variables and RE as the dependent variable.

Results presented in Table 8 show the RMSE, R-square, and MAE values using 10-fold cross-validation for Model A, B, C, and D. In this study, we have used a neural network with a single hidden layer, support vector machine with linear, and radial Kernel (Cortes & Vapnik, 1995; Hastie et al., 2009a; Schölkopf & Smola, 2002), random forest (Breiman, 2001; Liaw & Wiener, 2002), k-nearest model (Aha et al., 1991; Han et al., 2011), Boosted Generalized Linear Model (Friedman, 2001a), Generalized Additive Model using Splines (Hastie & Tibshirani, 1986; Wood, 2004), and Elastic Net (Friedman et al., 2010; Zou & Hastie, 2005).

It seems that the RMSE, R-Square, and MAE values of neural networks, elastic net and support vector machines are the best algorithms. However, R-square values are nearly similar for the PLS-

**Table 8. Model fit Parameters for models A, B, C and D of ML algorithms**

ML Algorithm	Model A				Model B				Model C				Model D			
	Novelty, PE, PU, SS->Satisfaction	RMSE	R-square	MAE	Parameters	RMSE	R-square	MAE	Parameters	RMSE	R-square	MAE	Parameters	RMSE	R-square	MAE
Neural Network	4 neurons with a single hidden layer	4.131	0.573	4.000	2 neurons with a single hidden layer	3.859	0.554	3.618	1 neuron with a single hidden layer	3.646	0.342	3.438	6 neurons with a single hidden layer	3.859	0.603	3.618
Support Vector Machine	Linear kernel with C = 1.052631	0.687	0.574	0.494	Linear kernel with C = 1.5789	0.900	0.563	0.658	Linear kernel with C = 1	1.000	0.351	0.754	Linear kernel with C = 1	0.866	0.606	0.631
	Radial Kernel with sigma = 0.4607 and C = 0.25	0.718	0.518	0.526	Radial Kernel with sigma = 2.1778 and C = 0.5	0.936	0.515	0.704	Radial Kernel with sigma = 8.6339 and C = 0.25	0.995	0.348	0.762	Radial Kernel with sigma = 2.776 and C = 0.50	0.933	0.526	0.681
Random Forest	try (no of variables selected at random) = 2	0.701	0.543	0.531	try (no of variables selected at random) = 2	0.978	0.494	0.735	try (no of variables selected at random) = 2	0.980	0.369	0.757	try (no of variables selected at random) = 2	0.887	0.572	0.662
KNN	K= 9	0.712	0.533	0.526	K= 9	0.910	0.551	0.688	K= 7	0.980	0.361	0.752	K= 9	0.898	0.562	0.670
GLM Boosting	mstop = 100	0.681	0.565	0.506	mstop = 150	0.899	0.572	0.662	mstop = 150	0.983	0.368	0.763	mstop = 100	0.858	0.595	0.638
Elastic Net	fraction = 1, and lambda = 0.0001	0.676	0.576	0.505	fraction = 1, and lambda = 0.1	0.891	0.566	0.657	NA				fraction = 1, and lambda = 0.0001	0.858	0.593	0.635

\*PE: Perceived Expectation; PU: Perceived Usefulness; SS: Service Speed; RE: Repeat Experience.

**Table 9. Variable importance for ML model D**

Machine Learning Algorithm	Variables*	Overall Variable Importance	Machine Learning Algorithm	Variables*	Overall Variable Importance
Neural Network	Trust	100	KNN	Trust	100
	PE	28.94		Novelty	39.51
	Novelty	28.89		PU	29.26
	PU	22.75		PE	27.45
	SS	22.1		Satisfaction	17.98
	Satisfaction	0		SS	0
SVM Linear	Trust	100	GLM Boosting	Trust	100
	Novelty	39.51		Novelty	31.671
	PU	29.26		PE	31.619
	PE	27.45		SS	9.063
	Satisfaction	17.98		Satisfaction	5.989
	SS	0		PU	0
SVM Radial	Trust	100	Elastic Net	Trust	100
	Novelty	39.51		Novelty	39.51
	PU	29.26		PU	29.26
	PE	27.45		PE	27.45
	Satisfaction	17.98		Satisfaction	17.98
	SS	0		SS	0
RF	Trust	100	Overall Mean Values	Trust	100
	Novelty	24.207		Novelty	34.68686
	Satisfaction	18.759		PE	26.62557
	PE	16.02		PU	20.989
	PU	7.133		Satisfaction	13.80971
	SS	0		SS	1.5105

\*PE: Perceived Expectation; PU: Perceived Usefulness; SS: Service Speed; RE: Repeat Experience.

SEM and ML models. The basic aim of the study is not to find the algorithms but to identify the features which affect the satisfaction and repeat experience. For the same, we will consider the variable importance. Variable importance score is a measure of how much each predictor variable contributes to the model's performance in terms of reducing the error or increasing the fitness of the model (Breiman, 2001; Friedman, 2001b; Hastie et al., 2009b; Nicodemus et al., 2010; Strobl et al., 2008). In this research, we calculated the variable importance for model D, where all the variables are included, and tabulated it in Table 9.

Ensembling, or ensemble learning, is a machine learning technique that combines multiple models or learners to create a stronger and more accurate model or learner (Hare & Kutsuris, n. d.; Sagi & Rokach, 2018; Tuv, 2002). In this paper, we combine the seven ML models to identify the most important features instead of a single model using the ensemble approach. Table 8 averaging the model D scores for all ML algorithms, the most important variables are Trust, Novelty, PE, PU, and Satisfaction and least important is Service Speed.

## 6. Discussion and implications

Larivière et al. (2017) used the term "Service Encounter 2.0" to describe the growing recognition of the interdependencies between technology (such as service robots) and customers (such as those dining in a restaurant). Introduce conceptual models that were developed to better represent various technological constellations at the point of service (De Keyser et al., 2019). Our research at

robot-service restaurants lends credence to the idea that robots in the service industry improve dining experiences for patrons. Our empirical findings corroborate the hypothesis that patrons who encounter a service robot will subconsciously feel like they are in the company of another social being at the eatery. These findings support Ryan and Deci's (2001) hypothesis that humanoid service robots improve the quality of life for hotel guests. Findings from this paper, based on service encounters with service robots, improve upon a previous study that looked at the correlation between encounter speed and satisfaction; clients place a high value on having a pleasant experience with the service provider (hedonic value). Surprisingly, customer happiness is unaffected by how valuable people think a product or service is. This result broadens the scope of previous research on the impact of hedonic value on consumer patronage in the retail setting (see, for example, Atulkar & Kesari, 2017) to include interactions with service robots. This discovery exemplifies the complex relationship between the client, the company leadership, and technology (De Keyser et al., 2019). Also, leadership is an important factor in this relationship (Ruiz-Palomino et al., 2023). We evaluated a no-human interaction scenario to see if the service robots could take over the duties of human workers during the service encounter. The findings indicate that highly practical service robots can replace human workers in fast casual dining establishments. This finding offers preliminary evidence for a "substitution role" in Service Encounter 2.0, where "technology promises to increase service encounter quality and efficiency, omitting inherent human staff variability".

### **6.1. Theoretical implications**

Important theoretical insights can be gleaned from our study's empirical findings about how customers interact with service robots in a robot service restaurant. To begin, we present evidence for the two parties' efforts comprising the "customer-technology" that ultimately benefits the consumer. Service systems today, known as Service Encounter 2.0 (Larivière et al., 2017), are complex ecosystems of interdependent technology, human actors, physical and digital settings, and business and consumer processes. Technology can supplement and even replace human labor in these situations. To get an edge in the market, businesses must strike a good balance between the many parties involved in the customer-technology relationship (Larivière et al., 2017). While it is clear that a balance must be struck between the many performers and their respective roles, nothing is known in the service literature on how to achieve this. This empirical article sheds light on how customers' impressions of service robots and human workers, two members of the service triad, influence their overall happiness with the experience. This is significant because it affects the ongoing discussion about whether frontline service technology should supplement or replace other service providers (Larivière et al., 2017). The empirical results contribute to the field of service management by illuminating the link between customers' enjoyment, speed, novelty perceptions and their satisfaction. We also show that speed and novelty are major drivers of utilitarian and hedonic value in the hospitality industry. Finally, our research shows that service robots can be an effective tool for improving diners' experience at fast-casual establishments. Most of the literature on robots in the hospitality industry is either theoretical or conducts laboratory tests using fictitious settings.

### **6.2. Managerial implications**

The findings of this research are useful for restaurant managers and other front-line service managers interested in incorporating service robots into their operations. To begin, we discover that service robots may one day be able to replace human workers in the hotel industry, which has traditionally been a "game of people". Restaurant owners can save money and increase efficiency by using service robots. Service robots may help reduce the spread of the virus, especially in the socially distant era of the COVID-19 pandemic. In addition, when there is a severe lack of personnel, service robots can help get the job done. The results of our empirical research suggest that service robots should not replace human workers but rather work in tandem with them. Our research shows that service robots' lower functional performance (i.e. utilitarian value) can be offset by human workers' ability to provide superior customer service. Service robots with poor utility can be supplemented by human workers with a high level of enthusiasm to help and

outstanding contacts with consumers. Our data on service robots is collected in a real-world environment providing crucial insights for robot engineers and designers. Our research shows that diners have a higher opinion of the practical and aesthetic worth of service robots when they give the impression that they have thoughts and feelings. This suggests that service robots should be programmed to exhibit social presence by thinking and feeling to add value for their human clients. It is also clear that service robots may eventually replace or supplement human workers in the hotel industry. The hotel industry's workforce needs to be ready for this shift, thus, policymakers should give workers the chance to reskill (in the event of job replacement) or acquire new skills (in the event of job augmentation). We argue for teaching people to work together effectively with a service robot.

## 7. Conclusion and recommendation for future research

This study focuses on the key factors influencing customer satisfaction and their intention to repeat the experience by using two staged hybrid approaches the approaches of PLS-SEM and Machine Learning. The finding confirms that perceived enjoyment, speed, and novelty influence customer satisfaction, whereas perceived usefulness has no influence. Additionally, the study uncovers that customer satisfaction and trust positively mediate the relationship and establish the link with repeat experience. The machine learning models (ANN, SVM, RF, KNN, Elastic Net) predict the intention to repeat the experience of the service robot with a goodness of fit of around 57%. We also discussed several new and useful theoretical and practical implications for enhancing the customer experience (Wali et al., 2016) during the visit to the restaurants.

This study suggests several potential future areas for research. To begin, our study is set in the real-world situation of a fast-casual eatery in India. The sample is further biased because the vast majority of respondents were Indian. These call for caution in extrapolating our results. Future research that replicates this investigation across cultural contexts and restaurant types would provide more light on this topic. If service robots were to play a more or less obvious role in hospitality settings other than fast casual eating restaurants, it would be interesting to see how different service employees might interact with them. Additionally, the hedonic qualities of the service robots used by the quick casual restaurant in our research were severely constrained. They had to talk to each other instead of the customers, and they could not joke around or pose for photos. This could explain why the hedonic value of service robots has not been shown to correlate with improvements in customer happiness. Scholars in the field of customer service today predict that service robots will soon be able to perform low-emotional jobs and those requiring higher levels of cognitive processing. To further untangle the service triad and the connection between the hedonic value of service robots, customer happiness, and the quality of employees' interactions (Skandrani et al., 2011), future service academics are invited to build on these findings by undertaking field investigations. It will be interesting future research which compares the service provided by robots against the service provided by humans. Also, future research can see if a restaurant which is governed by servant leaders in the kitchen or the restaurant, could play an important role in promoting better satisfaction and repeat intention among customers of restaurants that use robots. Next, servant leaders (Ruiz-Palomino et al., 2021), who are said to be important factors that foster satisfaction of customers and loyalty among customers would make a difference in making robots more effective in achieving satisfaction and repeat intentions or trust among customers. Future research could also benefit from examining how customers' actual actions, such as photographing or filming the service robot or dancing with the robot, demonstrate the hedonic value they perceive. Questions like, "How much of a role do customers' prior experiences with the robot or the type of party (friends versus family versus business relations) play in the interactions with service robots and the effects it has on customer outcomes?" would be interesting avenues for further study.

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#### Correction

This article has been corrected with minor changes. These changes do not impact the academic content of the article.

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## Annexure 1

### Instrument Used in the Study

#### Perceived Enjoyment (PE) (Davis, 1989)

PE1: It was a pleasurable experience using services from the robot

PE2: The service robot experience was pleasant

PE3: The technological newness of the service robot restaurant made me happier

PE4: The interaction with the service robots in the restaurant was fun

#### Service Speed (SS) (Lee, 2011)

SOS1: The robot was efficient in serving my order on time

SOS2: I didn't feel the waiting time

SOS3: My order arrived quite fast

#### Novelty (Bello & Etzel, 1985)

EN1: Eating at the service robot restaurant was a unique experience for me and my family and friends

EN2: In my opinion, most people would describe the dining experience at a service robot restaurant as memorable

EN3: Being served by a robot was a new experience for me and my family and friends

EN4: The service at the service robot restaurant is different from the service at other restaurants

EN5: After eating at the service robot restaurant, I believe that I did something new and different

#### Perceived Usefulness (PU) (Davis, 1989)

PU1: Robots are useful in restaurants

PU2: Robots were able to perform the same functions as employees

PU3: Robots enhanced my service experience

PU4: Robots had all the functionalities needed to do their job

#### Satisfaction (Tussyadiah et al., 2020)

ES1: My experience in the Restaurants was enjoyable

ES2: My experience in the Restaurants was memorable

ES3: My overall experience in the Restaurants was satisfactory

#### Repeat Experience (RE) (Dong & Siu, 2013)

EE1: I would recommend this robot service restaurant to my family and friends

EE2: I would encourage friends and relatives to visit this service robot restaurant

EE3: I would share this experience with my friends and family

EE4: I will visit this robot service restaurant again

#### Trust (Mcknight et al., 2011)

TRST1: The robot had the required features to serve food

TRST2: The robot provided me with the help I needed

TRST3: The robot flawlessly served food and drinks.

TRST4: Robots exhibited a level of trustworthiness comparable to that of humans