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Service Robots—An Innovative Sustainability in Rural Banking

Ravi Hariharan[1], Radhakrishna Vedapradha[2*], Elango Sudha[3], Krishnamurthi Subramani[1], Venkoba Rao Divyashree[1]

[1]School of Business & Management, CHRIST (Deemed to Be University), Yeshwanthpur Campus, Bangalore, India
[2]School of Commerce, Mount Carmel College, Autonomous, Bangalore, India
[3]School of Commerce, CHRIST (Deemed to Be University), Yeshwanthpur Campus, Bangalore, India
Email: *Vedapradha.r@gmail.com

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Abstract

Purpose: The purpose of this study is to experimentally test the hypothesized Three-Part Theoretical (TPT) Framework in order to evaluate the impact of the Artificial Intelligence enabled Service Robot, MAYA, among rural banking customers in exploring Customer Loyalty through Customer Satisfaction. The study is based on the Diffusion of Innovation Theory (DOI) and aims to confirm the implementation of such advanced technology in rural banking. **Methodology:** Multi-Stage Cluster sampling method was adopted to collect the responses from the 385 through Triangulation technique from customers across the rural banking customers across Southern States of India within age group between 21 - 50 years. SAS and Smart PLS 4 were used to apply Simple Percentage Analysis, and Structural Equation Modelling to validate the hypothesis. The key constructs are System Feature, Customer Feature, System Encounter feature, Customer Satisfaction & Customer Loyalty. **Results:** System feature, Customer feature of the Service Robot, MAYA have a direct positive influence on the Customer Satisfaction but System Encounter feature has a direct negative influence on the Customer Satisfaction. Customer Satisfaction has a direct positive influence on Customer Loyalty with higher predictive capacity. **Implications:** The benefits of using service robots include increased efficiency, improved safety, and reduced labour costs. It offers personalized assistance to customers, guiding them through the banking process and answering their queries. These findings of the study will facilitate banking managers to enhance rural marketing.

Keywords

Service Robots, Three-Part Framework Theory, Rural Banking, Customer Satisfaction & Customer Loyalty

1. Introduction

Rural banking is to the provision of financial services (Kishore & Sequeira, 2016) to people living in rural areas. It is an important aspect of rural development (Camarero & Olivia, 2019), as it helps to promote economic growth, reduce poverty, and improve the standard of living in rural communities (Azeez & Akhtar, 2021). Rural areas often lack proper infrastructure and communication facilities (Benami & Carter, 2021), may not have the necessary financial knowledge and skills (Ameraldo et al., 2019), lack access to modern technology and digital infrastructure which prevent rural banking customers from using banking services effectively (Rana et al., 2020). Artificial Intelligence (AI) has the potential (Biswas et al., 2020) to transform rural banking by enabling financial institutions to provide better services to rural communities (Li et al., 2019). Some of its application in rural banking facilitating in improving the efficiency, accessibility, and quality of rural banking services, which can promote financial inclusion and economic growth in rural communities (Kosec & Wantchekon, 2020). Artificial Intelligence (AI) is broadly grouped into various types namely, Analytics AI, Functional AI, Interactive AI, and Visual AI (Schwalbe & Wahl, 2020). ***RQ_1*****:** *How can Artificial Intelligence create value for rural banking customers?*

Customer service is a crucial aspect of rural banking as it can help to improve customer satisfaction and loyalty, which can ultimately lead to increased business and revenue for financial institutions (Kaya et al., 2019). AI-powered Chatbots (Mogaji et al., 2020), Virtual Assistants, Service Robots (Mhlanga, 2021) can help rural customers (Belk, 2021) to access banking services without the need for physical branches or agents, improving customer satisfaction, loyalty and reduces the service cost (Malali & Gopalakrishnan, 2020). ***RQ_2*****:** *How AI-based Service Robots improve customers' needs and loyalty?*

"Service Robot" encompasses a wide range of robots and applications, such as social robots, cleaning robots, disinfection robots, robotic waiters/waitresses (Lu et al., 2019), robotic chefs/kitchen robots (Choi et al., 2020), agricultural robotics, and underwater robots (Marakarkandy et al., 2017). They play an important role in rural banking by enabling financial institutions to provide better services to rural customers (Mehdiabadi et al., 2020). These robots are autonomous or semi-autonomous machines designed to perform a wide range of tasks that are typically done by humans (Srivastava, 2021). They are often used in industries such as healthcare, hospitality, retail, banking (Pambudi et al., 2021) and manufacturing, as well as in public spaces like airports and malls (Mende et al., 2019). ***RQ_3*****:** *To what extent can service robots attract new customers?*

Lakshmi was the first banking service robot launched earlier by City Union Bank (CUB) in Chennai, Tamil Nadu, India (Sriram, 2020). It was designed based on Artificial Intelligence supported with gestures and in a lifelike manner, offering more than 125 subject-based customer interactions pertaining to rendering banking related services (Meghani, 2020). However, it has limitations of using *"English"* as its only communicative language with customers. Hence, it's not feasible for rural banking customers due to their language barriers and illiterate status (Singh, 2020).

MAYA, a Banking Service Robot, developed by Engineering College Students at Hubballi, India was programmed expressly to serve the banking industry and is equipped for all banking tasks, including assisting with account opening and directing consumers to counters for questions (Sinha et al., 2023). Customers, both financially literate and illiterate, are anticipated to use the robot to execute banking activities such as money transfers, cash withdrawals, pin changes, information on current interest rates, various lending facilities, and others (Subudhi, 2019). Therefore, the researchers identified the research gap of empirically testing the theoretical framework proposed (Belanche et al., 2020) to examine the Customer Loyalty designed on Artificial Intelligence Service through Service Robots among the rural banking customers across southern India by applying Diffusion of Innovation (DOI) Theory.

2. Literature

2.1. Theoretical Contribution

Artificial Intelligence (AI) is transforming the service industry (Kaur et al., 2020) by providing more efficient and personalized services to customers. Self-driving cars, robotics, and automated machines (Manoharan, 2019) could be used by the postal and parcel industry to interact with customers, support supply chain planning, enhance transportation, and improve warehouse management. These technologies have the potential to have an impact on how these businesses operate on a daily basis (Ukpong et al., 2019). According to Aboobucker & Bao (2018), unlike technologies that demand the effort of customers or employees, service robots also function autonomously, guided by AI (Qasaimeh & Jaradeh, 2022), without the need for instructions or human assistance. In accordance with the peculiarities of the service encounter, such as adjusting the robot's contributions, this feature opens up new opportunities for interaction (Huang & Rust, 2018).

This technology has the potential to alter the banking business by providing customers with more efficient and effective services (Mhlanga, 2020). AI can be used to create virtual assistants or chatbots for customer care that can engage with customers and answer their questions in real time. These virtual assistants can understand and respond to customer queries using natural language processing (NLP) (Khan & Rabbani, 2021) and machine learning (ML) algorithms (Venniro et al., 2020), improving customer satisfaction and reducing the need for human staff in customer service roles (Guo & Li, 2018).

The Service robots are currently implemented in Retail & Logistics, Hospitality, Manufacturing, Agriculture, Inspection & Maintenance, Defense & Security, and Construction industries (Paulius & Sun, 2019). Sales of service robots have expanded drastically, as has research into the implications of artificial intelligence and service robots, which promise to raise productivity and save costs (Chiang & Trimi, 2020). They are enhancing the operational functions of the service industries due to their increased safety, superior speed, huge savings, protection, and greater consistency. The major factors driving the demand for service robotics (Lu et al., 2020) are the rising use of IoT in robots for cost-effective predictive maintenance and the increasing adoption of service robots for novel applications that offer high returns on investments (Samar et al., 2017). Some service robots are designed to operate in a specific environment, such as underwater or in space, while others are designed for general-purpose use which can be categorized into different types based on their function namely, Industrial, Frontline Service, Domestic, and Scientific (McCartney & McCartney, 2020).

The previous contributions to the literature have focused on the application of various technological adoption models like Technological Acceptance Model (TAM) (Ibrahim et al., 2017), Unified Theory of Acceptance and use of technology (UTAUT) (Al-Saedi et al., 2020), Technology Organization Environment (TOE) (Chatterjee et al., 2021), Technological Readiness Index (TRI) (Blut & Wang, 2020), Technology of Planned behaviour (TPB) (Kanimozhi & Selvarani, 2019) and Technology Continuance Theory (TCT) (Rahi et al., 2021). However, application of Diffusion of Innovation Theory (Min et al., 2021) applied to the rural banking industry has very limited literature supporting to explain how new banking products and services are adopted by customers. Banks are continually introducing new products and services, such as online banking, mobile banking, and contactless payments, and the speed and degree of adoption of these innovations can have a significant impact on the bank's success (Johnson et al., 2018).

The performance of these robots is driven by key components namely, Customer Acceptance, Customer Satisfaction, and Customer Loyalty. The theoretical background used in the current study is derived from Three-Part Framework Theory developed and proposed (Belanche et al., 2020) illustrating the Customer Acceptance of Service robots in rendering Services to the customers through Robot or System Design, Customer Features, and Service Encounter Features. The considered dimensions of Customer Acceptance involve System Design Features, Customer Features, and Service Encounter Features.

The conceptual framework was based on Diffusion of Innovation Theory (DOI) developed by E.M. Rogers to explain how new ideas, products, and technologies spread through a society or group over time (Dearing & Cox, 2018). This theory facilitates in testing the implementation of any advanced technology (Taherdoost, 2018). According to Rogers, there are five stages of the innovation adoption process: Knowledge, Persuasion, Decision, Implementation, and Confirmation (Carreiro & Oliveira, 2019).

The proposed research model illustrated in **Figure 1** borrows constructs, Customer Satisfaction & Customer Loyalty from the existing theories and models. System Feature, Customer feature, and System Encounter Features are the constructs developed based on the theoretical framework (Belanche et al., 2020). Customer Acceptance Dimensions are measured by System features, Customer features, and Service Encounter features. This acceptance leads to Customer

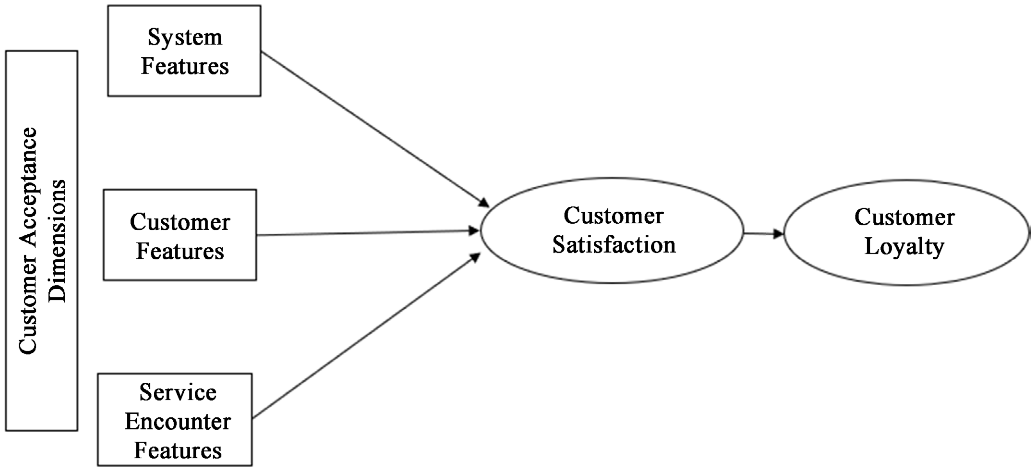

Figure 1. Conceptualized research model.

Satisfaction and then results in Customer Loyalty towards the rural banking services.

2.2. Hypothesis Development

Customer acceptance of technology is critical for the success of technological innovations in the banking sector (Ostrom et al., 2019). Banks need to consider these factors when introducing new technologies as it is a pivotal factor in banking sector when improves the speed or convenience of transactions, customers perceive it to be useful in meeting their needs, easy to use especially, is intuitive and requires little training (Roy et al., 2018). Therefore, the customer acceptance of technology is examined through System Features, Customer Features, and System Encounter Features that leads to Customer Satisfaction & results with Customer Loyalty.

2.2.1. System Features

Sensors on service robots allow them to comprehend their surroundings, detect objects and barriers, and interact with humans and other machines. They are built to move around and modify objects in their surroundings. They can be equipped with several types of movement systems, such as wheels, legs, or tracks, as well as robotic arms or grippers to manipulate things (Wan et al., 2020). Sensors, cameras, and mapping software can all be used through speech recognition, natural language processing, and other communication technologies, they can interact with humans and other machines (Lee et al., 2018). Hence, the first hypothesis designed is:

*H*1: *System Feature has a direct positive influence on Customer Satisfaction.*

2.2.2. Customer Features

Service robots are designed to have user-friendly interfaces that are easy for customers to interact which includes touch screens, voice commands, or other intuitive interfaces, recognize individual customers and tailor their interactions based on previous interactions and preferences. Emotion recognition technologies are applied to detect the emotional state of customers and adjust their interactions accordingly (Huang et al., 2021). Customization and adaptability features enable in meeting the specific needs and preferences of customers and equipped with safety features that ensure they operate safely around customers to support multiple languages to accommodate customers who speak different languages (Pozharliev et al., 2021). Thus, the second hypothesis stated is:

H2: *Customer Feature has a direct positive influence on Customer Satisfaction.*

2.2.3. System Encounter Features

In-Service system encounter features Robots refer to a robot's ability to interact with and respond to many types of interactions that they may encounter while doing their tasks. It is capable of recognizing social cues and correctly responding to social interactions (Becker et al., 2023). This can include recognizing and responding to facial expressions, tone of voice, and body language to adapt to changing situations and environments (Fernandes & Oliveira, 2021). They can detect errors in their operation and recover from them. This can include self-diagnosis, self-repair, or seeking help from humans when needed (Aure et al., 2018). Hence, the third hypothesis designed,

H3: *System Encounter Feature has a direct positive influence on Customer Satisfaction.*

2.2.4. Customer Satisfaction

Customer Satisfaction (Kurdi et al., 2020) in rural banking services depends on the ability of banks to meet the unique needs of rural customers through accessible, personalized, and timely services that build trust and confidence (Jörling et al., 2019). Services should provide personalized services to customers, taking into account their unique needs and circumstances. This can include offering customized loan products, providing financial education and training, and developing relationships with customers (Seo, 2022). Rural banking services need to be easily accessible to customers, especially those living in remote areas (Liu et al., 2018).

Building Customer Loyalty (Khairawati, 2020) in rural banking requires a focus on providing accessible, personalized, and high-quality services that build trust and confidence with customers. They should continuously monitor customer satisfaction and loyalty and make changes to their services (Kumar & Mokha, 2021) to better meet customer needs and build long-term relationships with customers. Rural banking services should be easily accessible to customers, especially those living in remote areas (Dubina et al., 2020). Therefore, the fourth hypothesis stated,

H4: *Customer Satisfaction has a direct positive influence on Customer Loyalty.*

3. Methodology

3.1. Measurement Development

The current research is a deductive study based on the existing theories and conceptualization. The proposed model comprises of Customer Acceptance Dimension constructs, comprising of 6 measurement items to measure System Features, Customer Features, and System Encounter Features respectively developed based on Three-Part Framework Theory (Belanche et al., 2020). The scales measuring the constructs, Customer Satisfaction (Chiang & Trimi, 2020) and Customer Loyalty (Prentice et al., 2020) consisted of 5 measurement items respectively were adapted and refined to suit the current study (See Appendix). The operational definition of the constructs with the source is listed in **Table 1**.

Pilot study was conducted with a sample size (n = 50 > 30, Albers & Lakens, 2018) rural banking customers to validate the developed scales on Three-Part Framework which resulted with a scale reliability (α = 0.837 > 0.70, Taber, 2018). Also, two expert opinions from the Information Technology and Banking Sector were considered before proceeding with further data collection.

3.2. Survey Design

The proposed study includes primary data collected from different sources in the form of Interviews, and Survey Questionnaire based on Triangulation method (Dzwigol, 2020). The questionnaire was divided into two parts. The first part consists of demographic profile of the customers and the second part consist of measurement item scale based on a five-point Likert scale used to represent the item indicators in the latent variables, with "1" being strongly disagree and "5" being "Strongly Agree". The current research model adopted a Quantitative method of research (Allan, 2020).

Table 1. Operational definitions of constructs.

Construct	*Definition*	*Literature Source*
System Features	System features are tasks that are carried out automatically by the system and offer value for the customers using the service while also ensuring a better user experience.	(Samoili et al., 2020)
Customer Features	Customer Features refers to the adoption of the services rendered by bots in context to customer service, perceived intelligence, gender, & culture.	(Belanche et al., 2020)
Service Encounter Features	It refers to any characteristics of discrete interaction between the customer and the service provider relevant to a core service offering.	(Robinson et al., 2000)
Customer Satisfaction	Satisfaction from the use of a product/service cultivates customer's belief in the quality of the product/service and results in repurchase intentions.	(Keshavarz and Jamshidi, 2018)
Customer Loyalty	Customer loyalty refers to both the overall value of the products or services that a customer gets from a business and the continuing good relationship that exists between a customer and a business.	(Fandos Roig et al., 2009)

Source: Authors' Compilation.

3.3. Sampling and Data Collection

The target population was grouped into various clusters based on the geographical location into Zones of South, East, West, and North. Then the population was further divided into Urban and Rural across various Southern states of India. The approximate Rural population of India as of January 2023 is 1,417,237,051 (CensusIndia.gov.in). The clustered rural population comprising of respondents between the age group of 21 to 50 years were selected systematically from all the states to arrive at the sample size. The pilot study confirms this age group predominantly using Service Robots for their banking (Shaikh et al., 2020) services. Self-administered 850 questionnaire were circulated to collect the responses from the respondents, who represent the population and serve sampling adequacy (Shrestha, 2021). A sample size of 385 was obtained through Multi-Stage Cluster Sampling technique of sampling based on the complete responses obtained from the customers using rural banking services.

3.4. Data Analysis

Partial Least Square Structural Equation Modelling (PLS-SEM) was deployed as it is considered (Purwanto, 2021) as one of the robust methods when the analysis is concerned with testing a theoretical framework from a prediction perspective and exploring theoretical extensions of established theories (Hair et al., 2019).

PLS-SEM using Smart PLS V. 4 and Simple Percentage Analysis using SAS (Statistical Analysis Software) were considered to validate and test the hypothesis. The measurement model's reflective approach is appropriate given that manifest variables are manifestations of constructs, changes in a construct result in changes in indicators, which share a common theme, and that a construct's conceptual domain is unaffected by the removal of an indicator (Sarstedt & Cheah, 2019).

4. Results

4.1. Simple Percentage Analysis

Cronbach's alpha (α) was calculated to test the internal consistency of the applied measurement instrument ($N = 385$, $\alpha = 0.958 > 0.70$, Sarstedt et al., 2019), confirming the items' high and excellent ($\alpha \geq 0.9$) reliability. **Table 2** describes the demographic profile describes that there were 36.7 percent of females and 63.3 percent of male customers availing the banking related services from MAYA. 53 percent of the customers fall within the age group of 21 - 30 years, 30 percent of the customers are aged between 31 - 40 years, and rest of the 17 percent of the customers are aged between 41 - 50 years.

4.2. Common Method Bias

Common Method Bias (CMB) which appears when both the independent and dependent variables are captured by the same response method that could be detrimental to the study's validity (Bou Reslan et al., 2021). The researchers

Table 2. Demographic profile of customers.

Demographic Variables	Percentage
Gender	
Male	63.3
Female	36.7
Age group	
21 - 30 years	53
31 - 40 years	30
41 - 50 years	17

Source: Authors' Compilation.

attempted ensured the anonymity of the respondents, introducing a time delay, increasing the physical separation of items, and/or creating a cover story to deemphasize any link between the independent and dependent variables as recommended by Chang et al. (2020). The absence of common method bias was statistically tested for presence using Variance Inflation Factors (VIFs) method and resulted (VIFs < 5, Çakıt, 2020).

4.3. Measurement Model

The proposed research model was evaluated initially through Confirmatory Factor Analysis (CFA) leading to assess the measurement of the model. The factor loadings of the constructs, Security Features, Customer Features, System Encounter Features, Customer Satisfaction, and Customer Loyalty resulted greater than the threshold values (>0.60, Hemsworth, 2018). Hence, all the indicators of the latent construct were retained. **Table 3** projects the summary of the Confirmatory Factor Analysis.

The Average Variance Extracted (AVE), Composite Reliability (CR), and Maximum Shared Variance (MSV) were in consideration while conducting validity and reliability. According to Hair et al. (2010), the minimal criterion should be CR > 0.7, AVE > 0.5, MSV < AVE, and MSV was used to represent the discriminant validity, AVE and CR were used to represent the convergent validity, and CR is used to indicate reliability.

Hetrotrait-Monotrait Ratio (HTMT) criterion was tested to confirm the discriminant validity of the constructs which is much below the recommended threshold value (<0.85, Hair Jr. et al., 2021) as shown in **Table 4**.

The investigation of the correlation between the independent variables makes use of multicollinearity which was evaluated using VIFs and tolerance settings (Sarma et al., 2022). VIF values larger than 10 or tolerance values less than 0.1 will have an impact on the outcome and reveal a multicollinearity issue (Hair & Alamer, 2022). The study has no multicollinearity issue as VIF was less than the threshold values as illustrated in **Table 5**.

4.4. Structural Model

The developed hypothesis was further validated by evaluating the structural model. The influence of the Customer Acceptance dimensions through System Feature, Customer Feature, and System Encounter Features were analyzed on the Customer Satisfaction. Similarly, the influence of Customer Satisfaction on

Table 3. Confirmatory factor analysis summary.

Constructs	Indicators	Loadings	Cronbach's α	AVE	CR	MSV
System Features	SF1	0.810	0.910	0.690	0.930	0.564
	SF2	0.922				
	SF3	0.783				
	SF4	0.856				
	SF5	0.775				
	SF6	0.827				
Customer Features	CF1	0.918	0.921	0.717	0.938	0.498
	CF2	0.779				
	CF3	0.815				
	CF4	0.815				
	CF5	0.812				
	CF6	0.928				
System Encounter Features	SEF1	0.794	0.901	0.668	0.938	0.585
	SEF2	0.826				
	SEF3	0.765				
	SEF4	0.795				
	SEF5	0.929				
	SEF6	0.786				
Customer Satisfaction	CS1	0.707	0.816	0.579	0.872	0.459
	CS2	0.671				
	CS3	0.746				
	CS4	0.836				
	CS5	0.831				
Customer Loyalty	CL1	0.941	0.948	0.830	0.960	0.566
	CL2	0.980				
	CL3	0.823				
	CL4	0.916				
	CL5	0.887				

Source: Authors' Compilation.

Table 4. Discriminant Validity—HTMT Criterion.

Construct	CF	CL	CS	SEF	SF
CF	0.746				
CL	0.284	0.811			
CS	0.670	0.621	0.761		
SEF	0.621	0.258	0.635	0.818	
SF	0.719	0.279	0.647	0.534	0.830

Source: Authors' Compilation.

Table 5. Multicollinearity VIF Summary.

Constructs	Customer Satisfaction	Customer Loyalty
System Feature	3.892	
Customer Feature	4.783	
System Encounter Feature	3.377	
Customer Satisfaction		3.385

Source: Author's Compilation.

Table 6. Path analysis of the constructs.

Structural Paths	β	t value	*p Value*	Hypothesis
SF → CS	0.135	2.680	<0.001	Supportive
CF → CS	0.603	5.256	<0.001	Supportive
SEF → CS	−0.173	3.716	<0.001	Supportive
CS → CL	0.902	8.712	<0.001	Supportive

Source: Authors' Compilation.

the Customer Loyalty was analyzed to establish the significance of the direct paths of the constructs through bootstrap resampling method with 5000 resamples (Ramli et al., 2018). **Table 6** examines the consequence association of the developed hypothesis.

A path coefficient indicates the direct effect of a variable assumed to be a cause on another variable assumed to be an effect. The path coefficient interpreted as expressing the size of a relationship between two latent constructs. The results describe a substantial and positive influence of System feature on the Customer Satisfaction ($\beta = 0.135$, $t = 2.680$, $p < 0.01$), supporting H_1 and a positive influence of Customer feature on the Customer Satisfaction ($\beta = 0.603$, $t = 5.256$, $p < 0.01$), supporting H_2. There was a negative influence of System Encounter Feature on the Customer Satisfaction ($\beta = -0.173$, $t = 3.716$, $p < 0.01$), not supporting H_3. The influence of the construct, Customer Satisfaction on the Customer Loyalty is positive ($\beta = 0.902$, $t = 8.712$, $p < 0.01$). Hence, H_4 was supportive.

Therefore, the path coefficients of the constructs portray the influence on the other within the acceptable threshold of at least 0.100 and at a significance level of at least 0.05 (Goetz & Wald, 2022). Therefore, it can be inferred that latent Customer Satisfaction has the largest and positive influence on the construct, Customer Loyalty.

Additionally, **Table 7** reflects the goodness-of-fit criterion of the model where the effect sizes (f^2) were calculated to determine how much an exogenous (predictive) variable adds to an endogenous variable's R^2 value. The results revealed that System features, Customer Features, and System Encounter Features can predict the Customer Satisfaction up to 32.3 percent (R^2 = 0.323 > 0.10, Fatin et al., 2019), and Customer Satisfaction can predict Customer Loyalty to the extent of 81.4 percent (R^2 = 0.814 > 0.70, Sharma et al., 2023) as per the model's predictive power.

There is larger effect size of System feature on Customer Satisfaction (f^2 = 0.398), Customer Feature on Customer Satisfaction (f^2 = 0.486), and Customer Satisfaction on Customer Loyalty (f^2 = 0.931). However, there is medium effect size of System Encounter Feature on the Customer Satisfaction (f^2 = 0.139) as per the guidelines for assessing f^2 are (Zeng et al., 2021) values of 0.02, 0.15, and 0.35, respectively, represent small, medium, and large effects of an exogenous latent variable on an endogenous latent variable.

5. Discussion & Conclusion

The maximum customers availing the rural banking services through MAYA, a banking service robot belong to the male category of gender aged between 53 percent proving that the users are youngsters who are acquainted with usage of the technology. The path coefficient (0.135) of System Feature, path coefficient (0.603) of Customer Feature indicates that the changes in these endogenous constructs that are associated with standard deviation unit changes in the predictor construct, Customer Satisfaction. SF2 (Robot Notification), CF6 (Gender), and SEF5 (Transactional) are the most influencing indicator of System Features, Customer Feature, and System Encounter Feature respectively. However, it can be observed that the construct, System Encounter Feature has a negative path coefficient (−0.173) on the Customer Satisfaction.

Therefore, it can be confirmed that System feature, Customer feature of the

Table 7. Goodness-of-fit criterion

Construct	R^2	f^2	Path	Conclusion
		0.398	SF → CS	Large effect
CS	0.323	0.486	CF → CS	Large effect
		0.139	SEF → CS	Medium effect
CL	0.814	0.931	CS → CL	Large effect

Source: Authors' Compilation.

Service Robot, MAYA have a direct positive influence on the Customer Satisfaction but System Encounter feature has a direct negative influence on the Customer Satisfaction. The changes in the Customer Satisfaction have a direct positive influence on Customer Loyalty considering its path coefficient (0.902).

Hence, the first research question, "*How can Artificial Intelligence create value for customers*?" leads to the answers that AI can create value for customers by providing personalized experiences, faster and more efficient service, predictive analytics, improved product quality, and enhanced security. Rural Banking can improve customer satisfaction, increase customer loyalty through competitive advantage by leveraging AI in business (Paschen et al., 2020). The second research question, *How AI-based Service Robots improve customers' needs and loyalty?* answers that these robots must offer more natural and intuitive interactions, increased personalization, better accuracy and reliability, enhanced safety and security, and faster response times (Libai et al., 2020). These improvements in rural banking provide effective and efficient service accelerates customer satisfaction and customer loyalty. Finally, third question of "To what extent can robots attract new customer?" answers include improved convenience, novelty, differentiation, and social media marketing. Rural banking can create a unique and compelling value proposition that can help them stand out in a crowded market and attract new customers (Bag et al., 2022).

5.1. Theoretical Contributions

DOI Theory is applied to the adoption of service robots (Borghi & Mariani, 2021) in banking at below phases. Knowledge: Customers become aware of service robots in banking, perhaps through media coverage, advertising or seeing them in use in their local branch. Persuasion: Customers who are interested in the idea of service robots may seek out more information to understand how they work and how they could benefit from using them (Amelia et al., 2022). Decision: Customers will weigh the pros and cons of using service robots, considering factors such as the perceived relative advantage (e.g., convenience, speed, accuracy), compatibility with their existing banking habits, and complexity of the technology. Implementation: Customers who decide to adopt the use of service robots will start using them for banking services such as opening accounts, deposits, withdrawals, and other routine transactions (Fairooz & Wickramasinghe, 2019). Confirmation: After using the service robots, customers will evaluate their experience and decide whether to continue using them or return to traditional banking methods. Positive experiences may lead to further adoption and advocacy, while negative experiences may lead to abandonment of the technology (Dozier & Montgomery, 2019).

5.2. Managerial & Practical Implications

Service robots have the potential to improve rural banking by allowing financial institutions to provide better services to their consumers (Bhatia et al., 2021).

These robots can be employed in rural bank branches as virtual assistants or receptionists to greet customers, answer their questions, and help them through the banking procedure (Yaacoub & Alouini, 2020). In terms of successful customer service, this can boost customer satisfaction and reduce the demand for human staff in rural branches. These robots can be employed at rural bank branches to automate cash handling tasks such as counting, sorting, and dispensing currency (Hasan et al., 2021).

This can improve accuracy and security while decreasing the need for human cashiers. These robots, when outfitted with cameras and sensors, can be used to monitor rural bank branches and detect suspicious activity. This can improve security and lower the likelihood of theft or fraud (Vinoth, 2022). It can be used to clean rural bank branches and perform basic maintenance chores such as light bulb replacement and equipment repair. This can lessen the requirement for human workers to do these activities while also improving the branch's overall cleanliness and look (Bai et al., 2019).

Service robots can execute functions that would ordinarily be performed by humans, decreasing the requirement for human resources and lowering bank expenses. Furthermore, service robots can function continuously without breaks, holidays, or sick leave, lowering operational costs even further (Srivastava, 2021). Customers can receive personalized support from them, leading them through the banking procedure and addressing their questions. This can boost customer satisfaction while also reducing the workload on human employees. Service robots can be deployed in distant places or areas with restricted access to regular bank branches to provide banking services to customers who previously did not have access to these services (Haralayya, 2021).

Service robots provide advantages such as better efficiency, improved safety, and lower labour expenses. However, there are concerns about job displacement and the ethical implications of utilizing robots (Kim et al., 2018) to perform work that humans have historically performed. As a result, it is critical to carefully assess the influence of service robots on society and guarantee that their development and deployment are done responsibly and ethically (Rahman et al., 2021).

5.3. Limitations & Future Scope of Research

Research study is confined only to Southern States of India covering the rural banking customers due to cost, resources and other restrictions. The study revolves around the validation of Service robots applicable in Banking Sector (Sharma et al., 2020). The aspiring researchers may focus on exploring the application, validation, acceptance of Agri robots, logistics & delivery robots, social robots, kitchen & restaurant robots, and underwater robots.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix: Measurement Item Scale of Service Robots

System Features (SF)

SF1: Aesthetics—Human appearance of a technological object increases customers' access.
SF2: Robot Notification—The awareness among customers of interacting with a robot determines their expectations of the interaction.
SF3: Formality—The level of formality in the customer-robot interaction varies by design as well.
SF4: Proactivity—Proactive service behavior occurs when the robot initiates the encounter.
SF5: Affect—The incorporation of emotions in robotic agents is among the most challenging.
SF6: Manipulability—The service experience might be customized by consumers.

Customer Features (CF)

CF1: Technology readiness—Technology-based services thus can trigger positive or negative feelings.
CF2: Age—Older people generally have more negative attitudes toward robots and technology.
CF3: Customer Tier—The effect of different customer tiers with regard to service robot acceptance.
CF4: Personality traits—Individual personality traits similarly may be crucial for establishing people's attitudes toward service robots.
CF5: Culture—Attitudes toward robots are shaped by culture.
CF6: Gender—Woman tend to express more negative perceptions than men.

System Encounter features (SEF)

SEF1: Information provision—Robots can be helpful at different stages of the customer journey.
SEF2: Involvement level—Customers' level of involvement affects their information processing and decision making.
SEF3: Failure & complain—Customers are especially sensitive to the service provided following a failure.
SEF4: Product or Service—Service provision can involve sales of both products and services.
SEF5: Transactional—Service robots may be especially useful in transaction-oriented service settings.
SEF6: Collaboration—Employees-AI collaboration help build customer-employee rapport.

Customer Satisfaction (CS)

CS1: I am generally pleased with Service Robots.

CS2: The Service Robot is enjoyable.

CS3: I am very satisfied with the services provided by Service Robots.

CS4: I am happy with the Service Robots.

CS5: I am satisfied with the technological assistance offered by Service Robots.

Customer Loyalty (CL)

CL1: Say positive things about the Service Robot to other people.

CL2: Recommend the Service Robot to someone who seeks your advice.

CL3: Encourage friends and others to use the Service Robot.

CL4: Consider Service Robot to be your first choice for future transactions.

CL5: Do more interactions Service Robot in the coming months.