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Service Robots Acceptance among Customers of Insurance Companies: *An Application of Service Robot Acceptance Model*

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Abstract

Drawing from the Service Robot Acceptance Model (sRAM), this paper investigates the acceptance of service robots among customers of Nepalese insurance companies. Using a cross-sectional survey design, data were collected from 243 customers of insurance companies through purposive sampling. Hypotheses were tested using Partial Least Squares Structural Equation Modelling (PLS-SEM). This paper found that Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Subjective Social Norms (SSN), and Perceived Social Interactivity (PSI) significantly influence Customer Acceptance of Service Robots (CASR). Additionally, PEOU significantly influences PU, and SSN significantly influences PU. However, Perceived Humanness (PH), Perceived Social Presence (PSN), Rapport (RAP), and Trust (TR) do not significantly influence CASR. This paper provides a significant evidence-based framework for developers and managers to prioritise the functional aspects, social presence, and social interactivity of service robots in the Nepalese insurance companies. This paper is one of the pioneering studies to explain service robot acceptance among customers of insurance companies by applying the sRAM in the Nepalese context.

INTRODUCTION AND STUDY OBJECTIVES

The service industry has undergone significant advancements recently, particularly through the widespread incorporation of AI (Artificial Intelligence) tools and automated technologies such as service robots, Chatbots, and virtual assistants (Gummerus et al., 2019). It includes Mezi, the personal travel assistant robot from American Express,

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the robot chef from Henn na Restaurant, and Josie Pepper, the customer service robot from Munich Airport (Liu et al., 2022). This growth has been fuelled by the COVID-19 pandemic because of the need of demand for contactless services, including robot receptionists, robot delivery, facial scan check-in, and voice-controlled guest services. Moreover, Robotics and AI offer various benefits for businesses, including potential cost reductions, enhanced efficiency, greater reliability, scalability, improved regulatory compliance, and strengthened security (Wirtz & Zeithaml, 2018). Fortune Business Insights (2020) forecasts a significant surge in the service robotics market, projecting growth from $12.88 billion in 2019 to $41.49 billion by 2027. Consequently, it becomes imperative to investigate the responses of consumers to the implementation of service robots within the Nepalese insurance companies.

To evaluate the acceptance of the technology, researchers have predominantly used the technology acceptance model (TAM) as a theoretical basis. TAM and its expanded versions have been extensively utilized for comprehending technology adoption, yet their effectiveness varies depending on the context (Lowe et al., 2019), and they may not adequately address emerging technologies (McLean & Osei-Frimpong, 2019). Hence, Wirtz et al., (2018) developed the sRAM model to identify the factors influencing customers' behavioural intentions, focusing on the social and relational elements of robot-delivered services. To comprehend customer acceptance of new technologies such as automated services, social and relational elements were integrated into the sRAM model alongside functional elements (Wirtz et al., 2018). Therefore, it is deemed appropriate to investigate the adoption behaviours of service robots within Nepalese insurance companies and institutions using the sRAM framework.

Despite modest progress, Nepal is advancing in digital transformation, exemplified by milestones such as the creation of Ginger, a waiter robot, by Paaila Technology (Neupane, 2018). Ginger, designed in a humanoid form, is the first of its kind in Nepal, providing human-like assistance. Likewise, Krispy Krunchy Fried Chicken (KKFC) at People's Plaza, Khichapokharai, is the country's pioneer in employing robots, followed by Naulo Restaurant, the first digitalized robotic eatery in South Asia (Jha & Yadav, 2022; Prasain, 2018). Moreover, Nepal SBI Bank introduced "Pari" a humanoid robot, initially stationed at the bank's digital branch, although it has since been replaced for undisclosed reasons (Xinhua, 2018). However, the contextual explanation of service robot acceptance has remained an understudied subject in the Nepalese context. Surprisingly, the government's approval of the "Digital Nepal Framework, 2019," aims to digitally empower Nepal, fostering governance, development, and prosperity (Giri, 2018). The policy preparation of the government for the digitization of the service sector and the lack of contextual studies on service robots has invited scholarly discussion. Therefore, this study aims

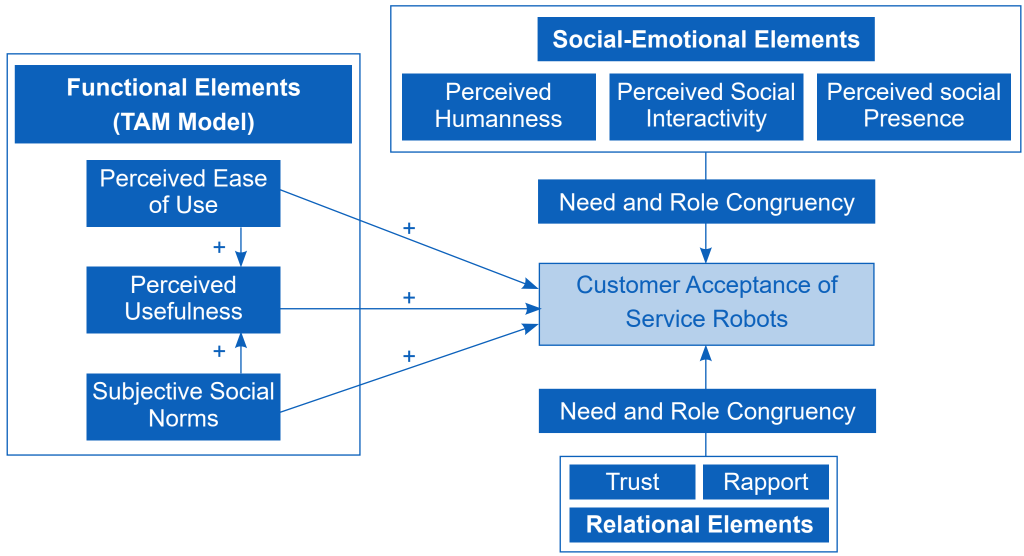

Figure 1. *Conceptual Framework*
Note. Adopted from:(Writz et al., 2018)

to investigate the acceptance of service robots in Nepalese insurance companies' by utilizing sRAM.

LITERATURE REVIEW

This section presents the literature review performed for the study.

Service Robot Acceptance Model (sRAM)

Wirtz et al. (2018) propounded the Service Robot Acceptance Model (sRAM), explores consumer perceptions, beliefs, and behavioural intentions regarding service delivered by a robot. Unlike many models, sRAM integrates both social and relational aspects of service robots. Acceptance, according to sRAM, is based on the robot's capacity to meet functional, socio-emotional, and relational demands (Davis, 1989; Fiske et al., 2007). The functional component refers to a technology's ease of use, usefulness, and compliance with societal norms. This component draws from the TAM (Davis, 1989). The sRAM model incorporates a social-emotional dimension, which also influences consumer acceptance (Fernandes & Oliveira, 2021; Heerink et al., 2010; Van Doorn et al., 2017). The social dimensions encompass perceived humanness, social interactivity, and social presence (Writz et al., 2018). Perceived humanness can manifest through physical attributes, behavioural cues, or both. Perceived social interactivity refers to the perception that the robot exhibits appropriate behaviours and 'emotions' in following societal norms. The sense of social presence, indicating that ‘someone is taking care’, impacts acceptance and subsequently influences customer behaviour. Finally, the sRAM model focuses on two key relational factors that influence user acceptance of the robot: Trust and Rapport (Heerink et al., 2010). Trust refers to users' confidence in the virtual agent's reliability during service encounters (Writz et al., 2018). Rapport involves the customer's perception of enjoyable interaction and personal connection with the service robot, including feelings of care and friendliness.

HYPOTHESES DEVELOPMENT

Perceived Ease of Use and Customer Acceptance of Service Robot

PEOU typically denotes the level of simplicity that a person perceives when employing a particular technology (Davis, 1989). Studies have documented that PEOU significantly influences customers' intentions to adopts technology (Ashfaq et al., 2019; Roy et al., 2018). Furthermore, Aslam et al., (2022) found that PEOU has a significant impact on the acceptance of Chatbots. This paper argues that the ease of using service robots in service counters would lead to customer acceptance. The paper proposes hypotheses based on the argument that:

H_1: PEOU positively influences the CA of service robots.

Perceived Usefulness and Customer Acceptance of Service Robot

PU represents the customer's belief that interacting with the robot benefits them (Fernandes & Oliveira, 2021). Furthermore, Choe et al. (2022) argued that PU has a positive effect on the attitude towards service robots in Korean restaurants. Similarly, Aslam et al. (2022) discovered that PU plays a significant role in determining the acceptance of Chatbots. When customers of insurance companies consider service robots useful in their operational jobs, they would use them to increase their efficiency. The paper proposes hypotheses based on argumentation that:

H_2: PU positively influences the CA of service robots.

Subjective Social Norms and Customer Acceptance of Service Robot

SSN represent individuals' perceptions of the opinions of significant others regarding what they ought or ought not to do in a particular scenario (Fernandes & Oliveira, 2021). Writz et al. (2018) contended that it is crucial for robots to conform to established social norms for human-robot interaction to be effective. It could involve demonstrating the correct behaviours and (superficial) emotional responses. Moreover, Lu et al. (2020) discovered a positive association between social influences and consumers' willingness to utilize robots in hotel and retail settings. This paper argues that friends, family members and colleagues' experience of using service robots would lead to customer acceptance of service robots. The paper proposes hypotheses based on the logic that:

H_3: SSN positively influences the CA of service robots.

Perceived Ease of Use and Perceived Usefulness of Service Robot

PU and PEOU are shown to be basic and unique constructs that influence decisions to adopt technology from a variety of discipline perspectives (Davis, 1989). Furthermore, Kao and Huang

(2023) argued that the favourable attitudes resulting from PEOU and PU play a crucial role in fostering a strong connection between customers and service robots. In addition, Saari et al., (2022) documented that PEOU and PU impact on behavioural intention to use social robots. Most recently, Yadav and Pokhrel (2023) reported that PEOU of ChatGPT leads to PU of accepting ChatGPT. It can be argued that ease of using service robots motivates insurance customers to use service robots. The paper proposes hypotheses based on the assumption that:

H_4: PEOU positively influences the PU of service robots.

Subjective Social Norms and Perceived Usefulness of Service Robot

Consistent with Venkatesh and Davis (2000), technology acceptance is influenced by SSN primarily through its connection to PU. In the context of AV adoption behaviour, Acheampong and Cugurullo (2019) found a significant positive relation between SSN and PU. Empirical findings from Rejón-Guardia et al. (2013) indicate that PEOU and SSN indirectly influence the intention to use, operating through their impact on PU. When prior users, whom we know, share the benefits of using service robots, customers tend to find service robots useful in the service counters of insurance companies. The paper proposes hypotheses based on the assumption that:

H_5: SSN positively influences the PU of service robots.

Perceived Humanness and Customer Acceptance of Service Robot

Writz et al. (2018) postulated that the perception of human likeness is linked to anthropomorphic characteristics, encompassing both the physical appearance and behaviour that a consumer identifies in a robot. This component is particularly relevant since robots can closely resemble humans. Furthermore, Mori's (1970) uncanny valley theory implies that the more a synthetic face resembles a human, the more it tends to be favoured. Li et al. (2010) found that in people processing services humanlike robots achieve higher customer acceptance rates for these services. This paper argues that the perception of the humanness of service robots in insurance companies results in the acceptance of service robots by customers. The paper proposes hypotheses based on the assumption that:

H_6: PH positively influences the CA of service robots.

Perceived Social Interactivity and Customer Acceptance of Service Robot

Writz et al. (2018) proposed that for humans and robots to be able to interact effectively requires robots to observe accepted social norms, including displaying the appropriate actions and (surface) emotions. Likewise, McLean and Osei-Frimpong (2019) suggest that when the robot engages in social interaction, demonstrates social skills, and aids its users in a “pleasant demeanour,” its social appeal might grow. Wirtz et al.(2018) postulated that individuals anticipate that robots will adhere to social norms, including displaying emotions and engaging in socially acceptable behaviours. This paper contends the ability of service robots to interact with customers leads to acceptance by customers. The paper proposes hypotheses based on the logic that:

H_7: PSI positively influences the CA of service robots.

Perceived Social Presence and Customer Acceptance of Service Robot

Social presence is the extent to which a robot creates the impression that a human or other social person is present (Heerink et al., 2010). Social presence plays a crucial role in the effectiveness of technology (McLean & Osei-Frimpong, 2019). Moreover, Fernandes and Oliveira (2021) found that there is a significant, positive relationship between CA of virtual voice assistance. When customers feel the presence of service robots is similar to humans in the service station, customers intend to use them for their work. The paper proposes hypotheses based on the assumption that:

H_8: PSP positively influences the CA of service robots.

Rapport and Customer Acceptance of Service Robot

In service robots, rapport means consumers feel the interaction is caring and personal, often through features such as voice recognition and personalized treatment Writz et al. (2018). Fernandes and Oliveira (2021) reported that RP has a positive influence on customer acceptance of virtual assistants. In the scenario of a full-service restaurant, customers tend to perceive a more robust rapport between themselves and the robot, leading to a heightened intention to embrace robotic services (Kao & Huang, 2023). The rapport-building ability of service robots leads to CA of service robots in insurance companies. The paper proposes hypotheses based on the assumption that:

H_9: RAP positively influences the CA of service robots.

Trust and Customer Acceptance of Service Robot

Writz et al. (2018) proposed that the more a robot is viewed as trustworthy and as having the customers' best interests as a priority, the higher seems the likelihood of adoption. Aslam et al., (2022) found that TR significantly affects the adoption of chatbots. Previous studies indicate that customers' propensity to use virtual assistants is positively impacted by trust (Fernandes & Oliveira, 2021). When customers experience the services provided by service robots as trustworthy, they tend to accept the use of service robots. The paper proposes hypotheses based on the assumption that:

H_{10}: TR positively influences the CA of service robots.

RESEARCH METHODS

This section provides information on research methods followed by this study.

Research Design

This paper applied a cross-sectional survey to collect data from 243 customers of insurance companies. The authors argues that the service robot acceptance in the insurance companies is a new area for the study and establishing causality was not the purpose of this paper. Moreover, previous studies also applied this design to investigate technology acceptance (e.g., Ooi et al., 2021; Pokhrel & K.C., 2023). Thus, it is deemed reasonable to apply a cross-sectional investigation designed to test the proposed model.

Population and Sample

The population of this study is customers of the Nepalese insurance companies which are located in Kathmandu valley. The majority of insurance companies are located in the Kathmandu valley and service robots are extensively used in the service sector such as insurance operations (Writz et al., 2018). Given that the head offices and customer base of these insurance companies are located in the Kathmandu Valley, the selection of Kathmandu Valley a site was a logical decision. Likewise, due to the unavailability of a sampling frame or active list of service robot users, this paper employed purposive sampling. This paper argues that the purposive sampling technique is the most reasonable for selecting a sample from the population with inclusion criteria (e.g., Pokhrel & K.C., 2023). Finally, Based on Hair et al.'s (2016) recommendation, the sample size could vary from 185 to 370, the sample size for this study is determined at 243. Given the homogeneity of the population of service robot users, the researchers presumed that this sample size would adequately reflect the population. The argument for sample size is aligned with previous studies (e.g., Pokhrel & K.C., 2023; Yadav & Pokhrel, 2023).

Measures

To measure service robot acceptance, this paper used nine measures with 32 items. The surveys employed a 5-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The researcher employed adapted questionnaires from various sources to measure different constructs: perceived ease of use (Venkatesh & Davis, 1996), perceived usefulness (Kim & Shin, 2015), perceived subjective norm (Bhattacherjee, 2000), perceived humanness (Söderlund & Oikarinen, 2021), perceived social interactivity (Bozkurt et al., 2021), social presence (Hassanein & Head, 2007), trust (Roca et al., 2009), customer acceptance of service robots (Venkatesh et al., 2003), and Perceived Rapport (Holdack et al., 2022).

Data Collection and Analysis Procedures

Pilot testing was conducted on the modified questionnaires to verify their reliability, face validity, and readability. The pilot study involved thirty MBA students from various colleges in the Kathmandu Valley. The full-scale survey was administered from January 10th, 2024, to February 28th, 2024, after input and confirmation of Cronbach alpha values above 0.60. A total of 243 responses were obtained from the

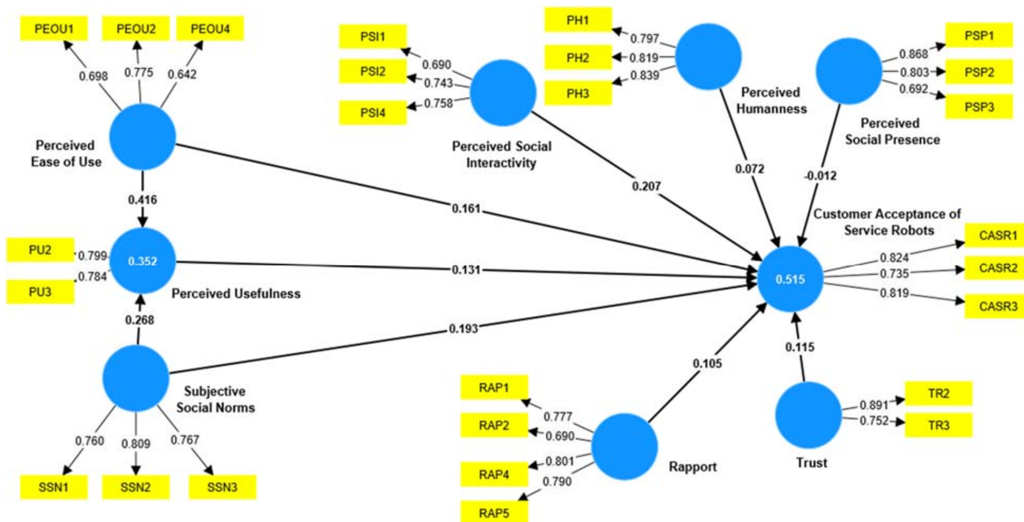

Figure 2. *Measurement Model*

300 printed questionnaires distributed. These responses were analysed using Statistical Packages for Social Sciences (SPSS) and Partial Least Square Structural Equation Modelling (PLS-SEM).

DATA ANALYSIS AND DISCUSSION

Demographic variables including age, gender, occupation, and education were examined to understand the characteristics of the 243 samples. The majority of respondents fall within the age range of 27-42 (n=158, 65%). Additionally, most respondents are female (n=135, 55.6%) and employed (n=176, 72.4%). The predominant educational qualification among respondents is at the master's level (n=117, 48.1%).

Common method biases

To address method variance, this paper used surveys authored by different individuals. After collecting data, the traditional Harman single factor technique was applied, and found un-rotated single factor showed 29.37%. With Herman's single-factor test yielding a value below 50%, method variance is unlikely to affect the structural model results (Podsakoff et al., 2003). Thus, researchers can draw conclusion that no common method biases are present in the dataset.

Structural Equation Modelling (SEM)

PLS-SEM was applied in this paper because the model is complex and it is relatively robust compared to other statistical techniques in exploratory nature of the study (Hair et al., 2020).

Measurement Model

Researchers used reliability and validity techniques to estimate the measurement model (Bido et al., 2014). Both Cronbach Alpha (CA) and Composite Reliability (CR) values surpassed the threshold of 0.744, confirming reliability (Hair et al., 2011).

Table 1
Reliability and Validity of Model

Construct	Indicators	Loadings	AVE	CR (rho_a)	CR (rho_c)	Alpha
Customer Acceptance Model	CA1	0.824				
	CA2	0.735	0.630	0.720	0.836	0.708
	CA3	0.819				
	PEOU1	0.698				
	PEOU2	0.775	0.500	0.510	0.749	0.500
Perceived Ease of Use	PEOU4	0.642				
	HUM1	0.797				
	HUM2	0.819	0.670	0.763	0.859	0.755
Perceived Humanness	HUM3	0.839				
	PSI1	0.690				
Perceived Social Interactivity	PSI2	0.743	0.535	0.575	0.775	0.570
	PSI4	0.758				
	PSP1	0.868				
Perceived Social Presence	PSP2	0.803	0.626	0.807	0.833	0.719
	PSP3	0.692				
	PU2	0.799	0.626	0.404	0.770	0.404
Perceived Usefulness	PU4	0.784				
	RAP1	0.777				
	RAP2	0.690	0.586	0.775	0.849	0.630
	RAP4	0.801				
Rapport	RAP5	0.790				
	SN1	0.760				
	SN2	0.809	0.606	0.683	0.822	0.677
Subjective Social Norms	SN3	0.767				
	TR2	0.891				
Trust	TR3	0.752	0.680	0.590	0.809	0.542

Note. Based on authors' calculation

Convergent validity was assessed using Average Variance Extracted (AVE), with values between 0.535 and 0.670 across constructs, exceeding the recommended threshold of 0.50 (Fornell & Larcker, 1981). However, factors with low loadings (PEU, PU, PSI, RAP, and TR) were excluded from the model (see Table 1).

Discriminant Validity

The Hetero-trait-Mono-trait Ratio (HTMT) criteria and Fornell and Larcker's (1981) methods were applied to assess discriminant validity. According to the study, AVEs fulfilled Fornell and Larcker's criterion because their square roots were greater than their correlations with other

Table 2
Discriminant Validity (Fornell and Larcker's Criterion and HTMT Ratios)

Constructs	1	2	3	4	5	6	7	8	9
1. CSAR	0.794	0.83	0.941	0.954	0.563	0.405	0.659	0.762	0.831
2. PSI	0.544	0.731	0.792	1.008	0.499	0.469	0.668	0.597	1.015
3. PU	0.512	0.38	0.791	1.19	0.744	0.646	0.860	0.903	0.872
4. PEOU	0.567	0.522	0.545	0.707	0.634	0.701	0.774	0.817	1.021
5. PH	0.425	0.340	0.412	0.395	0.818	0.765	0.477	0.637	0.646
6. PSN	0.321	0.307	0.356	0.423	0.534	0.791	0.195	0.471	0.448
7. RAP	0.493	0.437	0.481	0.478	0.349	0.145	0.765	0.574	0.730
8. SSN	0.536	0.373	0.469	0.484	0.459	0.347	0.419	0.779	0.757
9. TR	0.534	0.563	0.417	0.521	0.405	0.291	0.463	0.467	0.825

Note. Based on authors' calculation; CASR: Customer Acceptance of Service Robots; PEOU: Perceived Ease of Use; PU: Perceived Usefulness; PH: Perceived Humanness; PSI: Perceived Social Interactivity; SSN: Subjective Social Norms; PSN: Perceived Social Presence, RAP: Rapport; TR: Trust; the values below the diagonal indicate Fornell and Larcker's Criteria, while those above represent HTMT Ratios.

constructs. Teo et al. (2008) state that the HTMT values, nevertheless, were higher than the suggested threshold of 0.90.

Structural Model

This paper assessed the multi-collinearity assumptions before estimating the presented hypotheses using the structural model. The assessment demonstrated that all Variance Inflation Factor (VIF) values remained under 5, showing that multi-collinearity is not a problem (Hair et al., 2019). Therefore, the structural model estimation proceeded (See Figure 3).

Table 3 results indicate support for H_1, H_2, H_3, H_4, H_5, and H_7 in the study. The findings suggested that one unit change in PEOU, PU, SSN, PEOU, SSN and PSI of the service robot increased CSAR by 0.080, 0.063, 0.055, 0.066, and PU by 0.059, 0.061 respectively CA and PU of service robot. However, H_6, H_8, H_9, and H_{10} were not supported in the study. This suggests that the relationships among variables related to customer acceptance of service robots in the insurance companies are not significant enough.

CONCLUSION AND IMPLICATIONS

The service sector has seen notable advancements, notably with the rise of digital technologies such as AI. Yet, research on automated technology remains largely theoretical (Fernandes & Oliveira, 2021). Despite the multiple applications of service robots in insurance companies, the factors associated with customers' acceptance have remained under-examined in the Nepalese context. In response to the call of Wirtz et al.(2018), this paper investigated service robots' acceptance among Nepalese customers by applying s-RAM. This paper found that PEOU, PU, SSN, and PSI of service robots are important predictors of explaining service robot acceptance. The findings could provide a critical juncture for researchers and insurance companies to design their services by using service robots in the workplace. The detailed discussion with respective implications is elaborated in different points.

First, this study found a positive correlation between PEOU and CASR among customers in insurance companies, consistent with previous research (Aslam et al., 2022; Calli, 2022). This implies that smoother interactions with robots lead to greater willingness to use them for intended tasks. The findings support the claim of TAM model (Davis, 1989) that if a technology is perceived as easy to use, users are more likely to find it acceptable and integrate it into their regular tasks. However, Fernandes and Oliveira (2021) found that that the acceptance of digital voice assistance was unaffected by perceived ease of use in their study. This paper resolved the contradiction by illustrating PEOU positively influences CASR. Hence, the service robots must be effortless for customers to accept for insurance purposes. When insurance companies will be designing their routine and repetitive tasks, they could install service robots in designing servicescape. They should consider the ease of using service robots because customers are likely to use service robots that are easy to use.

Second, this study found a positive association between PU and CASR in insurance, aligning with prior research (Aslam et al., 2022; Choe et al., 2022). This highlights that when technology aids users in task efficiency, it enhances the acceptance of service robots. These results support the TAM model's assertion (Davis, 1989) that when consumers see robots as valuable, acceptance rises. This result suggests that the way people

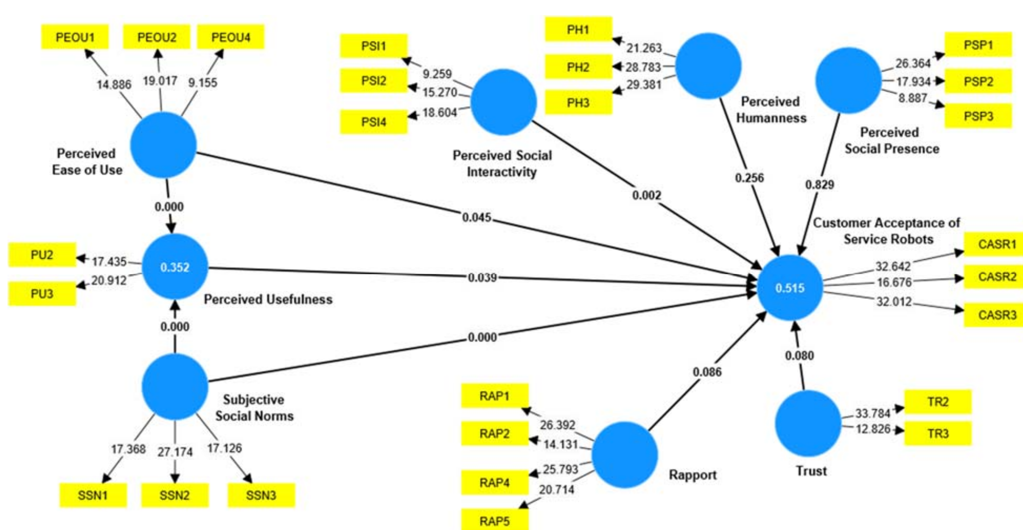

Figure 3. Structural Model

Table 3
Results of Structural Model

Hypotheses	Standardized Beta β	T statistics	P values	Decision
H_1. PEOU -> CASR	0.080	2.005	0.045	Supported
H_2. PU -> CASR	0.063	2.062	0.039	Supported
H_3. SSN -> CASR	0.055	3.509	0.000	Supported
H_4. PEOU -> PU	0.059	7.057	0.000	Supported
H_5. SSN -> PU	0.061	4.429	0.000	Supported
H_6. PH -> CASR	0.063	1.136	0.256	Unsupported
H_7. PSI-> CASR	0.066	3.141	0.002	Supported
H_8. PSP -> CASR	0.054	0.216	0.829	Unsupported
H_9. RAP -> CASR	0.061	1.719	0.086	Unsupported
H_{10}. TR -> CASR	0.065	1.752	0.080	Unsupported

Note. Based on authors' calculation; CASR: Customer Acceptance Service Rotbo; PEOU: Perceived Ease of Use; PU: Perceived Usefulness; SSN: Subjective Social Norms; PH: Perceived Humanness; PSI: Perceived Social Interactivity; PSP: Perceived Social Presence; PRP: Perceived Rapport; RAP:Rapport; TR: Trust

perceive the usefulness or practicality of service robots plays a significant role in their decision-making process regarding whether or not they will use these robots. Thus, service robots must prioritize delivering tangible benefits for customers to be embraced in insurance contexts. Customers should be informed about the ease of using service robots through social media and other information-sharing lplatforms. It would increase the adoptability of the technology in the insurance companies.

Third, this paper discovered that SSN positively influences CASR for insurance purposes, consistent with prior studies (Lu et al., 2019). This suggests that adherence to social norms enhances customer acceptance of service robots in insurance. This aligns with Writz et al., (2018) argument. However, Aslam et al., (2022) found no significant impact of perceived social norms on Chatbot use, and Fernandes and Oliveira (2021) similarly found no positive relationship between perceived social presence and virtual voice assistant acceptance. In the context of insurance, adherence to social norms enhances customer acceptance of these technologies, demonstrating the critical role of social influence in technology adoption. By understanding and leveraging SSN, insurance companies can effectively promote the acceptance and integration of service robots in their operations.

Fourth, this paper revealed a positive link between PEOU and PU, consistent with prior research (Fernandes & Oliveira, 2021; Forgas-Coll et al., 2022). This suggests that users are more inclined to view service robots as useful when they find them easy to use in insurance companies and institutions, aligning with Kao and Huang's (2023) argument.

This results also align with the assertion made by Davis (1989) in which PU and PEOU are shown to be basic and unique constructs that influence decisions to adopt technology from a variety of discipline perspectives. This suggests that customers who perceive the service robots as both user-friendly and beneficial are more inclined to embrace their usage. Thus, when perceived as both easy to use and advantageous, service robots are more likely to be adopted.

Fifth, this paper found that SSN positively impacts PU, echoing prior studies (Acheampong & Cugurullo, 2019; Rejón-Guardia et al., 2020). It suggests that when a social group views an activity as acceptable and valuable, positive subjective social norms enhance perceived usefulness, consistent with Venkatesh and Davis (2000). Thus, service robots meeting individuals' social expectations within insurance customer communities contribute to increase perceived usefulness. In addition, Insurance companies could apply referral mechanisms for promoting the benefits of using service robots by customers so that customers can reduce their waiting time for basic operational functions.

Sixth, the study revealed that PH doesn't directly impact CASR in insurance companies. This aligns with Fernandes and Oliveira's (2021) findings on virtual voice assistants, suggesting that perceived humanness may not be crucial for service robot adoption. Customers prioritize functionality over appearance; thus, if a service robot effectively answers queries, its human-like attributes become inconsequential. This finding resonates with Aslam et al., (2022). It's supported by the uncanny valley theory, indicating discomfort with highly human-like yet artificial faces (Mori, 1970; Tinwell et al., 2011). Ultimately, consumers prioritize the robot's actions over its appearance in insurance services.

Seventh, the study found that PSI positively impacts CASR in insurance services, consistent with previous research on Chatbots (Aslam et al., 2022). This underscores the importance of robots adhering to social norms and displaying appropriate actions and emotions. These findings align with Writz et al. (2018) argument and highlight the significance of robots understanding customer emotions and conforming to social norms tailored to insurance contexts.

Eighth, the study found that PSP negatively impacts CASR. This contrasts with previous research on virtual voice assistants (Fernandes & Oliveira, 2021). However, this suggests that PSP might not be crucial for service robot adoption, especially when customers recognize the robot's autonomous nature. This aligns with Aslam et al. (2022) argument, emphasizing the importance of functionality over social presence. Ultimately, customers prioritize accurate responses and proper insurance operations over the robot's social attributes.

Ninth, the study found that RAP negatively impacts CASR in the insurance companies. This contrasts with findings from Fernandes and

Oliveira (2021) and Aslam et al. (2022), suggesting interactions with robots might lack warmth and empathy, hindering personal connections. This contradicts Writz et al., (2018) assertion. Thus, the results emphasize challenges for service robots in insurance to foster personal connections, potentially leading to less enjoyable interactions. Additionally, tech-savvy customers may consider building rapport with robots either impossible or unnecessary, as the tech-savvy customers do not view service robots as a genuine substitute for human-delivered service in insurance services (Bolton et al., 2018).

Finally, the study found that TR negatively affects CASR, contrary to prior research (Aslam et al., 2022; Fernandes & Oliveira, 2021). This contradicts Writz et al., (2018) assertion and highlights ambiguity in the role of trust in AI robot acceptance. In SST research, reliability, or the capability to deliver the promised service accurately, is crucial for customer acceptance. (Fernandes & Pedroso, 2017). Accurate performance, or "doing its job," is a major source of satisfaction, especially for newer technologies that could make consumers suspicious (Meuter et al., 2000). This sentiment may be especially pronounced with service robots, as they rely on algorithms powered by artificial intelligence (AI), a technology still in its early stages with untapped potential (Tuzovic & Paluch, 2018). As such, consumers found that it is challenging to trust "a machine's judgment" and to have confidence in AI recommendations and the use of their data for insurance purposes.

Limitations and Directions for Future Research

Although this study has made some noteworthy contributions, this research presents several and areas for further exploration. First, while it focused on service robot acceptance in insurance companies using sRAM, future studies could explore acceptance behaviours with the hedonic motivation system adoption model (HMSAM). Second, employing experimental designs could help establish causality beyond the cross-sectional survey design used in this paper. Third, investigating concerns such as privacy, ethics, and fairness in service robot acceptance could be valuable as a sub-dimension of corporate digital responsibility. Lastly, studying resistance to service robot acceptance across different service settings such as banks, hospitals and restaurants holds promise for future research.

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Conflict of interest

The authors declare having no conflicts of interest.

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