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How Cyber Security Enhances Trust and Commitment to Customer Retention: The Mediating Role of Robotic Service Quality

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Abstract: Cyber security is supportive of robotic service provision, the objective of which is to help marketers achieve their aim of providing a high level of service. Marketers need to be aware of cyber security issues and adhere to established cyber security policies. We investigate trust and commitment in relation to customer retention while assessing the mediating role of robotic service quality (RSQ). We employ a survey-based study that utilises 231 valid responses from customers in São Paulo, Brazil. To analyse the data, we used partial least squares structural equation modelling (PLS-SEM). The results show that trust and commitment have a positive impact on customer retention. RSQ has a partial mediation effect on the relationship between the latent constructs of trust, commitment, and customer retention. Thus, it can be suggested that RSQ, which embeds trust and commitment, assists in building a loyal customer base. Marketers outside the Latin American region can benefit from the results of this study since it incorporates cyber security awareness and policy within marketing strategy implementation, ensuring that RSQ is aligned in terms of the digitalisation goals of the company.

Keywords: commitment; customer retention; cyber security; partial least squares structural equation modelling; robotic service quality; trust

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1. Introduction

Robotic services empowered by artificial intelligence (AI) have gained much traction in recent years. Advances in machine learning (ML) are providing marketers with the opportunity to extend product and brand offerings and enhance customer engagement by providing a higher level of customer satisfaction [1–4], which is necessary in terms of customer retention [5–7]. With respect to the deployment of AI/ML in the service sector, service bots are known to have several advantages, such as the ability to provide quick and accurate responses that enhance customer-brand interaction that underpins value co-creation [8–10].

Examples exist of how robots are assisting and enhancing service provision. Medical services are drawing more on robotic medical assistance in medical centres, and this covers both applications to examine patients and help diagnose symptoms and monitor patients through time [11]. AI assists in the analysis of big data in a number of ways. Information processing robots create personalised learning experiences that aid the learning process [12], and information-based robotic services are becoming well-established in other sectors, such as banking and legal services, where chatbots are used to direct customer service engagement. The advantage of this is that it allows mundane tasks to be undertaken quickly by robots, and more complex tasks can be dealt with by human operatives. This is useful to note that a computer network environment is protected by government policymakers [13], which allows businesses to function normally and achieve their objectives. However, as regards the use of AI technology, marketers need to be aware of emerging cyber security vulnerabilities and the level of increased complexity.

One way in which robotic technologies contribute to increasing the loyalty of customers is their ability to withstand cyber-attacks. It is useful to note that research undertaken by Pleshakova et al. [14] into cryptography and privacy and discrimination, in particular, has raised a number of issues regarding generative models and adversarial training. The focus of that work was establishing how general neural networks are able to learn to communicate in a secure manner, which is achieved through creating a neural network architecture that can learn mixing functions like exclusive OR (XOR) [14]. This can be considered essential research in the current marketing operational environment, because to maintain customer trust, firms increasingly need to pay attention to cyber security awareness. This ensures potential vulnerabilities are dealt with and a secure infrastructure is in place. In addition, network operations need to be managed effectively. For example, people use smartphones to access information and communicate with their friends and the wider public. Hence, in order for mobile phone companies to deliver a satisfactory service to their customers, marketing managers need to understand how emerging 6G technologies, which heighten human-network interaction, are influenced by AI and ML, and how AI and ML play a key role in terms of simplifying network management and helping staff to defend against cyber-attacks [14]. In terms of enhancing customer trust and safeguarding data, Mizinov et al. [15] suggest that facial geometry-biometric systems and voice modality systems have a number of vulnerabilities and are prone to attack. This raises questions about AI and ML-generated images and message recordings and how the systems in place can be protected. Thus, staff need to be able to undertake risk mitigation strategies that draw on the input of various in-house experts. Indeed, cybercriminals and state actors can easily identify organisational security-related vulnerabilities and exploit them through various means, including the deployment of ransomware. The reason for this is that RSQ needs to be viewed as both helping the organisation to achieve its marketing goals and ensuring that the organisation has adequate cyber security provisions, which manifest in the company's ability to withstand various forms of cyber-attacks and maintain its residency.

There is a growing market for smart machines that can be preprogrammed and/or controlled remotely, and there are also robots that can be controlled by voice messages. Hence, cyber security needs to be placed in the context of evolving technology and how next-generation technology will be prone to cyber-attacks [16]. Indeed, Chan et al. [16] (p. 2) suggest that AI can be used to monitor various factors and "identify patterns of normal and abnormal activity" that can help identify malicious activity and then help mitigate the attack. By focusing cyber threat detection on neural networks and expert systems [16], security experts can ensure that the AI systems in place are robust. Liu and Li [17] have referred to the complexity of a multi-robot system by explaining that in the case of an intelligent warehouse, robots are able to undertake various tasks. However, there are also threats that include collisions and congestion.

Liu and Li [17] emphasise the fact that multi-robot systems draw on AI/ML and involve automation and advanced sensing technologies. What can be deduced from this is that vulnerabilities are likely to manifest if, that is, security is not taken seriously [18]. The issue of security affects consumers' perception of trust in a brand and their willingness to be engaged with the brand. Nevertheless, Wirtz and Lovelock [19] consider service robots, which are system-based and have flexible interfaces that deliver interactive services to customers, to constitute a growth market in the future. New applications of service robots will come onto the market in the next decade. Hence, it is imperative that marketers pay close attention to how such services are free from harm and disruption as well as how cyber security concerns are addressed, leading to better customer retention.

Robots are perceived as intelligent, with the ability to perform certain human activities with the ultimate aim of solving problems through deep learning, or natural language processing with input of external data for predefined goals and tasks [20,21]. Concerning the use of AI technology relating to customer service and personalisation, Przegalinska et al. [22] point out that the issue of trust needs to be addressed for the success of human and bot interaction.

By reflecting on trust-commitment theory [23], this research addresses a significant research gap relating to service bots and how RSQ mediates the relationship between trust and commitment [8]. Service robots play an essential role in quality improvement. However, the adoption of service bots raises the issue of trust vis-à-vis how consumers perceive them and how they are able to influence consumer behaviour. Service robot usage can be viewed from the perspective of trust and how robotic services are adopted because customers appear keen to maintain prolonged relationships [24]. Advancements in the deployment of technology mean that robots can function like humans; however, robots cannot recreate human-like experiences. For example, in a personalised service, robots are not able to mimic human touch like humans nor engage in sincere interactions that humans are known for in relation to service delivery [25,26]. Having said this, researchers suggest that in the years ahead, AI-powered robots will be able to develop an emotional rapport with consumers as they become more sensitive to their emotions when interacting with them [27].

The next section of the paper is constructed as the materials and methods, enabling us to develop the conceptual model and related hypotheses in trust, commitment, customer retention, and RSQ. This paper then carefully tests the conceptual model using partial least squares structural equation modelling (PLS-SEM). In the latter part of the paper, key findings and implications of research are discussed, and lastly, limitations and future research avenues.

2. Materials and Methods

2.1. Theoretical Background and Hypotheses

2.1.1. Service Bots in Marketing

It is useful to reflect on the way in which the market is changing and being influenced by consumers. This is due to the effect of digital technology, which enables personalised services [28]. Various ‘Internet of Things’ (IoT) devices enable marketers to advertise products that better meet customer needs and enable customers to access and purchase the products marketed to them. For example, consumers can use such devices to search for valid product information, place orders, query certain issues, and obtain automated and personalised solutions [3,6]. This trend is highly common in today’s marketing environment and is expected to continue in the future.

Marketers are aware that in order to assess consumer needs adequately, they need to monitor customer interactions and utilise the personal and sensitive data of individuals, which needs to be protected. Marketers understand that granting authentication and/or authorisation [28] to databases and computer networks is embedded in company policy guidelines, and marketing staff are expected to adhere to the rules set. Marketers are availing themselves of the opportunity to use robots more extensively in service provision as frontline service employees to deliver customer service as e-service providers [19]. For example, at ALoft hotels, the Botlr service robot assists guests with room services. E.ON Energy Company employs Cognigy.AI to provide customer service around the clock. Daewoong Pharmaceutical, which deploys robotic process automation powered by SAP S/4HANA, saves man hours significantly. SocialPilot is an Instagram automation tool that enables users to schedule posts, share content, and provide analytics for shared content.

Growth in this sector is clear to see, and the consulting company Mordor Intelligence, in a 2022 report, estimated that the market for customer service robots was USD 3.78 billion in 2021 and that the market is expected to grow by 30.29% by 2027.

Service robots in the service industry play roles synonymous with customer service employees [8]. As robots increasingly become an inevitable aspect of service in the quest for customer retention, robots need to be integrated into service delivery to ensure quick and accurate provision of services [10]. Research has shown that service robots' human-like characteristics can improve a customer's impression, thereby facilitating human–robot interactions [29]. Moreover, consumers perceive service robots to have more outstanding service outcomes [30,31]. Although existing research has systematically investigated the way consumers and service robots interact [8,32,33], they have not examined how customer retention is maximised by using service robots, especially because unlike humans, they cannot engage in rather creative thinking and problem-solving activities when undertaking a professional service role [27].

Huang and Rust [6] point out that although marketers are aware of how to use AI to segment markets, much more can be accomplished with AI than is the case at present. Indeed, AI can be thought of as a tool to increase customer retention. Therefore, the harnessing of AI can be considered fundamental in terms of enhancing service provision through ML algorithms. The European Union Agency for Cyber Security [34] (p. 4) clearly states how managers should utilise AI and suggests that ML is "the ability for machines to learn from data to solve a task without being explicitly programmed to do so". By understanding how ML algorithms operate and undertake tasks, marketers can utilise better AI capabilities vis-à-vis interpreting the information gained from AI-assisted data analysis.

2.1.2. Customer Retention

Pansari and Kumar [35] insist that customer retention is vital for growth, and customer satisfaction is viewed as an important antecedent for customer repurchase intention. Integrating robots into service and providing quick and accurate services is pivotal to enhancing customer-brand interaction that results in satisfaction and retention [36]. Retaining existing customers is much cheaper than attracting new ones [37]. Therefore, firms must rigorously keep their loyal customers by providing improved services. However, if an organisation suffers a cyber-attack and incurs reputational damage, then the consequences may be severe. The regulator can impose a fine, and also, the loss in customer confidence may affect consumer purchase intention. It is because of this that marketers need to liaise with product development staff, IT specialists, and those involved with risk management in order to ensure that the risk management process is thorough and any uncertainty that arises is dealt with so that a crisis does not escalate into an emergency.

The relationship that exists between consumers and brands is influenced by the level of customer satisfaction [35]. The digital age has driven up customer expectations; as a result, organisations try to enhance service quality, ensuring that their needs are met [38] strategically through the use of various chatbots to facilitate self-service procedures as well as customer support [39]. The increasing use of service bots bodes well in terms of consumer interactive experience. Marketers are paying increased attention to the sociological and psychological aspects of consumer emotional experience [40], how a bot's service quality increases a consumer's interactive experience [41] and how satisfied customers help generate future sales through positive electronic word-of-mouth reviews. It is vital to note that a positive customer experience provides an excellent opportunity for firms to retain existing customers, enhance their repurchase intentions, and increase the conversion rate in the long run. However, it is also essential to note that negative reviews enable companies to evaluate the effectiveness of their policies and improve existing strategies to focus on customer expectations and needs [42].

According to Wirtz and Lovelock [19], service refers to a process or performance that offers value to stakeholders. They further broadly categorise service into four major areas, namely, people processing, possession processing, mental stimulus processing, and information processing. Hence, marketers are the beneficiaries of technology (e.g., chatbots) and use such technology to extend their organisation's product offering. To enhance customer intention through the use of bot services, an organisation must ensure data integrity and reliability. This is because the information used for devising a personalised service must be reliable and, at the same time, sufficiently competent to be able to prevent customer data from being hijacked, such as when the organisation's website is closed down or when a fake website that emulates the organisation's website is created. Thus, a perpetrator's actions not only result in potential customers being scammed but can also contaminate the data used to provide the robotic service. This, of course, raises questions relating to trust and trustworthy behaviour, as well as how product development, service provision, and the maintenance of security are all integrated into the company's resilience strategy.

2.1.3. Trust

There is no single definition of trust in the literature [43]. Trust has been thought of as a belief, an attitude [44], an adequate response, a sense of willingness [45], a form of mutual understanding [46], and an act of reliance [47]. Marketers are aware of how trust materialises and why it is important to maintain trust-based relationships with customers. For example, malicious software can be used to create fake profiles and generate false information that is made public via social media sites [48]. Counteracting such behaviour can be costly but is deemed essential for maintaining the loyalty of the customer base and the organisation's image. By understanding this, cyber security can be considered a component of enhancing perceived trust.

Customer trust can be explained as the customer's readiness to repurchase a product or service [49]. Similarly, Park et al. [50] defined the concept of trust as being honest and capable of performing a specific task. Trust in robots is considered crucial as service robots are increasingly being used in the provision of customer service. Hancock et al. [51] indicate the importance of trust in relation to automation due to the concept of trust having essential implications vis-à-vis gaining customer commitment. Glikson and Woolley [52] explain that service bots deployed in dynamic and unstructured environments possess the ability to navigate in uncertain areas and can work alongside humans. Working alongside humans has a positive effect in the sense that bots can help form and maintain trust [52].

With regard to the concept of trust, Lankton and McKnight [53] share the view that the issue is not only attribute to humans but can be extended to technology. They also describe trust in technology as the extent to which a specific technology has the necessary attributes to undertake a particular task, such as providing advice to perform a task and engaging consistently in activities. Drawing from the above, this paper defines trust based on a utilitarian approach, thus offering practical benefits for developing appropriate robot behaviour through planning and control [54]. This leads us to propose the following research hypothesis:

Hypothesis 1 (H_1). *Customer trust in the service bot has a positive effect on customer retention.*

2.1.4. Commitment

The concept of commitment is considered as the interplay and connection between two agents; namely, one agent assures the other party that they implement agreed actions and vice versa [55]. This becomes a useful social phenomenon because it makes people willing to perform actions. Credible commitments enable agents to predict each other's behaviours regardless of their fluctuating desires and interests [56]. As a result, agents build and maintain long-term relationships with each other's goals and expect to secure reliability as the fundamental agreement [57].

When one commits to an action, they are less likely to focus on other activities (or no effort at all). However, some unexpected options that maximise one's interests and are more advantageous than the committed action may alter an individual's actions and loyalty. Regarding commitments, this study proposes that managing commitments is a social skill that needs capacities independent of the capabilities required to perform actions. In this paper, commitment is modelled as something aggregated to the activities of a specific task and linked to expectations to further consider commitment as a reduction in uncertainty. Drawing from the above definition of commitments, the service robot must be able to promptly provide various cues that contribute to a human's awareness of expectations [58]. Based on the above rationale, we developed the following hypothesis:

Hypothesis 2 (H_2). *Customer commitment to the service bot has a positive effect on customer retention.*

2.1.5. Robotic Service Quality

The two major categories of robots are industrial and service robots. Industrial robots are predominantly used in the manufacturing sector; they are commonly involved in the production process. On the other hand, service robots are devices that can mimic human behaviour in providing services to humans in the service sector [58,59]. Service robots are becoming increasingly popular in the service industry. Service quality is defined as customers' perceptions and value evaluations of a product or service. Shi et al. [60] emphasise that service quality has been perceived as a relevant factor for competitive advantage due to positive customer responses leading to more significant market share and customer satisfaction, eventually consolidating loyalty [61].

Moorman et al. [62] described trust as the strong relationship between two parties (in this context, robotic services and customers), with one party perceived as the other party possessing the know-how and benefits. Therefore, trust results from the gradual development of a mutual relationship established between a business and its customers. Service robots are "semi-autonomous" or "fully autonomous" and have the ability to use their mobility and communicative devices to interact with their human operators in a number of environments, including the hospitality sector, the retail industry, and healthcare, for example. Although it can be suggested that service bots have a limited ability, their AI capability will increase in the years ahead, and this will allow them to provide a wide variety of services. This will result in an improved level of service that exceeds that of human operators [63]. This suggests that service bots are accepted and trusted by the customer [64]. Customers' behaviour has shown a positive correlation with the service quality of robots [65], as consumers perceive service robots as companions or friends [66]. Consequently, using service robots in service provision helps to improve customer trust and satisfaction [67]. However, the inverse relationship is hardly evident in the extant literature; hence, we argue that the relationship between the perceived trust and service quality of robots has a positive correlation [65].

Hypothesis 3 (H_3). *Customer trust in robotics positively influences the evaluation of RSQ.*

Service quality is considered a prerequisite for customer satisfaction, which is the foundation for customer commitment and retention. Service quality refers to customers' perceptions and assessments of the services a business provides, mainly based on the value judgement of services [68]. Robotic services and performance influence customers' evaluation of service quality, leading to customer satisfaction, commitment, and retention [69]. Hence, we propose the following hypotheses:

Hypothesis 4 (H_4). *Customer commitment in robotics positively influences the evaluation of RSQ.*

Hypothesis 5 (H_5). *RSQ positively influences customer retention.*

2.1.6. Mediating Role of RSQ

Morgan and Hunt [23] conceptualised trust as the self-assurance that establishes reliability and integrity between service providers and customers and the belief that a business acts, which results in positive outcomes. Hence, trust leads to a high level of affective commitment. Trust is also related to the issue of controlling resources and benefits [62].

Morgan and Hunt [23] further indicate that trust and commitment play an essential role in establishing a relationship between two parties. Therefore, trust and commitment are essential for a healthy relationship that avoids switching behaviours or searching for alternatives. A strong relationship plays a significant role in a business's ability to retain existing customers [70]. However, failure to implement cyber security procedures may result in a vulnerability being exploited, which results in reputational damage, or an inadequately performing chatbot may result in misunderstandings that militate against future chatbot use. This could also give rise to another cyber security issue in the sense that it could lead to a disinformation campaign on social media against the company. Disinformation is perceived as a legitimate attack vector, and it is important for marketers to realise this and liaise with public relations staff and ensure that should a disinformation campaign be waged against the company, there is a counteractive strategy in place. Hence, the company's risk mitigation policy needs to be updated over time, and this means having input into the policy from key staff such as the risk manager, the information technology (IT) manager, and various other managers.

Drawing on the above, trust stimulates customer involvement, and customers are motivated to repurchase a product or service because of a sense of affiliation and identification with the brand [71]. The more customers trust RSQ, the more effectively committed to the provider the customer becomes. On this premise, this paper investigates the following hypothesis:

Hypothesis 6 (H_6). *RSQ mediates the relationship between customer trust and customer retention.*

Commitment is defined as the willingness to continue a relationship. Morgan and Hunt [23] explain that commitment is the mutual belief in an exchange between two parties in a relationship. Service providers are keen to obtain customers' commitment [72]. This is one of the reasons why managers in the service sector are adopting emerging technologies, especially AI and the IoT, and smart robots are gradually replacing humans in the provision of services [63].

Increasingly, advancements in robotic services have increased in many sectors for various jobs and services [59]. Service quality is based on the consumer's whole assessment of the service experience and is, therefore, a subjective cognitive opinion held by the customer rather than an objective measure. Service quality is considered a measure of customers' views on the performance of the service delivered [73]. Expectation disconfirmation theory [74] further confirms that when customers' expectations for RSQ are higher than the actual service experience, the customer becomes dissatisfied. In contrast, when their expectation for RSQ is lower than the actual experience, the customer becomes satisfied, which leads to commitment and intentions to rebuy. This leads to the following hypothesis:

Hypothesis 7 (H_7). *RSQ mediates the relationship between customer commitment and customer retention.*

By considering all hypothesised relationships, Figure 1 shows our conceptual model.

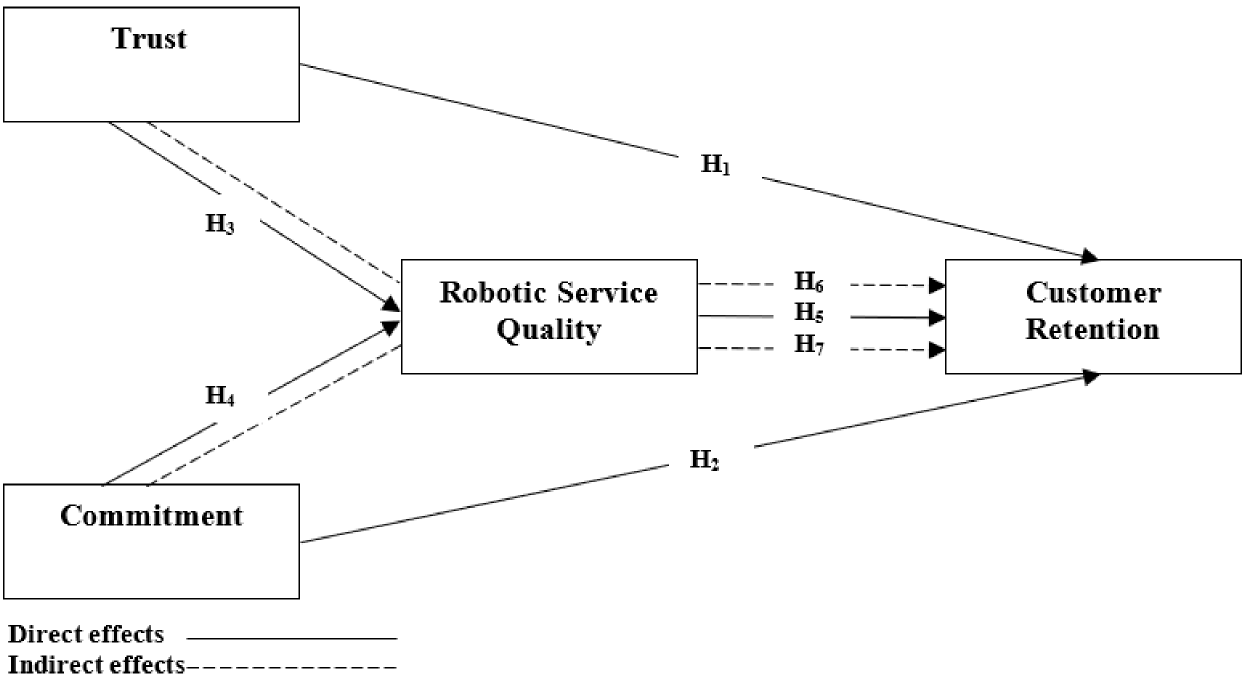

Figure 1. Graphic representation of the conceptual framework used in this study.

2.2. Research Methods

The data were collected in São Paulo, a high-tech, multicultural city that serves as Brazil's financial hub [75]. Brazilians are prone to using new technology and want to gain access to and interact with such technologies. In particular, in regions with greater purchasing power in the country, such as the southeast region, where the state of São Paulo is located, citizens are well accustomed to using technology [76].

Brazil, and specifically São Paulo [77], has a very efficient electronic government, with all public services being carried out, scheduled, or monitored digitally. In addition, the city is considered the most technological and innovative in Latin America. It is also the largest ecosystem of innovation and entrepreneurship with a technical and digital impact in the region and one of the largest in the world in this area [78]. In addition, since the COVID-19 pandemic, the country has had a substantial increase in the use of chatbots and virtual assistants powered by AI, demonstrating that the choice for the present study was appropriate [79]. The demographic profile of São Paulo also includes a high concentration of young adults and highly educated individuals, who are the groups most likely to adopt digital technologies and innovations [80].

In terms of privacy and security, the National Household Sample Survey indicates that 72% of internet users in the São Paulo metropolitan area express concerns about the security of their personal information, particularly in digital interactions [81]. This behaviour is influenced both by the Brazilian General Data Protection Law (LGPD) and by extensive media coverage of privacy and data protection issues. This level of awareness makes São Paulo an ideal environment for studying the impact of privacy concerns on consumer trust in technologies like robotic customer service.

2.2.1. Measures

Operationalisation refers to developing or adopting indicators to measure a latent variable [82,83]. Therefore, we adopted scales and items from existing research. Furthermore, adopted scales and items were verified by two senior managers specialising in marketing research and accumulated retail industry experience spanning 10–20 years. As a result, we improved the final questionnaire's wording and meaning to meet the research needs, thus establishing the questionnaire's validity. Concepts that were adopted from previous studies include trust adopted from Soh et al. [84], commitment from Meyer and Allen [85] and Moreira and Silva [86], and customer retention, from Bahri-Ammari and Bilgihan [87], Hennig-Thurau [88], and Zeithaml et al. [89]. RSQ, mainly covering automation, was adopted from Prentice and Nguyen [8].

2.2.2. Procedure

A survey instrument was used to collect the data. We translated the English version of the research questionnaire into Portuguese since the research context was Brazil, where most people speak and understand Portuguese. We expected a higher return rate of the questionnaire by doing so. The questionnaire anchored the ranking between 1 and 5, from strongly disagree to strongly agree, as per the Likert scale. The first section included three demographic-related questions, while the 14 items shared among four latent variables were in the second half of the questionnaire (Appendix A).

The questionnaire was transformed into a Google Form and disseminated via social media through direct and indirect contacts of the researchers. The researchers directly reached out to professional and personal contacts through digital media platforms using email and WhatsApp. Indirectly, we employed Facebook to connect potential respondents whom the researchers do not directly know, following a snowball pattern. The sample composition consisted of higher education students, co-workers, and various other online audiences. We added a screening question that only selected respondents who had exposure to robotic services. All the questions were compulsory by default to avoid missing values. PLS-SEM proved ideal because it was used to test the conceptual framework. PLS-SEM is superior in terms of some critical property model estimations compared to covariance-based structural equation modelling (CB-SEM) [90]. For example, PLS-SEM has an advantage compared to CB-SEM in that it can work with smaller sample sizes and it has no preference for the normal distribution of data [90,91]. Moreover, PLS-SEM aims to maximise the explained variance, while CB-SEM focuses on maximum likelihood estimation [91]. Finally, we chose PLS-SEM for the current study because it aims at prediction rather than model fit and theory confirmation [90,91]. SmartPLS 4 was used to assess the measurement and structural model of the derived conceptual model. The latest version of SmartPLS was selected for use in this study since it can be considered user-friendly and improves the quality of the reporting results.

3. Results

3.1. Sample Profile

A total of 237 responses were received; however, six questionnaires were discarded due to monotonous responses. Finally, 231 responses were retained for the data analysis. Please see Table 1 for details of the respondent's characteristics.

Table 1. Respondents' profiles.

		Frequency	Percentage (%)
Gender	Male	111	48.1
	Female	120	51.9
Age (Years)	18–29	85	36.8
	30–39	77	33.3
	40–49	42	18.2
	Above 50	27	11.7
Education	High School	59	25.5
	Undergraduate	62	26.8
	Postgraduate	110	47.6

3.2. Finite Mixture Partial Least Squares (FIMIX-PLS)

To confirm the authenticity and robustness of our research model, it was important to verify any issues related to unobserved heterogeneity since there can be hidden reasons for data that could be biased if not treated systematically [92]. Therefore, we conducted FIMIX-PLS segmentation to check for unobserved heterogeneity [92,93]. FIMIX-PLS segmentation is a method for detecting heterogeneity in the model [92,93]. However, the data represented no unobserved heterogeneity in terms of the sum of AIC_3 and CAIC, which shows a lower value for no segmentation situation [93]. Therefore, all 231 responses were analysed without segmenting the dataset since no unobserved heterogeneity existed (Table 2).

Table 2. FIMIX-PLS.

	1 Segment	2 Segments
AIC_3 *	852.455	847.418
CAIC **	876.552	899.055
$\sum$ (AIC_3: CAIC)	1729.007	1746.473
EN (normed entropy statistic)	0	0.882

* Modified Akaike's information criterion with factor 3. ** Consistent with Akaike's information criterion.

3.3. Analysing the Measurement Model

The first step of analysing a PLS-SEM path model is to evaluate the measurement model. Analysing the measurement model requires the calculation of outer loadings and quality criteria. In our constructed path model, there were two exogenous variables (trust and commitment), a mediating variable (RSQ), and an endogenous variable (customer retention). Regarding the outer loadings, the item loadings ranged from 0.713 to 0.915, except for the item customer retention, which was 0.691 (see Appendix A). We decided to retain the item after analysing the construct's internal consistency, reliability, and convergent validity [91]. Furthermore, we found previous research that retains outer loadings falling between 0.6 and 0.7, such as Damberg et al. [94] and Morales-Pérez et al. [95]. Additionally, we measured the VIF value for the outer model, which ranged from 1.342 to 3.804. We concluded that there is no severe issue with regard to multicollinearity in our measurement model (see Appendix A) [91].

Two metrics were employed to measure the internal consistency reliability aligned with the published literature: Cronbach's alpha and convergent reliability. Cronbach's alpha, the standard conservative measure of internal consistency reliability, shows >0.70 in all constructs; thus, internal consistency reliability was established. However, some intrinsic limitations of Cronbach's alpha composite reliability (e.g., tau equivalence, measurement error calculation to each item, sensitivity to numbers of items) have attracted researchers' attention [96]. In this measurement model, the composite reliability values ranged from 0.765 to 0.911, which exceeds the threshold value of 0.70 [91], confirming the internal consistency reliability of the model. In contrast, convergent validity can be measured using the average variance extracted (AVE), which shows all values ranging from 0.622 to 0.846 are >0.50, confirming the measurement model's convergent validity. Table 3 further depicts internal consistency reliability and AVE figures in greater detail.

Table 3. Metrics employed to measure the reliability and validity of the model.

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Commitment	0.804	0.837	0.622
Customer retention	0.845	0.853	0.688
RSQ	0.753	0.765	0.671
Trust	0.909	0.911	0.846

Discriminant validity is the extent to which a latent variable is significantly different to other latent variables empirically [91]. With the limitations of the Fornell–Larcker criterion, heterotrait–monotrait (HTMT) ratio has been proposed to analyse the discriminant validity of a path model. In a nutshell, HTMT is the "ratio of the between-trait correlations to within-trait correlations" [91] (p. 122). The accepted threshold for HTMT is <0.90, as evidenced in Table 4.

Table 4. HTMT ratio for the data used in this study.

	Commitment	Customer Retention	RSQ	Trust
Commitment				
Customer retention	0.876			
RSQ	0.835	0.874		
Trust	0.609	0.738	0.788	

3.4. Analysing the Structural Model Evaluation

An essential assessment in the structural model is to check the multicollinearity issues using VIF values in the inner model [97]. All the VIF values in the inner model are below the threshold value of 5 [91], as indicated by the VIF value in Table 5, which ranges from 1.466 to 2.335. Furthermore, Harman's single-factor test has checked for common method bias (CMB) [98]. We ran principal axis factoring in SPSS 28 with rotation set as none and factors to extract set as 1 and found that maximum variance explained by a single factor is 48.55; thus, CMB is not an issue (<50) as per Harman's single-factor test. Previously, Kamath et al. [99], Fox et al. [100], and Saxena et al. [101] have employed Harman's single factor for CMB analysis.

Table 5. Collinearity statistics (VIF)—inner model.

	1	2	3	4
Commitment (1)		1.929	1.466	
Customer retention (2)				
RSQ (3)		2.335		
Trust (4)		1.858	1.466	

3.5. Hypotheses Testing

The hypotheses were tested using beta coefficients (β), the *t* statistic, and *p* values as the standard practice [90,91]. The β coefficient refers to the expected change in the dependent variable compared to one unit of increase in the reference independent variable, while all other independent variables remained constant [91]. On the other hand, the *t* statistic measures whether an individual β is significantly different from zero or another hypothesised value [90,91]. Upon calculating the *t* statistic, the *p* value is measured using the area under the *t* distribution curve that lies beyond the *t* statistic value in both tails [91]. Every time the *p* value is below the desired significant level, there is strong evidence to reject the null hypothesis in the relationship [91].

3.5.1. Direct Relationships

The significance of the path coefficient was calculated using the bootstrapping procedure by 5000 subsamples (Figure 2). H_1 is supported ($\beta = 0.173$, $t = 3.435$, $p < 0.001$) by claiming a direct and positive relationship between trust and customer retention. In a similar vein, H_2 found a direct and positive relationship between commitment and customer retention ($\beta = 0.363$, $t = 6.206$, $p < 0.000$). H_3 ($\beta = 0.410$, $t = 7.418$, $p < 0.000$) and H_4 ($\beta = 0.445$, $t = 8.492$, $p < 0.000$), predicting trust and commitment to RSQ, had positive relationships. Finally, in H_5, the relationship between RSQ and customer retention ($\beta = 0.417$, $t = 7.872$, $p < 0.000$) also showed a positive relationship. The summary of all direct relationships is included in Table 6.

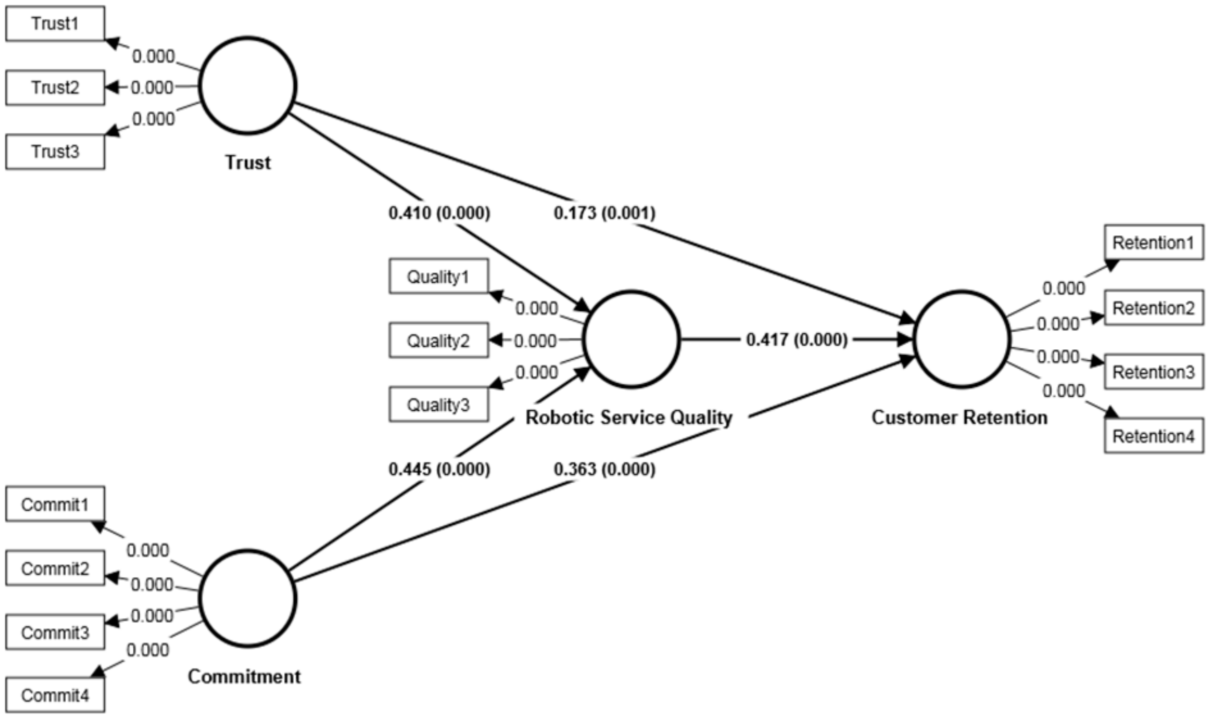

Figure 2. Bootstrapped path model.

Table 6. Direct relationships.

Latent Constructs	β	*t* Statistics	*p* Values *	Decision
H_1: Trust → customer retention	0.173	3.435	0.0010	Supported
H_2: Commitment → customer retention	0.363	6.206	0.0000	Supported
H_3: Trust → RSQ	0.410	7.418	0.0000	Supported
H_4: Commitment → RSQ	0.445	8.492	0.0000	Supported
H_5: RSQ → customer retention	0.417	7.872	0.0000	Supported

* At 0.1% significant level ($p < 0.001$).

3.5.2. Mediation Effect

This study measures the mediating role of RSQ between the relationship of trust and customer retention and commitment and customer retention. The findings revealed a significant indirect relationship between trust and customer retention via RSQ (β = 0.171, $t = 5.585$, $p < 0.000$), supporting our H_6 hypothesis (Table 7). The mediating relationship from RSQ between commitment and customer retention also had a significant indirect effect (β = 0.186, $t = 5.644$, $p < 0.000$), supporting our H_7 hypothesis (Table 7). Since direct impact and indirect paths are significant, it can be concluded that two of the mediation pathways of this research become partially mediated. Furthermore, trust and commitment showed a 34% and 54% total effect on customer retention at the established significance level (Table 7).

Table 7. Indirect effects—mean, STDEV, *t* values, *p* values.

	β	Total Effect	*t* Statistics	*p* Values *	Decision
H_6: Trust → RSQ → customer retention	0.171	0.344	5.585	0.0000	Supported
H_7: Commitment → RSQ → customer retention	0.186	0.549	5.644	0.0000	Supported

* At 0.1% significant level ($p < 0.001$).

3.6. Explanatory Power of the Model

The coefficient of determination (R^2) is the most common explanatory power measurement in model estimation, characterising in-sample predictive power [91]. Values for R^2 can vary from 0 to 1, where higher values have higher explanatory power [91]. In this structural model, R^2 for customer retention was 0.707, and RSQ was 0.572. This shows a moderate level of explanatory power in this model. The effect size (f^2) is another indicator for measuring the strength of the structural model [91]. The effect size measures the changes in R^2 when a predictor variable is omitted from the model. Table 8 shows the f^2 effect size of the structural model, where commitment to RSQ has a large effect (0.316) but a moderate impact (0.255) on customer retention. Nevertheless, trust has a very weak effect on customer retention (0.055).

Table 8. f^2 effect size of the structural model.

	Commitment	Customer Retention	RSQ	Trust
Commitment		0.234	0.316	
Customer retention				
Retention				
RSQ		0.255		
Trust		0.055	0.267	

3.7. $PLS_{Predict}$

Previously, Stone–Geisser's Q^2 statistic was the mainstream measurement for analysing the predictive power of a structural model [91]. Thus, the blindfolding procedure was applied in PLS measurement models. However, with the increasing acceptance of out-of-sample predictive power, $PLS_{Predict}$ has attracted researchers' attention. The $PLS_{Predict}$ technique divides the dataset into training and testing samples, where it increases the accuracy of the prediction of a model [93]. Table 9 illustrates the $PLS_{Predict}$ values regarding $PLS\text{-}SEM_{RMSE}$ vs. LM_{RMSE} and $PLS\text{-}SEM_{MAE}$ vs. LM_{MAE}. Since the majority of LM values (RMSE and MAE) are greater than PLS-SEM values (RMSE and MAE), conclusively, this model shows a medium predictive power overall [91].

Table 9. $PLS_{Predict}$ values for $PLS\text{-}SEM_{RMSE}$ vs. LM_{RMSE} and $PLS\text{-}SEM_{MAE}$ vs. LM_{MAE}.

	Q²predict	$PLS\text{-}SEM_{RMSE}$	LM_{RMSE}	$PLS\text{-}SEM_{MAE}$	LM_{MAE}
Retention1	0.458	0.832	0.881	0.653	0.703
Retention2	0.414	0.947	0.964	0.742	0.753
Retention3	0.481	0.911	0.916	0.713	0.701
Retention4	0.349	**0.877**	0.844	**0.683**	0.623
Quality1	0.400	0.932	0.939	0.725	0.730
Quality2	0.468	**0.941**	0.924	**0.752**	0.723
Quality3	0.255	0.925	0.928	0.721	0.728

Bold colour: $PLS\text{-}SEM_{RMSE} > LM_{RMSE}$ and $PLS\text{-}SEM_{MAE} > LM_{MAE.}$

4. Discussion

4.1. Discussion of Key Findings

Drawing upon the trust–commitment theory [23], this study investigated the mediating effect of RSQ on the relationship between trust/commitment and customer retention in the context of São Paulo, Brazil. Our results show that customer trust and commitment increase the likelihood of positive customer evaluation of RSQ, which, in our study, refers to automation and directly reflects the customer's experience and evaluation of the service robot [8]. The perceived satisfactory level of service bot performance mediates the strength of the relationship between trust and customer retention, as well as the relationship between commitment and customer retention. In other words, the perception of service bot performance quality plays a critical role in the evaluation of a brand and a customer's trust in the brand. This suggests that the respondents in this research are sensitive to service bot performance in terms of delivering relevant and personalised information that encourages engagement [1–4], but also that service bots are able to protect customers by distinguishing between their pattern of searching behaviour and those who are engaging in malicious activity [18]. This may be explained by the particular market environment in São Paulo. According to FecomercioSP [102], 75% of São Paulo consumers use the Internet as their primary tool to search for product information online before making a purchase. The Internet provides convenience, easy accessibility, and faster problem resolution. Digital service user confidence may be enhanced by LGPD and well-regulated digital services [103]. For example, a firm complies with LGPD-implemented automating processes that involve minimal data handling by humans and ensure transparency in interactions [103]. This reinforces the argument that although government policymakers provide a protective computer network environment, it is important that marketers are aware of the types of vulnerabilities that are emerging and that need to be managed. This is because companies need to retain their customers.

Based on the result of this study, it can be suggested that AI technology should be deployed to improve a personalised service [104]. Furthermore, cyber security awareness must take into account how customers place their trust in AI service providers. This is subject to a firm's commitment to having in place a cyber security strategy for dealing with cyber-related issues. In addition, individual managers must be committed to developing their knowledge and skills in order to identify and mitigate the risks that are known to create vulnerabilities that affect customers. Evidence for this is seen in the RSQ mediation effect, which is bigger than the direct effect in the relationship between trust and customer retention, as well as the relationship between commitment and customer retention. A firm's ability to identify and deal with cyber-related risks affects the level of quality service provision that it offers to its customers. Overall, our findings suggest that in order for service robots to be beneficial to customers and thus help costumer retention, a service bot's performance should be linked more firmly with the ability of the firm vis-à-vis the protection of its customers. This insight, we feel, makes a meaningful contribution to both the literature and business practice.

4.2. Theoretical Implications

Regarding the relational marketing approach, marketers need to understand the role robotic technology plays in enhancing customer service experience [104]. The present study contributes to the service and relationship marketing literature in two ways. First, our research extends the trust-commitment theory by applying it to the AI and cyber security perspectives. Specifically, we investigate the effect of customers' commitment and trust in service robots on customer retention in the context of firms incorporating cyber security awareness in their digital marketing strategies, i.e., the use of robotic technologies. Second, our results also show that customers who have developed trusting and committing connections with service robots as a result of the company's cyber security initiatives are more likely to accept the use of robots by service firms. These results corroborate the trust–commitment theory, which indicates that commitment and trust are the keys to strengthening relationships and preventing partners' intentions to terminate them [23]. However, the original theory mainly considers human partnerships (i.e., internal, supplier, lateral, and buyer partnerships) in the pre-digital business environment [23]. We propose that these relationships also apply to the human–robot partnership under the cyber security background. We highlight that trust and commitment take place between customers and service robots when companies can ensure the robustness and cyber security of service robots, which influences customers' intention to engage with service robots. Our results corroborate prior research suggesting that trust and commitment can be developed in environments with AI [105,106].

Importantly, our research emphasises the mediating role of customers' evaluation of RSQ in the trust-customer retention and commitment-customer retention relationships. In the previous literature, RSQ is usually considered an antecedent of service outcomes [107] and mostly refers to customers' evaluation. Therefore, we are particularly interested in factors, i.e., trust and commitment, that can influence customers' evaluation of RSQ. Our results show that customers' trust and commitment to service robots are strong predictors of their evaluation of RSQ, which positively impacts customer retention. These results corroborate prior research conducted in different cultural contexts that the AI's serviceability enhances customers' intentions to use it [29]. Our research contributes to the service literature by highlighting the perceived RSQ as an important explanatory mechanism to the customer-service robot relationship.

4.3. Managerial Implications

Our findings provide several practical implications for service firms. Firstly, our results suggest that customers' evaluation of RSQ depends on the level of trust they place in service robots. For customers who have developed trust and commitment to service robots, they are more likely to view their service quality positively. This finding suggests that RSQ is based on subjective evaluation, which can be influenced by customer relationships and service robots. Customers who are unsure about the cyber security of the robotic service providers can develop negative evaluations of RSQ regardless. Based on these findings, we highlight the importance of firms effectively communicating with customers about the benefits of service robots [23], especially guaranteeing the cyber security of their AI systems. We recommend that marketers and service firms develop cyber security awareness and implement corresponding policies and strategies to ensure cyber security. In the meantime, effective communication with customers regarding the organisation's cyber security policies and strategies is also crucial for building trust and commitment to service robots.

Further, developing trusting and committing relationships between customers and service robots can also promote customers' intention to continue using service robots. As discussed above, customers who trust service robots are more likely to evaluate their RSQ positively. This positive evaluation, in turn, can strengthen the relationship between customers and service robots, which prevents customers' resistance to using service robots. It further shows that firms can benefit from bridging the relationships between customers and service robots by implementing effective cyber security policies and strategies; this strategy can create a positive cycle that strengthens customers' positive perception of service robots and their intention to use them continuously. We would like to note that this may require a firm's continuous effort as customer-service robot relationships are not static. Therefore, we recommend marketers have a dynamic vision when developing AI and cyber security policies and strategies. Regular monitoring and control mechanisms can be effective in detecting any early issues and errors so that they can be handled promptly.

5. Conclusions

5.1. General Conclusions

Acknowledging the importance of cyber security in today's business environment, our study aims to investigate how customers' trust and commitment to service robots impact customer retention through RSQ. To assess our research model, we employed a survey-based study with 231 valid responses from São Paulo, Brazil. Data were analysed by using the PLS-SEM technique. Our results show that trust and commitment positively predict customer retention. Moreover, RSQ positively mediates the trust-customer retention and the commitment-customer retention relationships. Our study contributes to the theory by extending the trust-commitment theory to the AI and cyber security context and examining trust and commitment as important antecedents of customers' evaluation of RSQ. We also shed light on managerial practices by highlighting the importance of marketers developing cyber security awareness and policy within their digital marketing strategy implementation. Specifically, we recommend focusing on detecting cyber and eliminating potential threats on neural networks and expert systems to ensure the robustness of their service robots.

5.2. Limitations and Future Research Avenues

Although our study shows compelling findings, we acknowledge several research limitations. We investigated the mediating role of customer-evaluated RSQ in the trust-customer retention and commitment-customer retention relationships. We specifically focused on automation in the RSQ as it captures the overall performance of service robots [8]. Future research could consider other RSQ dimensions, such as personalisation and efficiency [8]. It would be interesting to see which RSQ dimension is more effective in bridging the associations between trust, commitment, and customer retention of service robots. Furthermore, future research could explore potential moderators impacting the mediating relationships. For example, what physical or emotional features of service robots can strengthen or weaken the relationships between customer trust and evaluation of RSQ [108]? Although we specify service robots in this study, it may be valuable to differentiate the types of service robots (e.g., physical robots vs. AI chatbots) in future research [107]. Specifically, does the customer-robot relationship differ in service robot types? This study visualised the propensity to retain through trust, commitment, and RSQ. Future studies could also consider more contextual and economic factors, such as product price and the level of technological advancement, to add more insights.

The second limitation relates to the methods. Our research relies on cross-sectional self-reported data. Although the data analysis shows high validity of the results, a future study may extend discussions about the phenomenon by analysing longitudinal data to examine how the customer–robot relationship develops over time [107]. Although our sample size is significant (n = 231) in demonstrating adequate statistical significance (Table 9), future studies can further enlarge the sample size. For example, using multiple samples from different cultures or time points would further benefit the generalisation. Further, as our study involves customer behaviour (e.g., the use of service robots), retrospective data may limit capturing the impact of behavioural factors. Therefore, we suggest future research to overcome this challenge by considering a lab-based design [109].

The last limitation relates to the research context. Although our data were collected from a single market—Brazil—it is one of the largest innovative economies in the world, having a deep connection with cyberculture and the digital world, and it shares great similarities with other innovative economies [78]. Therefore, we expect our results to be sufficient to generalise to other digitalised markets with cyber security concerns. However, we acknowledge the impact of external factors (e.g., cultural and economic factors) on firms' AI and cyber security policies and strategies, as well as customers' responses to AI systems. We recommend that future research incorporate such conditions to add insights by, for example, analysing data from both developing and developed markets to reveal any similarities or differences in customer-AI relationships. While the results are generalisable to other sectors, it would be valuable to incorporate multiple sectors, such as healthcare, education, and B2B partnerships [110]. Customers from these sectors may have different attitudes, behavioural patterns, and relationships with service robots. For example, customers in the healthcare sector may be more resistant to trusting robotic service providers [109]. Future research can use multi-sector data to further generalise the findings.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in this study.

Data Availability Statement: The data that supports the findings of this study are available from the authors upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Items, Outer Loadings, and VIF

Items	Outer Loadings	VIF
Trust (willing to use)—drawn from Soh et al. [84]		
I am willing to rely on using robotic services when making purchase-related decisions.	0.940	3.804
I am willing to make important purchase-related decisions based on robotic services.	0.915	3.153
I am willing to recommend the services that I have bought in robotic services to my friends or family.	0.905	2.655
Commitment—drawn from Meyer and Allen [85] and Moreira and Silva [86]		
Even if I could, I would not stop using this service bot provider because I like the relationship I have with service bots.	0.814	2.116
I want to remain as a part of the group of customers who resorts to this service bots due to my rewarding relationship with service bots	0.858	2.217
My emotional connection with this service bot provider is the main reason why I keep using its services	0.763	3.202
My affective connection with this service bot provider is the main reason why I keep using its services	0.713	3.034
Robotic Service Quality—*Automation drawn from* Prentice and Nguyen [8]		
Robots operate reliably	0.835	1.667
Robots perform effectively	0.876	1.854
Robots function dependably	0.741	1.342
Customer Retention—drawn from Bahri-Ammari and Bilgihan [87]; Hennig-Thurau [88]; and Zeithaml et al. [89]		
In the future, I will use robotic services	0.834	2.202
I am a loyal customer to robotic services	0.869	2.422
I feel that I should continue my relationship with this robotic service	0.908	3.189
This robotic service is my first choice when it comes to purchasing services	0.691 *	1.407

* Retained for further analysis.

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