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Service Robot Acceptance Among Customers of Insurance in Kathmandu Valley

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Abstract

Purpose: Service robots equipped with automation and artificial intelligence, especially generative AI, are increasingly integrated into service interactions worldwide. Despite their advanced capabilities, research on factors influencing customer acceptance of service robots remains limited. To examine the acceptance of service robots among insurance customers in Kathmandu Valley, Nepal, using the sRAM framework.

Design/Methodology/Approach: A crosssectional survey collected data from 243 insurance customers in Kathmandu Valley using selective sampling. Hypotheses were tested employing SPSS statistical analysis.

Findings: Perceived Ease of Use (PEOU) and Subjective Social Norms (SSN) significantly impact customer acceptance of service robots. Similarly, Perceived Social Influence (PSI) and Robot Anxiety Perception (RAP) also have a significant positive influence. However, Perceived Usefulness (PU), Perceived Humanness (PH), Perceived Social Norms (PSN), and Trust (TR) showed no significant effect on acceptance among these customers.

Practical Implications: This study enriches the literature on service robot adoption and offers actionable insights for Nepal's insurance industry to optimize the deployment of robotic services.

Originality: Among the first studies to investigate service robot acceptance specifically within Nepal's insurance customer context.

Keywords: perceived ease of use, perceived humanness, uerceived usefulness, service robot acceptance model, subjective social norms

Introduction

The advent of robotics, a process spanning decades across various industries, has now reached the service sector (Belanche et al., 2020). With advanced robotics, artificial intelligence (AI), and machine learning technologies, service providers can deliver services with enhanced productivity, effectiveness, and efficiency (Writz et al., 2018). In recent years, the service industry has witnessed significant advancements, particularly through the widespread adoption of artificial intelligence (AI) tools and automated technologies such as service robots, chatbots, and virtual assistants (Gummerus et al., 2019). Consumers are increasingly incorporating technological assistance into their daily routines (Kunz et al., 2019), ushering in new opportunities and challenges (Kaplan & Haenlein, 2019).

Numerous studies have explored the role of service robots, especially within services management contexts (Seo & Lee, 2021). For instance, Chatbots and virtual assistants offer banking services Bornet et al. (2021) and provide medical advice to patients Yoon and Lee (2018). Embodied service robots like Nao and Pepper are employed in the hospitality sector to offer information and room service (Tung & Au, 2018). Initial academic research suggests that businesses adopting these technologies can improve service efficiency and customization, ultimately contributing to value creation (Van Doorn et al., 2017). Various theories are available to elucidate technology acceptance behavior, including the adoption of service robots. The Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Theory of Planned Behavior (TBA) are commonly utilized to explicate technology adoption and user behavior (Chaudhary et al., 2023). In the context of accepting service robots, the Service Robot Acceptance Model (sRAM) holds particular significance. This model, originally developed by Wirtz et al. (2018), aims to investigate consumer perceptions, beliefs, and behavioral intentions regarding services delivered by robots.

Nepal has been lagging behind in the adoption of modern technology compared to other nations. There's a pressing need for more policy level involvement in AI, although the integration of AI based technologies in banking and healthcare sectors shows Nepal's efforts to bridge this technological gap (Kalwar, 2023). Despite its slow pace of development, Nepal is gradually catching up with the global digital transformation trend (Shrestha et al., 2020). One prominent development is the increasing use of robots, not only in industrial production but also in services and addressing personal needs (Bataev et al., 2020). The financial sector, in particular, stands out as a promising domain for the application of service robots. Robotics has revolutionized artificial intelligence and device research in financial services (Maharjan & Chatterjee, 2019). Within the insurance sector, robots play crucial roles in enhancing customer service, streamlining operations, and boosting overall efficiency. For instance, Nepal SBI Bank has introduced a humanoid robot named "Pari" at a local branch, stationed within the bank's digital branch known as the in Touch branch. Pari serves as an information resource and assists customers (Xinhua & Sharma, 2018).Therefore, this study intends to investigate Service Robots acceptance among customers of insurance in Kathmandu valley applying sRAM model.

Research Objective

The purpose of this study is to examine the acceptance of service robots among insurance customers in Kathmandu Valley by using the Service Robot Acceptance Model (sRAM), focusing on the influence of functional factors (perceived ease of use, perceived usefulness, and subjective social norms), social emotional elements (perceived humanness, perceived social interactivity, and perceived social presence), and relational factors (trust and rapport) on customer adoption of service robots in the insurance sector.

Literature Review

Artificial Intelligence (AI) is a multidisciplinary field focused on creating computer systems capable of performing tasks that traditionally require human intelligence. The concept originated in the mid 20th century with foundational theories by pioneers like Alan Turing, who introduced the idea of machines exhibiting intelligent behavior (Turing, 1950). Early AI research aimed to replicate human reasoning and problem solving through algorithms, but faced limitations due to insufficient computational power and restricted data availability (McCarthy et al., 2006). The subsequent rise of machine learning a subset of AI involving data driven algorithmic improvement marked a significant evolution, leading to breakthroughs in natural language processing, computer vision, and pattern recognition (Mitchell, 1997; Martin & Jurafsky, 2019; Bishop, 2006). Deep learning, employing multilayered neural networks to process vast datasets, has propelled AI's current capabilities and real world applicability (LeCun et al., 2015).

AI has been transformative across diverse sectors. In healthcare, AI facilitates early disease diagnosis through medical imaging analysis, enhancing detection of conditions like cancer and Alzheimer's disease (Litjens et al., 2017). Financial institutions utilize AI driven algorithms for risk assessment, fraud detection, and algorithmic trading, thus improving operational decision making and security (Deng et al., 2013). In manufacturing, AI powered robotics automate repetitive tasks and maintain quality control, contributing to increased productivity (Javaid et al., 2022). Customer service has benefited from AI chatbots and virtual assistants leveraging natural language processing to improve responsiveness and efficiency (Ngai et al., 2021). AI also supports environmental conservation by employing predictive models for climate monitoring, disaster preparedness, and resource optimization (Sharma et al., 2022).

Robot development traces roots to ancient automata rituals and 19th century mechanical inventions (Gunnar, 1992). The industrial revolution introduced robots into manufacturing to relieve humans from hazardous tasks, with early industrial robots performing operations such as welding and assembling (Garcia et al., 2007). Advances in computing and integration of intelligent control systems broadened robot functionalities, culminating in specialized forms including surgical, mobile, rehabilitation, and humanoid robots (Garcia et al., 2007). Since the 1990s, robots migrated from manufacturing to service domains, fueling rapid growth in service robotics deployed in sectors like healthcare and tourism (Sun & Wang, 2022).

Service robots, defined by standards organizations as autonomous systems executing useful tasks outside industrial automation, interact dynamically within human environments and exhibit foundational intelligent behavior (Wirtz et al., 2018; Haidegger et al., 2013). They are categorized mainly as professional or personal service robots based on application areas (Sun & Wang, 2022). AI driven advancements have enhanced their productivity and efficiency, fostering adoption in diverse contexts including education, healthcare, hospitality, and domestic settings (Holland et al., 2021). Noteworthy examples include the robot staffed Hennna Hotel in Japan, demonstrating service automation in hospitality (Nakanishi et al., 2020), and humanoid robots in special education supporting social engagement and interaction (Lekova et al., 2022). AI powered chatbots employed by platforms like Amazon and Facebook streamline digital commerce, enhancing consumer engagement effectively (Thompson, 2018; Luo et al., 2019).

In the Nepali context, service robots are emerging as transformative tools despite initial slow technology uptake (Shrestha et al., 2020). Locally developed humanoid robots such as "Ginger," created by Paaila Technology, assist in hospitality roles, reflecting growing innovation in robotic applications (Neupane, 2018). Nepalese enterprises like Krispy Krunchy Fried Chicken and Naulo Restaurant integrate service robots to improve operational efficiency, with robots embodying advanced technology and ease of use (Prasain, 2018). Financial institutions have also adopted robotic solutions, exemplified by Nepal SBI Bank's humanoid "Pari" in digital branches and Macchapuchhre Bank's chatbot "MAYA," facilitating customer service and information delivery Shrestha et al. (2022).

Collectively, the evolution of AI and robotic technologies underscores their expanding role in enhancing industry productivity, augmenting human capabilities, and reshaping service delivery worldwide, with Nepal progressively aligning with these global trends through localized innovation and application.

Conceptual Framework

A conceptual framework clearly articulates the research problem and offers a graphical or textual representation of how such factors interact with one another. The first thing that a conceptual framework does is to offer structure for the research process (Knopf, 2006). It is a structured assembly of related ideas that helps develop an illustration or picture of how concepts in the course of research relate to one another within the conceptual framework (Grant & Osanloo, 2014). On the basis of Technology Acceptance Model (TAM) this research examines eight key variables: perceived ease of use, perceived usefulness, subjective social norms, perceived social presence, perceived social interactivity, perceived humanness, perceived rapport, perceived trust and customer acceptance of service robots.

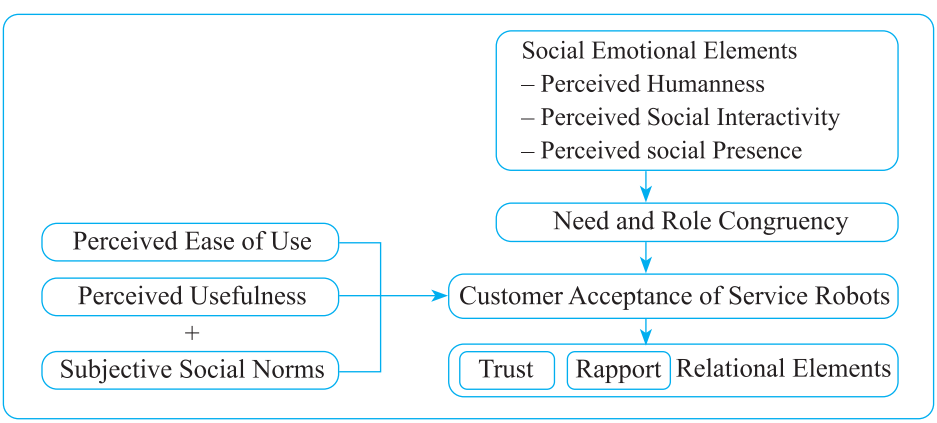
TAM argues that the Perceived Ease of Use (PEOU) of robots plays a crucial role in shaping customers' preferences for service robots (Shin & Jeong, 2020). This implies that when customers find robots easy to operate, they are more likely to favor or select service robots for various tasks or services. Additionally, PEOU positively influences the attitude towards using service robots in the hotel industry (ÇALLI, 2022). Similarly, Perceived Usefulness (PU) is positively linked to the Adoption Intention of technology (Davis, 1989). Choe et al. (2022), noted that PU positively impacts Attitude towards service robots in Korean restaurants. This indicates that PU plays a constructive role in shaping people's attitudes toward service robots in Korean restaurant settings.

Furthermore, (Writz et al., 2018), proposed that the perception of human likeness in robots is associated with anthropomorphic characteristics, including both physical appearance and behavior, which consumers identify with. Research indicates that consumers often anthropomorphize technology leading to a sense of connection with non human entities (van Pinxteren et al., 2019). Li et al. (2010), discovered that in service oriented settings, humanlike robots tend to garner higher acceptance rates from customers.

Personal Social Presence (PSP) plays a significant role in trust building, as individuals tend to trust others more when they interact in person. Shen (2012), discovered that PSP positively impacts Perceived Usefulness (PU) and perceived enjoyment of social shopping websites. Additionally, research on the adoption of online services, such as that conducted by Kaur and Arora (2021), underscores the significant role of trust in influencing behavioral intentions and subsequent decisions regarding usage. Aslam et al. (2022), found that Perceived Trust in the Robot (PTR) significantly impacts Chatbot acceptance. Perceived Rapport (PR) has been recognized as a crucial factor influencing customers' positive responses toward service providers (Chang et al., 2020). Additionally, Pontes et al. (2017), found in their investigation of Self Service Technology (SST) that reliability is a crucial factor influencing customer acceptance, referring to the system's ability to deliver the promised service accurately.

Figure 1

Conceptual Framework



Note. Adopted and modified form Writz et al. (2018)

Perceived Ease of Use and Customer Acceptance of Robots

The likelihood of adopting a system depends on one's intention to use it, which is influenced by the perceived ease of use associated with the system. The Perceived Ease of Use (PEOU) of robots plays a crucial role in shaping customers' preferences for service robots (Shin & Jeong, 2020). This implies that when customers find robots easy to operate, they are more likely to favor or select service robots for various tasks or services. Aslam et al. (2023), discovered that PEOU significantly influences the acceptance of Chatbots. This suggests that when individuals perceive using service robots as simple or user-friendly, it positively impacts their overall attitude or willingness to utilize these robots in the insurance sector.

H1: Perceived Ease of Use positively influences Customer Acceptance of service robots.

Perceived Usefulness and Customer Acceptance of Service Robot

Perceived Usefulness (PU) is positively linked to the Adoption Intention of technology (Davis, 1989). When consumers perceive technology as useful, they are more likely to adopt it. Furthermore, Choe et al. (2022), noted that PU positively impacts Attitude towards service robots. This indicates that PU plays a constructive role in shaping people's attitudes toward service robots in Insurance industry.

H2: Perceived Usefullness positively influences Customer Acceptance of service robots.

Subjective Social Norms and Customer Acceptance of Robots

The Technology Acceptance Model (TAM) proposed by Davis (1989), primarily focuses on understanding and addressing subjective social norms associated with technology adoption. Luo et al. (2019), discovered a positive relationship between social influences and consumers' willingness to use robots. In service delivery contexts, customers tend to conform to the norms, behaviors, and attitudes of their social groups when deciding whether to use AI service devices. Additionally, Alaiad et al. (2013), found that social influence significantly predicts the usage intention of robots in insurance sector.

H3: Subjective Social Norms positively influences Customer Acceptance of service robots.

Perceived Humanness and Customer acceptance of Service Robots

Writz et al. (2018), proposed that the perception of human-likeness in robots is associated with anthropomorphic characteristics, including both physical appearance and behavior, which consumers identify with. This aspect is particularly relevant given the increasing likeness between robots and humans. Research indicates that consumers often anthropomorphize technology, leading to a sense of connection with non-human entities. Li et al. (2010), discovered that in service-oriented settings, humanlike robots tend to garner higher acceptance rates from customers.

H4: Perceived Humanness positively influences Customer Acceptance of service robots.

Perceived Social Interactivity and Customer Acceptance of Service Robot

Writz et al. (2018), proposed that the importance of aligning customers' needs, their perceptions of a robot's social skills, and robot performance for widespread adoption of service robots. Additionally, Kaur and Arora (2021), discovered that customers' perceived interaction quality with a service robot positively influenced their perception of the robot's usefulness and ease of use, consequently enhancing their attitudes toward the robot.

H5: Perceived Social Interactivity positively influences Customer Acceptance of service robots.

Perceived Social Presence and Customer acceptance of Service Robots

Personal Social Presence (PSP) plays a significant role in trust-building, as individuals tend to trust others more when they interact in person. Writz et al. (2018), argued that robots have the capacity to generate a certain level of Automated

Social Presence (ASP) in service encounters. Additionally, Chattaraman et al. (2019), identified humanness, social presence, and interactivity as positive factors influencing service robot acceptance, based on the Social-Robot Acceptance Model (sRAM).

H6: Perceived Social Presence positively influences Customer Acceptance of service robots.

Perceived Trust and Customer Acceptance of Service Robots

The perceived trustworthiness of a robot and its prioritization of customers' best interests are key factors influencing its likelihood of adoption. This implies that when individuals perceive a robot as trustworthy and dedicated to fulfilling their needs, they are more inclined to accept and utilize it. Additionally, research on the adoption of online services, such as that conducted by Kaur & Arora (2021), underscores the significant role of trust in influencing behavioral intentions and subsequent decisions regarding usage.

H7: Perceived Trust positively influences Customer Acceptance of service robots.

Perceived Rapport and Customer Acceptance of Service Robots

Perceived Rapport, as defined by Gremler & Gwinner (2000), refers to a customer's perception of an enjoyable interaction with a service provider employee, characterized by a personal connection between the two parties. Writz et al. (2018) suggested that establishing rapport is particularly important in service contexts where social closeness and affiliation play a central role, such as in education, elderly care, and high-risk financial services. This underscores the significance of rapport in fields where personal connections significantly influence service outcomes. PR has been recognized as a crucial factor influencing customers' positive responses toward service providers (Chang et al., 2020).

H8: Perceived Rapport positively influences Customer Acceptance of service robot.

Methodology

Research Design

This study employed a cross sectional survey research design to examine the acceptance of service robots among customers in the insurance sector of Kathmandu Valley. Cross sectional design is appropriate here, as it facilitates the assessment of relationships among variables at a single point in time without manipulating any factors, enabling an efficient snapshot of customer perceptions and acceptance behaviors (Setia, 2016) . Given the study's objective to investigate the influence of independent variables Perceived Ease of Use, Perceived Usefulness, Perceived Social Presence, Perceived Humanness, Perceived Social Interactivity, Subjective Social Norm, Trust, and Rapport on the dependent variable, customer acceptance of service robots, this design allows for correlational analysis through regression techniques.

Population, Sample, and Sampling Method

The target population comprised individuals who are consumers of insurance services or possess substantial knowledge about insurance within Kathmandu Valley. This region was chosen due to its growing population and documented challenges in insurance service delivery, including extended wait times, transaction errors, and rising customer concerns about data security and privacy amid increased digital transformations. The growing deployment of AI integrated service robots in Nepal's service sectors, including insurance, further motivates this focus.

A purposive sampling technique was utilized to select participants who are frequent insurance customers with awareness or interest in AI based service robotics. This non probability sampling approach optimizes relevance and data richness by targeting informed respondents, facilitating focused insights into robot acceptance.

Research Instrument and Data Collection

Data were collected using a structured questionnaire divided into two sections:

demographic profile and Likert scale items measuring the study constructs. The instrument employed closed ended questions to standardize responses and improve reliability and validity. The questionnaire was administered online via Google Forms, resulting in a sample size of 243 respondents.

Data Analysis

Collected data were organized and analyzed using Statistical Package for Social Sciences (SPSS) and Microsoft Excel software. Regression analysis was applied to test hypothesized relationships between independent variables and customer acceptance of service robots, assessing both significance and direction of influence.

Results and Discussion

Demographic profile of respondent

This section describes the demographic characteristics of the respondents who participated in the entrepreneur intention survey. The respondents' profiles provide an overview of their combined personal attributes, which include gender, age group, academic background, and work title. Understanding demographic features is necessary for entrepreneur intention in the graduate area industry.

Table 1

Demographic Profile of Respondents

Variables	Particular	Frequency	Percentage
Age	Below 26	64	26.3
	27–42	158	65.0
	43–58	21	8.6
Gender	Male	108	44.4
	Female	135	55.6
	Others		
Education	Below Bachelor	19	7.8
	Bachelor level	107	44.0
	Master level	117	48.1
Employment	Unemployed	25	10.3
	Employed but not self-employed	176	72.4
	Self Employed	41	16.9
	Total	243	100.0%

In the above table, the majority of the respondents in the study were in the age group of 270–42 years (n= 158 or 65%) with female respondents (n=135, or 55.6%) followed by male respondents (n=108, or 44.4%). Most of the respondents are at the master's degree level (n=117, or 48.1%) and bachelor's degree level (n=107, or 44%). The majority of participants (n=176, or 72.4%) were employed but not self employed.

Descriptive Statistics and Correlation

Descriptive statistics is a means of summarizing and displaying the features of a dataset for instructive purposes. In this study, a descriptive statistical analysis was employed to analyze and report the extracted information from the quantitative data. The degree to which two variables are closely related is measured by correlation. It is described as two variables being associated (McLeod et al., 2018). The collected data is summarized with descriptive statistics analysis.

Table 2

Descriptive Statistics and Correlation

	Mean	S.D	1	2	3	4	5	6	7	8	9
PEOU	3.563	0.599	1								
PSP	3.197	0.804	0.399**	1							
SSN	3.491	0.665	0.470**	00.326**	1						
TR	3.506	0.611	0.673**	0.292**	0.525**	1					
PH	3.037	0.858	0.390**	0.567**	0.457**	0.501**	1				
AP	3.682	0.610	0.562**	0.251**	0.476**	0.550**	0.455**	1			
PU	3.651	0.989	0.335**	0.100	0.199**	0.320**	0.075	0.245**	1		
CASR	3.572	0.692	0.551**	0.286**	0.528**	0.550**	0.413**	0.527**	0.263**	1	
PSI	3.619	0.596	0.602**	0.344**	0.408**	0.588**	0.365**	0.514**	0.351**	0.552**	1

Based on author survey; CASR: Customer Acceptance of Service Robot; PEOU: Perceived Ease of Use; PH: Perceived Humanness; PRP: Perceived Rapport; PTR: Perceived Trust; PSI: Perceived Social Interactivity; PSP: Perceived Social Presence; PU: Perceived Usefulness; PRP: Perceived Rapport; SSN: Subjective Social Norms **. Correlation is significant at the 0.01 level (2 tailed).

The table 2 presents descriptive statistics and correlations among key constructs related to Service robot acceptance: PEOU, PSP, SSN, TR, PH, RAP, PU, CASR, and PSI. The values of mean and standard deviations reveals that customers are agreed toward eight independent variable and acceptance of robot service. The standard deviation ranges from 0.59 to 0.97 shows that noteable variability in responses.

The correlation analysis relationship between the various variables used in this study. There is a positive correlation between perceived ease of use and customer acceptance of service robot, as indicated by the correlation coefficient of 0.602. Similarly, there is a positive correlation between Perceived Social Presence and Customer acceptance of Robot Service, as indicated by the correlation coefficient of 0.344. Furthermore, there is a positive correlation between Subjective Social Norms and feedback and Customer Acceptance of Robot Service, as indicated by the correlation coefficient of 0.408. Furthermore, there is a positive correlation between Subjective Social Norms and feedback and Customer Acceptance of Robot Service, as indicated by the correlation coefficient of 0.408. Likewise, the correlation value of 0.588 states that there is a positive relationship between trust rapport and the training and acceptance of robot services. In a similar way Perceived Humanness has positive relationship with acceptance of robot services with correlation coefficient of 0.365. Moreover, the correlation coefficient of 0.541, 0.351 and 0.552 shows that there is a good bond between Perceived Rapport, Perceived Usefulness and Perceived Social Interactivity and Customer Acceptance of Service Robot. As a result, it is possible to conclude that all of the independent variables influence acceptance of service robot.

Normality Test

Normality tests are used to determine whether data was drawn from a normally distributed population. The testing can be done through numerical statistical methods such as Skewness and Kurtosis. Skewness and Kurtosis are intuitive methods used to understand normality.

Table 3

Normality Test

	Skewness		Kurtosis	
	Statistic	**Std. Error**	**Statistic**	**Std. Error**
Perceived Ease of Use	-0.402	0.156	0.792	0.311
Perceived Social Presence	-0.324	0.156	-0.517	0.311
Subjective Social Norms	-0.218	0.156	-0.140	0.311
Trust	-0.513	0.156	0.445	0.311
Perceived Humanness	-0.544	0.156	-0.155	0.311
Rapport	-0.459	0.156	-0.129	0.311
Perceived Usefulness	4.819	0.156	40.498	0.311
Customer Acceptance of Service Robot	-0.462	0.156	0.034	0.311
Perceived Social Interactivity	-0.587	0.156	1.162	0.311

In table 3, a comprehensive summary scale is provided, encompassing all identified constructs along with their corresponding Skewness and Kurtosis values. The standard ranges of Skewness coefficient is within -3 to +3 and Kurtosis is from -10 to +10. The values falls within the range. It is considered as normal for further analysis.

Multi-Collinearity Test

Multi-collinearity indicates that no independent variable can account for a specific variance in the dependent variable and that the variance explained by the independent variables overlaps with each other. This can be confirmed by carrying out a multivariate regression and then calculating the Variable Inflation Factor (VIF) for each independent variable (O'Brien, 2007).

Table 4

Multi-collinearity test

Particulars	Tolerance	VIF
Perceived Ease of Use	0.418	2.393
Perceived Social Presence	0.601	1.663
Subjective Social Norms	0.632	1.583
Trust	0.403	2.479
Perceived Humanness	0.495	2.019
Rapport	0.548	1.823
Perceived Usefulness	0.830	1.204
Perceived Social Interactivity	0.528	1.893

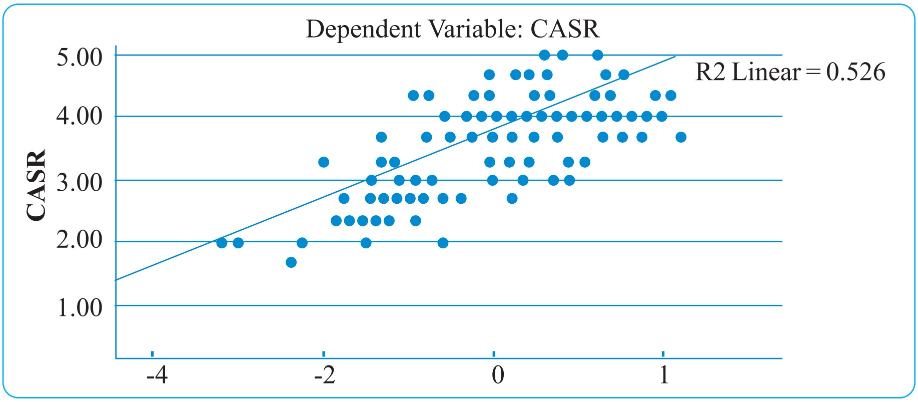
In this test, multi-collinearity is predicted using the VIF method. The value of VIF in the multicollinearity test ranges from 1 to 3 considered good, 3 to 5 is considered acceptable, and above 5 is considered questionable. With the given ranges, all the VIF values of variables PEOU, 2.393; PSP, 1.663; SSN, 1.583; TR, 2.479; PH, 2.019; RAP, 1.823; PU, 1.204; PSI, 1.893; fall under the first category i.e. good. Therefore, there is no issue is the multi-collinearity test.

Homoscedasticity

Homoscedasticity refers to a situation where variance of errors remains consistent across all levels of the independent variable. But, when the variance of errors varies at different values of the independent variable, then heteroscedasticity is indicated.

Figure 2

Regression Standardized Residual



The homoscedasticity assumption was tested using a residual PP Plot and residuals were found to be dispersed around a diagonal line. Therefore, this study satisfies the homoscedasticity criteria

Autocorrelation

The Durbin Watson test is employed to check the autocorrelation among the variables. The Durbin Watson statistic ranges from 0 to 4. A value of the test around 2 is considered to be no autocorrelation, while a value closer to 0 shows positive autocorrelation, likewise, a value around 4 indicates negative autocorrelation. The result of the Durbin Watson test in this study is 2.51, which indicates no autocorrelation. This means that autocorrelation is not a problem in data collection

Hypothesis Testing

Hypothesis testing encompasses assessing the probability of the observed data under the null hypothesis and comparing the obtained probability with a predetermined threshold which helps to determine whether the null hypothesis can be rejected (Gelman et al., 2019). The widely used statistical method to estimate the relationship between dependent and independent (one or more than one) variables is OLS (Ordinary Least Square). OLS regression is used in this research because of its high level of reliability in the obtained results as well as it is considered a reliable tool to analyze the linear relationship between the dependent and independent variables as well as to recognize the most significant factors influencing the outcome variable.

Table 5

Hypothesis Testing

HYP	Relation	Beta	t Values	p Values	HS
1	PEOU→ CASR	0.147	2.007	0.046	YES
2	PU→ CASR	0.026	0.502	0.616	NO
3	SSN→ CASR	0.224	3.763	0.000	YES
4	PH→ CASR	0.081	1.198	0.232	NO
5	PSI→ CASR	0.221	3.383	0.001	YES
6	PSP→ CASR	-0.030	-0.498	0.619	NO
7	TR→ CASR	0.086	1.152	0.251	NO
8	RAP→ CASR	0.141	2.209	0.028	YES

Based on the author calculation; β= Standardized Beta Coefficients, HS= Hypotheses Supported; CASR: Customer Acceptance of Service Robot; PEOU: Perceived Ease of Use; PH: Perceived Humanness; PRP: Perceived Rapport; PTR: Perceived Trust; PSI: Perceived Social Interactivity; PSP: Perceived Social Presence; PU: Perceived Usefulness; PRP: Perceived Rapport; SSN: Subjective Social Norms

The result of the regression, table 5 indicated that five predictors were explained by 45.7% of the variance (R square = 0.457). First, it was found that PEOU significantly predicted CASR (β = 0.147, t = 2.007, $p < 0.01$). It implies hypothesis 1 is supported. One unit increase in PEOU will increase EI by 0.147. Second, it was found that PU did not significantly predict CASR (β = 0.026, t = 0.502, $p < 0.01$). It implies hypothesis 2 is not supported. Third, it was found that SSN significantly predicted CASR (β = 0.224, t= 3.763, $p < 0.01$). It implies hypothesis 3 is supported. One unit increase in SSN will increase CASR by 0.224. Forth, it was found that PH significantly predicts CASR (β = 0.081, t = 1.198, $p < 0.01$). It implies hypothesis 4 is supported. Fifth, it was found that PSI significantly predicted CASR (β = 0.221, t= 3.383, $p < 0.01$). It implies hypothesis 5 is supported. Sixth, it was found that PSP did not significantly predicts CASR (β = -0.030, t = -0.498, $p < 0.01$). It implies hypothesis 6 is not supported. Eight, it was found that TR did not significantly predict EI (β = 0.086, t = 1/152, $p < 0.01$). It implies hypothesis 7 is not supported. Six, it was found that RAP significantly predicted CASR (β = 0.141, t= 0.141, $p < 0.01$). It implies hypothesis 8 is supported. One unit increase in RAP will increase CASR by 0.141.

Discussion

The service industry has witnessed remarkable progress with the integration of artificial intelligence (AI) and automation technologies; however, acceptance of such automated technologies like service robots remains an emerging area of research, particularly in Nepal's insurance sector. This study, grounded in the Service Robot Acceptance Model (sRAM) by Wirtz et al. (2018), analyzes multiple factors influencing customer acceptance of service robots. Consistent with the Technology Acceptance Model (TAM) (Davis, 1989), perceived ease of use positively influences adoption, aligning with prior findings (Aslam et al., 2022). Contrarily, perceived usefulness was not significant in this context, suggesting that utility alone does not guarantee acceptance, a deviation from TAM predictions. Subjective social norms significantly affect acceptance, validating social influence theories (Jembere et al., 2023; Wirtz et al., 2018), although some opposing results exist (Aslam et al., 2022; Fernandes & Oliveira, 2021). Similarly, perceived humanness does not significantly impact acceptance, supporting the uncanny valley concept (Tinwell et al., 2011) and highlighting the priority of functional emotional responsiveness over human resemblance. Perceived social interactivity fosters acceptance, emphasizing robots' need to exhibit socially appropriate behaviors (Wirtz et al., 2018), while perceived social presence unexpectedly deters acceptance, possibly due to awareness of robot autonomy. Trust negatively influenced acceptance, challenging earlier assumptions and indicating user skepticism, whereas rapport positively affected acceptance, underscoring the importance of empathetic, personable interactions (Fernandes & Oliveira, 2021; Wirtz et al., 2018).

This nuanced understanding of acceptance factors is aligned with broader AI research emphasizing emotional and intelligent interactions to enhance user engagement, as explored by Mishra and Mishra (2024) in student behavior contexts and Mishra et al. (2025) regarding artificial and emotional intelligence in employee engagement. Furthermore, the potential impact of AI on organizational venturing in healthcare, analyzed by Mishra (2025), underscores the transformative opportunities and challenges AI introduces across sectors, highlighting the critical need for acceptance studies to inform sustainable AI integration.

Conclusion

This study aimed to examine the acceptance of service robots among insurance customers in Kathmandu Valley using a quantitative approach, with questionnaires distributed to customers and hypotheses tested through regression analysis. The findings reveal that Perceived Ease of Use (PEOU), Subjective Social Norms (SSN), Perceived Social Influence (PSI), and Rapport (RAP) significantly and positively affect customer acceptance of service robots, while Perceived Usefulness (PU), Perceived Social Presence (PSP), Perceived Humanness (PH), and Trust (TR) have positive yet statistically insignificant influences. These outcomes suggest that although customers recognize the usefulness and benefits of service robots in insurance services, their acceptance relies more heavily on the ease with which they can use the robots and the alignment of these technologies with prevailing social norms and relational dynamics.

Subjective social norms play a pivotal role, indicating the necessity for service robots to conform closely to societal expectations and cultural contexts to facilitate user acceptance. The importance of robots exhibiting appropriate social behaviors and emotional responses further reinforces that social interactivity and rapport building capabilities enhance the likelihood of adoption. Interestingly, the less significant effect of trust and perceived social presence highlights challenges regarding customer skepticism and awareness of robotic autonomy, emphasizing the need for transparent communication and trust building in deployment strategies.

From a managerial perspective, insurance providers in Nepal should prioritize designing service robots that emphasize user friendliness and cultural congruence while fostering positive relational interactions. Understanding the complex interplay of functional, social emotional, and relational factors can guide the development and integration of robotic services that resonate with customer expectations and improve interaction quality. Expanding frameworks like the Service Robot Acceptance Model (sRAM) to explore the interrelationships among these dimensions offers valuable opportunities for refining adoption strategies. Ultimately, this study equips Nepalese insurance industry stakeholders with critical insights essential for navigating the incorporation of service robots, promoting enhanced customer experiences and operational efficiencies in the digital transformation era.

References

Aslam, W., Ahmed Siddiqui, D., Arif, I., & Farhat, K. (2023). Chatbots in the frontline: Drivers of acceptance. *Kybernetes*, 52(9), 3781–3810. https://doi.org/10.1108/K-11-2021-1119

Bataev, A. V., Dedyukhina, N., & Nasrutdinov, M. N. (2020, February). Innovations in the financial sphere: Performance evaluation of introducing service robots with artificial intelligence. *2020 9th International Conference on Industrial Technology and Management* (*ICITM*) (pp. 256–260). IEEE. https://doi.org/10.1109/ICITM48982.2020.9080379

Belanche, D., Casaló, L. V., Flavián, C., & Schepers, J. (2020). Service robot implementation: A theoretical framework and research agenda. *The Service Industries Journal*, *40*(3/4), 203–225. https://doi.org/10.1080/02642069.2019.1672666

Bishop, D. V. (2006). What causes specific language impairment in children? *Current Directions in Psychological Science*, *15*(5), 217–221. https://doi.org/10.1111/j.1467-8721.2006.00439.x

Bornet, P., Barkin, I., & Wirtz, J. (2021). *Intelligent automation: Welcome to the world of hyperautomation: Learn how to harness artificial intelligence to boost business & make our world more human*. Author.

ÇALLI, L. (2022). How does trusting belief affect service robot adoption in hotels as an antecedent of affective reaction? *Acta Infologica*, *6*(2), 245–263. https://doi.org/10.26650/acin.1117238

Chang, S. Y., Tsaur, S. H., Yen, C. H., & Lai, H. R. (2020). Tour member fit and tour member–leader fit on group package tours: Influences on tourists' positive emotions, rapport, and satisfaction. *Journal of Hospitality and Tourism Management*, *42*, 235–243. https://doi.org/10.1016/j.jhtm.2020.01.016

Choe, J. Y., Kim, J. J., & Hwang, J. (2022). Innovative robotic restaurants in Korea: Merging a technology acceptance model and theory of planned behaviour. *Asian Journal of Technology Innovation*, *30*(2), 466–489. https://doi.org/10.1080/19761597.2021.2005466

Choudhary, S., & Ahuja, Y. (2025). A nuanced picture of young consumers' motivation for using intelligent voice assistants through a curvilinear analysis lens. *Journal of Global Marketing*, 1–25. https://doi.org/10.1080/08911762.2025.2511090

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3) 319–340. https://doi.org/10.2307/249008

Deng, L., Li, J., Huang, J. T., Yao, K., Yu, D., Seide, F., & Acero, A. (2013, May). Recent advances in deep learning for speech research at Microsoft. *2013 IEEE International Conference on Acoustics, Speech and Signal Processing* (pp. 8604–8608). IEEE. https://doi.org/10.1109/ICASSP.2013.6639345

Fernandes, T., & Oliveira, E. (2021). Understanding consumers' acceptance of automated technologies in service encounters: Drivers of digital voice assistants adoption. *Journal of Business Research*, *122*, 180–191. https://doi.org/10.1016/j.jbusres.2020.08.058

Garcia, E., Jimenez, M. A., De Santos, P. G., & Armada, M. (2007). The evolution of robotics research. *IEEE Robotics & Automation Magazine*, *14*(1), 90–103. https://doi.org/10.1109/MRA.2007.339608

Gelman, A., Goodrich, B., Gabry, J., & Vehtari, A. (2019). *R-squared for Bayesian regression models.* The American Statistician. https://doi.org/10.1080/00031305.2018.1549100

Grant, C., & Osanloo, A. (2014). Understanding, selecting, and integrating a theoretical framework in dissertation research: Creating the blueprint for your "house". *Administrative issues journal*, *4*(2), 11–26.

Gummerus, J., Lipkin, M., Dube, A., & Heinonen, K. (2019). Technology in use—Characterizing customer self-service devices (SSDS). *Journal of Services Marketing*, *33*(1), 44–56. https://doi.org/10.1108/JSM-10-2018-0292

Gunnar S. Bolmsjö. (1992) *Industriell robotteknik. Studentlitteratur, Lund, 1992.* (2nd ed.). Studentlitteratur AB

Haidegger, T., Barreto, M. E., Gonçalves, P., Habib, M. K., Ragavan, S. K. V., Li, H., Vaccarella, A., Perrone, R., & Prestes, E. (2013). Applied ontologies and standards for service robots. *Robotics and Autonomous Systems*, *61*(11), 1215–1223. https://doi.org/10.1016/j.robot.2013.05.008

Holland, J., Kingston, L., McCarthy, C., Armstrong, E., O'Dwyer, P., Merz, F., & McConnell, K. (2021). Service robots in the healthcare sector. *Robotics*, *10*(1), 1–47. https://doi.org/10.3390/robotics10010047

Javaid, M., Haleem, A., Vaishya, R., Bahl, S., Suman, R., & Vaish, A. (2020). Industry 4.0 technologies and their applications in fighting COVID-19 pandemic. *Diabetes & Metabolic Syndrome*: *Clinical Research & Reviews*, *14*(4), 419–422. https://doi.org/10.1016/j.dsx.2020.04.032

Kalwar, S. (2023, January 12). ChatGPT: And the rise of artificial intelligence. *The Himalayan Times*.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Kaur, S., & Arora, S. (2021). Role of perceived risk in online banking and its impact on behavioral intention: Trust as a moderator. *Journal of Asia Business Studies*, *15*(1), 1–30. https://doi.org/10.1108/JABS-08-2019-0252

Knopf, J. W. (2006). Doing a literature review. *PS: Political Science & Politics*, *39*(1), 127–132. https://doi.org/10.1017/S1049096506060264

Kunz, W. H., Heinonen, K., & Lemmink, J. G. (2019). Future service technologies: Is service research on track with business reality? *Journal of Services Marketing*, *33*(4), 479–487.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539

Lekova, A., Tsvetkova, P., Tanev, T., Mitrouchev, P., & Kostova, S. (2022). Making humanoid robots teaching assistants by using natural language processing (NLP) cloud-based services. *Journal of Mechatronics and Artificial Intelligence in Engineering*, *3*(1), 30–39.

Li, R., Fan, W., Tian, G., Zhu, H., He, L., Cai, J., Xu, X., Fang, H., Tang, M., Li, J., Liu, J., Zhang, F., Li, H., Wang, X., Chen, L., Zhao, Z., Wang, J., & Wang, J. (2010). The sequence and de novo assembly of the giant panda genome. *Nature*, *463*(7279), 311–317. https://doi.org/10.1038/nature08696

Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis*, *42*, 60–88. https://doi.org/10.1016/j.media.2017.07.005

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science, 38*(6), 937–947. https://doi.org/10.1287/mksc.2019.1192

Maharjan, R., & Chatterjee, J. M. (2019). Adoption and impacts of robots in service sectors of Nepal. *Research Journal of Science, Technology and Management*, *1*(2), 63–84.

Martin, J. H., & Jurafsky, D. (2019). Vector semantics and embeddings. *Speech Lang. Process*, 1–31.

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A proposal for the dartmouth summer research project on artificial intelligence, August 31, 1955. *AI Magazine, 27*(4), 12–14. https://doi.org/10.1609/aimag.v27i4.1904

McLeod, S. A. (2018). *Correlation: Meaning, types, examples & coefficient*. Simply Psychology.

Mishra, S., & Mishra, A. K. (2024). AI Influencing factors among students. *Rabi Sangyan*, *1*(1), 1–8. https://doi.org/10.3126/rs.v1i1.74673

Mishra, A. K., Nirubarani, J., Radha, P., Priyadharshini, R., & Mishra, S. (2025). *Artificial and emotional intelligence for employee*. Intellectuals' Book Palace. https://doi.org/10.5281/zenodo.14810072

Mishra, A. K. (2025). AI's potential impact on organization venturing in healthcare. *GS WOW*: *Wisdom of Worthy Research Journal*, *4*(1), 1–6.

Mitchell, T. M. (1997). Does machine learning really work?. *AI Magazine*, *18*(3), 11–11.

Nakanishi, J., Kuramoto, I., Baba, J., Ogawa, K., Yoshikawa, Y., & Ishiguro, H. (2020). Continuous hospitality with social robots at a hotel. *SN Applied Sciences*, *2*(3), 452.

Neupane, A. (2018, May 10). Ginger, the waiter robot, made in Nepal. *My Republica*.

Ngai, E. W., Lee, M. C., Luo, M., Chan, P. S., & Liang, T. (2021). An intelligent knowledge-based chatbot for customer service. *Electronic Commerce Research and Applications*, *50*, 101098. https://doi.org/10.1016/j.elerap.2021.101098

O'Brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality and Quantity*, *41*(5), 673–690. https://doi.org/10.1007/s11135-006-9018-6

Pontes, N., Palmeira, M., & Jevons, C. (2017). Brand expertise and perceived consistency reversals on vertical line extensions: The moderating role of extension direction. *Journal of Retailing and Consumer Services*, *34*, 209–218.

Prasain, K. (2018, September 3). Kathmandu restaurants employ robot waiters. *The Kathmandu Post*.

Seo, K. H., & Lee, J. H. (2021). The emergence of service robots at restaurants: Integrating trust, perceived risk, and satisfaction. *Sustainability*, *13*(8), 4431. https://doi.org/10.3390/su13084431

Setia, M. S. (2016). Methodology series module 3: Cross-sectional studies. *Indian Journal of Dermatology*, *61*(3), 261–264. https://doi.org/10.4103/0019-5154.182410

Sharma, N., & De, P. K. (2023). Application of machine learning in climate change for the transport sector: Literature review and data preparation. In *Towards net-zero targets: Usage of data science for long-term sustainability pathways* (pp. 175–196). Springer. https://doi.org/10.1007/978-981-19-5244-9_8

Shen, J. (2012). Social comparison, social presence, and enjoyment in the acceptance of social shopping websites. *Journal of Electronic Commerce Research*, *13*(3), 198–212.

Shin, H. H., & Jeong, M. (2020). Guests' perceptions of robot concierge and their adoption intentions. *International Journal of Contemporary Hospitality Management*, *32*(8), 2613–2633. https://doi.org/10.1108/IJCHM-09-2019-0798

Shrestha, R., Chatterjee, J. M., & Parajuli, H. N. (2022). The scope of AI-embedded chatbot for customer interaction in the banking industry of Nepal. *LBEF Research Journal of Science, Technology and Management*, *4*(1), 1–15.

Sun, Y., & Wang, R. (2022). The research framework and evolution of service robots. *Journal of Computer Information Systems*, *62*(3), 598–608. https://doi.org/10.1080/08874417.2020.1870904

Thompson, C. (2018). *Assessing chatbot interaction as a means of driving customer engagement*. Haaga-Helia Ammattikorkeakoulu.

Tinwell, A., Grimshaw, M., Nabi, D. A., & Williams, A. (2011). Facial expression of emotion and perception of the Uncanny Valley in virtual characters. *Computers in Human Behavior*, *27*(2), 741–749. https://doi.org/10.1016/j.chb.2010.10.018

Tung, V. W. S., & Au, N. (2018). Exploring customer experiences with robotics in hospitality. *International Journal of Contemporary Hospitality Management*, *30*(7), 2680–2697. https://doi.org/10.1108/IJCHM-06-2017-0322

Turing, A. M. (1950). Computing machinery and intelligence. *Mind*, *59*(236), 433–460. https://doi.org/10.1093/mind/LIX.236.433

Van Doorn, J., Mende, M., Noble, S. M., Hulland, J., Ostrom, A. L., Grewal, D., & Petersen, J. A. (2017). Domo arigato Mr. Roboto: Emergence of automated social presence in organizational frontlines and customers' service experiences. *Journal of Service Research*, *20*(1), 43–58. https://doi.org/10.1177/1094670516679272

Van Pinxteren, M. M., Wetzels, R. W., Rüger, J., Pluymaekers, M., & Wetzels, M. (2019). Trust in humanoid robots: Implications for services marketing. *Journal of Services Marketing*, *33*(4), 507–518. https://doi.org/10.1108/JSM-01-2018-0045

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: service robots in the frontline. *Journal of Service Management, 29*(5), 907–931. https://doi.org/10.1108/JOSM-04-2018-0119

Xinhua, Sharma, S. (2018, August 24). *Feature*: Made-in-Nepal service robots' eye global market. *New China*.

Yoon, S. N., & Lee, D. (2018). Artificial intelligence and robots in healthcare: What are the success factors for technology-based service encounters? *International Journal of Healthcare Management*, *12*(3), 218–225. https://doi.org/10.1080/20479700.2018.1498220