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Unlocking Customer Adoption of AI Chatbots: Insights from the Sri Lankan Telecom Sector

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Abstract

Artificial Intelligence (AI) has swiftly revolutionised customer service provision, with chatbots being one of the most extensively used applications across several sectors. In the telecommunications industry, where consumer discontent with conventional service channels remains prevalent, AI chatbots provide a potential to offer expedited, economical, and tailored assistance. This research examines the factors influencing AI chatbot adoption within the Sri Lankan telecommunications sector by synthesising the Technology-Organization-Environment (TOE) framework with the Diffusion of Innovation (DOI) theory. Data were gathered from 368 respondents using a structured online survey and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS 4. The findings indicate that managerial support, relative advantage, market uncertainty, complexity and technical capability substantially facilitate chatbot adoption. Conversely, compatibility, government involvement, and competitive environment were identified as inconsequential determinants in this setting. These results emphasise that internal organisational preparedness and customer-perceived value are more significant catalysts for adoption than external influences. This study theoretically enhances the TOE–DOI literature by substantiating the significance of direct effects in elucidating adoption without mediation or moderation. The research offers practical lessons for telecom operators, highlighting the need of robust management commitment, streamlined user experiences, and the transmission of relative benefits to cultivate consumer trust and loyalty. The report elucidates the strategic use of AI chatbots to boost consumer engagement and performance in developing markets.

Keywords: AI Chatbots, Customer Adoption, Telecom Industry, TOE Framework, DOI Theory, PLS-SEM

Introduction

Interactions between brands and people are rapidly developing. Businesses are already confronting the difficulties of a new era driven by natural language technologies: conversational commerce. By integrating sophisticated visual interfaces with AI technology, companies may enhance relevant, personalised, and beneficial interactions with consumers (Saoud & Romman, 2024), hence boosting total customer service. Consequently, the use of these technologies is seen as a commercial opportunity, since the automation of mundane and repetitive tasks enhances organisational productivity, creativity, and efficiency (Saoud & Romman, 2024).

Messaging apps are consumers' preferred contact method and the fastest-growing medium for branded interactions, helping organisations build lasting customer relationships (Sboui *et al.*, 2024). Chatbots on social media and messaging apps are DCAs. Over 100,000 Facebook Messenger chatbots have been created in one year (Nguyen, 2024), ranging from sending airline tickets to delivering health, financial, and retail advice (Nyongesa *et al.*, 2020). These agents may actively engage customers and improve their experience, but their impact on post-interaction feelings is understudied. This study examines how chatbots affect telecommunications customer experience.

Research has established criteria for the successful adoption of AI (Nyongesa *et al.*, 2020) and examined the ways in which organisations integrate technological advancements. Research in AI has concentrated on methodologies and applications (Nyongesa *et al.*, 2025). Nevertheless, challenges related to organisational or management aspects of AI, particularly factors influencing successful AI adoption, are overlooked. There is a lack of empirical studies validating the direct effects of AI characteristics alongside the factors of technology, organisation, and environment. This study aims to explore the following enquiries: What criteria do telecommunications companies evaluate when implementing AI chatbots? What is the impact of these characteristics on the adoption of AI chatbots? Do these characteristics have an equal influence on AI adoption? This study integrates the TOE framework (Tornatzky & Fleischer, 1990) with DOI (Rogers, 1995) theory to analyse the impact of various variables on AI adoption. This approach takes into account the external environment, organisational capabilities, and AI innovation. A literature review of research concerning innovation, dissemination, implementation, and acceptance of information technology identified ten key characteristics that contribute to the successful adoption of AI. This study contributes to the existing body of knowledge regarding the unexamined aspects of AI adoption. It facilitates decision-making regarding AI adoption and the allocation of resources by enterprises.

Review of Literature

AI and Telecom Industry

The field of AI was established in 1956, marking the formal definition of its name and objectives. The primary objective of AI is to facilitate machines in executing intricate tasks that usually necessitate human cognitive abilities. Initial studies on AI were significantly shaped by philosophical concepts, logical theories, and literary fiction (Nyongesa *et al.*, 2025). The swift advancement of AI is significantly transforming the global landscape. Nonetheless, the application of AI in practical use cases remains limited.

The AI application was utilised to enhance the operations and maintenance of telecommunications networks and services. This application initiated research on the use of AI in the telecommunications sector. Macleish and Townes-Anderson (1988) illustrates the utility of first-generation expert systems in diagnosing complex telecom equipment in an off-line mode. Seshadri (1996) provides a summary of AI technologies and their applications within telecom operators, highlighting their potential to address practical challenges in the telecom sector. Post-2000, the telecom industry shifted its emphasis from fundamental telephone and Internet services to advanced, data-driven networks. The change resulted in a transition from voice calls to video and data services. Telecom operators globally are investigating the implementation of AI technology and have attained positive outcomes in various domains.

IT Adoption and AI adoption

The adoption of new technology can facilitate business success (Chen, 2019). Prior studies have concentrated on the adoption of innovative information technology or new systems by individuals and organisations (Nyongesa *et al.*, 2025). Tornatzky and Fleischer (1990) present the TOE framework to elucidate the influence of technical and environmental factors on organisations' adoption of technological innovations. The TOE framework (Tornatzky & Fleischer, 1990) posits that the technical, organisational, and environmental contexts of a business influence technological innovation. DOI Theory, established by Rogers in 1995, posits that the diffusion of technological innovations is influenced by specific characteristics, including relative advantage, complexity (CO), compatibility (CP), observability, and trialability. These characteristics impact the five categories of adopters to differing extents. Thoutem and Jalasri (2024) validate Rogers' findings, indicating that innovative traits, along with various social, organisational, psychological, and economic factors, influence organisational adoption and dissemination. Golubev *et al.* (2021) assert that the TOE framework provides a more comprehensive perspective for examining the adoption of IT innovations within organisations. The characteristics of the three contexts may vary across studies; however, the TOE framework has been successfully employed to evaluate IT adoption at the organisational level (Hoosen, 2020; Jais *et al.*, 2024; Nyongesa *et al.*, 2025; Saoud & Romman, 2024). Numerous studies utilising the TOE framework examine the success factors of IT adoption (Nyongesa *et al.*, 2025; Saoud & Romman, 2024).

Numerous studies (e.g., Nyongesa *et al.*, 2025; Hoosen, 2020; Jais *et al.*, 2024; Nyongesa *et al.*, 2020; Saoud & Romman, 2024) examine AI. Additional research investigates the theoretical foundations of AI (Hoosen, 2020; Saoud & Romman, 2024) as well as its applications. Research on AI adoption, particularly within organisations, is limited. Articles on AI within the field of information systems are infrequent. AI is pervasive, and a lack of research on organization-level AI adoption limits the expansion of existing concepts. The adoption of AI is a complex process that encompasses software, hardware, infrastructure, and the necessity for patience. The empirical assessment of AI adoption remains lacking. Therefore, a study should investigate the factors that affect AI adoption as well as the capabilities and environment of an organisation. The review of AI adoption studies indicates that the TOE framework serves as an effective foundation, as it emphasises the particular context of the adoption process and facilitates the evaluation of factors influencing AI adoption. This study employs the TOE framework as its theoretical foundation. This study employs the TOE framework and DOI theory to investigate AI adoption, as these frameworks have been utilised in academic research on IT adoption (Sboui *et al.*, 2024).

Research model and hypotheses

The literature study reveals the lack of understanding on the enabling variables that facilitate organisations' adoption of AI, as well as the interplay and influence of these factors on the choice to use AI. This paper provides a research methodology that integrates the TOE framework with DOI theory to investigate the success variables influencing AI adoption at the organisational level. This research classifies the success elements into qualities of AI innovation, organisational capabilities, and external environment. Figure 1 illustrates that the innovative qualities of AI encompass CP, relative advantage (RA), and CO. Elements within the realm of organisational capacity include managerial support (MS) and technical capability (TC). Elements within the external environment include governmental involvement (MI), market uncertainty (MU), and competitive Environment (CE).

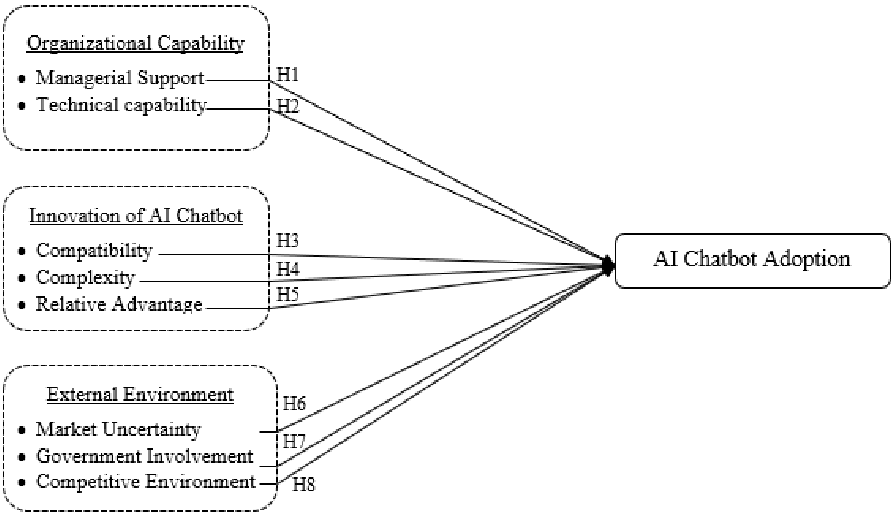

Figure 1.Research model for AI Adoption.

Organizational capability

Organisational capabilities include the resources of leadership, management expertise, and technical proficiency that facilitate the implementation of an invention. These qualities are often organization-specific, nontransferable, and ingrained inside an organisation. Organization-specific competencies distinguish businesses from their rivals.

Managerial Support

MS is a pivotal element in significant organisational transformations, since it directs resource allocation and service integration (Co, Eddy Patuwo, & Hu, 1998). Researchers see MS as a crucial element in information systems deployment (Teh *et al.*, 2024) and in information technology adoption. Amini and Bakri (2015) contends that MS must be unwavering and continuous during project execution; else, the project may fail. Managers, particularly at higher levels, might appoint essential staff to supervise specific projects and provide substantial financial and other resources to these initiatives. Conversely, insufficient MS may adversely affect a project (Amini & Bakri, 2015). Considering the critical role of managers in IT adoption, AI applications need MS and alignment with the strategic objectives of the organisation. This results in the following hypothesis.

- **H1:** MS has a positive effect on customer adoption of AI chatbots in the telecom industry.

Technical capability

TC denotes the physical assets necessary for the adoption of new technologies, including computer hardware, data, and networking (Amini & Bakri, 2015). Simultaneously, it signifies the aggregate resources that a corporation holds to provide a flexible and scalable basis for business applications (Teh *et al.*, 2024). TC encompasses intangible assets, including technical knowledge, IT development, collaborative methods, and application procedures that facilitate the efficient integration of new technologies (Nyongesa *et al.*, 2025). It is a key element influencing IT adoption (Jais *et al.*, 2024; Hoosen, 2020). Robust TC mitigates integration problems, enabling the IT department to deploy AI technology swiftly and effectively. A corporation may successfully deploy AI applications when it effectively delivers technical solutions and efficiently integrates new AI technology into its current infrastructure. This results in the following theory.

- **H2:** TC has a positive effect on customer adoption of AI chatbots in the telecom industry.

Innovation Attributes of AI

The attributes of innovation in AI highlight the essential factors influencing AI adoption within the technological context. Existing literature has extensively examined the influence of innovation characteristics on the innovation process (Gama & Magistretti, 2025; Iwuanyanwu & Igoche, 2021). Rogers (1995) identifies five characteristics of innovation in DOI theory: CP, relative advantage, CP, trialability, and observability. However, only the first three are consistently associated with innovation adoption at the organisational level (Tornatzky & Fleischer, 1990; Gama & Magistretti, 2025).

Compatibility

CP serves as a crucial factor influencing the adoption of innovation (Gama & Magistretti, 2025; Iwuanyanwu & Igoche, 2021). This pertains to the degree to which the innovation delivers value and experience in alignment with the needs of potential adopters (Rogers, 1995). The DOI theory indicates that the CP of an innovation with existing experiences and requirements is positively correlated with its adoption. A high degree of CP may lead to favourable adoption outcomes. The higher the CP, the more rapid the adoption (Al-Haji & Bakar, 2024). When firms convert their network architectures to software-defined networking using virtualisation technologies that facilitate automation, AI can utilise these capabilities to enable networks to self-diagnose, self-heal, and self-orchestrate. CP of AI technology with existing IT environments is likely to result in reduced implementation costs and time requirements. Consequently, the adoption of AI can be facilitated. This results in the subsequent hypothesis.

- **H3:** CP has a positive effect on customer adoption of AI chatbots in the telecom industry.

Complexity

CO refers to the degree to which an innovation is viewed as challenging to comprehend and utilise (Iwuanyanwu & Igoche, 2021). CO refers to the obstacles or barriers to the adoption of AI. The simplicity of integrating technology into business operations correlates positively with the likelihood of its adoption (Gama & Magistretti, 2025). The CO of AI is attributed to its immaturity, insufficient technological expertise and IT specialists, time consumption, and high costs. The characteristics of AI suggest that its primary barrier to adoption is its lack of maturity. Prior research indicates that the degree of IT maturity has a significant impact on firms' strategic decisions regarding the acquisition and deployment of IT/IS. Mature technologies enable firms to have a clearer understanding of their implementation processes. Firms are more inclined to adopt new technology if they recognise their ability to collaborate effectively with vendors (Al-Haji & Bakar, 2024). This results in the subsequent hypothesis.

- **H4:** CO has a negative effect on customer adoption of AI chatbots in the telecom industry.

Relative advantage

Relative advantage refers to the extent to which an innovation is viewed as superior to the method it replaces (Iwuanyanwu & Igoche, 2021). Rogers (1995) indicates that the perceived advantages of an innovation influence an organization's intention to adopt new technology. AI possesses significant computational power, advanced deep learning abilities, and facilitates cross-border integration (Gama & Magistretti, 2025). AI has the potential to significantly contribute to the broad dissemination of new services. The integration of AI technologies with large datasets will undoubtedly foster innovation and provide competitive advantages for organisations. Currently, AI has been utilised in customer service chatbots, speech and voice services for consumers, and automated network operations (Al-Haji & Bakar, 2024). These applications reduce operational costs, enhance service quality, improve customer experiences, and promote efficiency within firms. Upon raising awareness, individuals may embrace and engage in the beneficial transformations facilitated by AI. This results in the subsequent hypothesis.

- **H5:** Relative Advantage (RA) has a positive effect on customer adoption of AI chatbots in the telecom industry.

External Environment

The external environment encompasses the industry, competitors, regulations, and GI (Chau & Tam, 1997). Institutional theory emphasises the significance of institutional environments in influencing organisational structures and behaviours. The external environment influences firms' adoption of new technologies by presenting both incentives and barriers. Organisations are inclined to implement and utilise AI due to external pressures from governmental entities, competitors, and consumers (Cruz-Jesus, Pinheiro & Oliveira, 2019).

Market uncertainty

Market factors, including product demand, competition levels, and customer loyalty, are beyond the control of firms yet can significantly influence their performance (Awa & Ojiabo, 2016). Many AI technologies and applications remain underdeveloped, and there is a lack of qualified professionals and technical personnel. Nevertheless, AI has demonstrated significant potential and offers companies enhanced competitive advantages. Customer service chatbots and voice assistants enhance organisational efficiency and lower labour costs. Despite numerous applications remaining in development and testing, this does not deter innovative companies from entering the AI sector. This results in the subsequent hypothesis.

- **H6:** MU has a positive effect on customer adoption of AI chatbots in the telecom industry.

Government involvement

GI significantly influences the stimulation of IT innovation (Amini & Bakri, 2015). Awa and Ojiabo (2016) demonstrate that government can facilitate IT diffusion and that regulations can establish or eliminate barriers to the introduction of new IT or systems. AI, as a disruptive technology, encompasses various issues including security, privacy, and social ethics. Therefore, AI requires a robust legislative or regulatory framework. Consequently, comprehensive planning and AI legislation at the national level can facilitate the positive advancement of the AI industry. Furthermore, due to the transformative impact of AI on various aspects of human life and society, governments globally have allocated significant resources to invest in the technology and have implemented national AI development plans and policies.

GI creates a conducive environment for AI, facilitating its diffusion and impact (Awa & Ojiabo, 2016). This results in the subsequent hypothesis.

- **H7:** GI has a positive effect on customer adoption of AI chatbots in the telecom industry.

Competitive Environment

CE serves as a catalyst for technological innovation. The adoption of new technology is frequently a strategic imperative for maintaining competitiveness in the marketplace (Cruz-Jesus, Pinheiro, & Oliveira, 2019). Awa and Ojiabo (2016) assert that IT innovation has the potential to transform industry structure, modify competitive rules, enable new strategies for surpassing competitors, and reshape the CE. The adoption of new technologies is frequently essential for firms to maintain competitiveness in the marketplace. Companies experience pressure when competitors implement specific new technologies. These technologies are adopted promptly to sustain competitiveness (Awa & Ojiabo, 2016). Companies that effectively implement new AI technologies to enhance their products and services will achieve competitive advantages over rivals. Consequently, CE compels firms to implement AI technologies and applications. This results in the subsequent hypothesis.

- **H8:** CE has a positive effect on customer adoption of AI chatbots in the telecom industry.

Methodology

Measurement instruments and pilot test

The measuring questions for each construct are utilised a Likert scale with seven points, ranging from 1 (strongly disagree) to 7 (strongly agree) the evaluation was carried out. The survey items were derived from prior research. Three pieces for each construct were generated from earlier research. Using English for the survey questions reduced the chances of translation problems. Before the main research, the survey questionnaire had a pre-test with 30 respondents. The sample consisted of students, academic staff, and working professionals who were requested to provide comments on the questionnaire's phrasing, contents, organisation, and layout. The primary study's final online questionnaire was developed after some slight adjustments and modifications.

Participants and Data Collection

All customers of telecom service providers in Sri Lanka were considered as the study population. According to the Telecommunications Regulatory Commission of Sri Lanka, the total number of mobile subscribers in the country exceeds 30 million, which indicates a highly competitive and technology-driven market (TRCSL, 2024). Due to the lack of a comprehensive sampling frame, this study employed a convenient sampling methodology instead of a probabilistic approach, in line with earlier studies that have adopted similar strategies (Rathnayake *et al.*, 2025; Livera *et al.*, 2025). Data were collected through an online survey designed using Google Forms, which specifically targeted telecom customers who had prior experience with AI-based chatbot services. The survey link was disseminated via multiple channels, including Facebook, WhatsApp, and LinkedIn, to ensure wider reach. In addition, the link was distributed by email through customer networks, and some telecom customer service groups were requested to share it further with their contacts.

The size of the sample was established by referring to the results of earlier research. According to the formula, using the G*Power application (Faul *et al.*, 2009) formula [n = N/(1 + N(e)^2)] and the recommended sample size for this inquiry was approximately 400, with a margin of error of 5%, 368 respondent participated in the online survey. When conducting investigations utilising Structural Equation Modelling (SEM), it has been determined from previous research that a sample size of at least 200 is sufficient (Shameem & Sanjeetha, 2021). No missing data or partial replies were found in the online survey since all items were mandatory, preventing incomplete questionnaires from being submitted.

Table 1: Respondents' Demographic Information

Profile	Frequency	Percentage
Gender		
Male	222	60.3
Female	146	39.7
Age		
18-25 years	41	11.1
26-35 years	117	31.8
36-40 years	206	56
Above 40	4	1.1
Internet Experience		
< 2 years	14	3.8
2 – 5 years	103	28

> 5 years	251	68.2
Occupation (Relevant to Chatbot Use)		
Students	65	17.7
Customer Service/Support	56	15.2
Business/Service Sector	82	22.3
IT/Technology Professionals	118	32.1
Other (general users)	47	12.8

Data Analysis

According to the findings of a study conducted by Nyongesa *et al.* (2020), the use of the Partial Least Square Structural Equating Model (PLS-SEM) is very suitable for the purpose of validating essential components, forecasting, and clarifying target constructs in an empirical model. When conducting our data analysis and model evaluation, the researchers utilised a technique known as PLS-SEM, which was carried out with the assistance of Smart PLS 4 software. In addition, the PLS-SEM technique was utilised by the authors in the manner of the following. In accordance with the methodology proposed by Saoud & Romman. (2024), there are relevant measurement model criteria in order to evaluate the internal consistency reliability, convergent validity, and discriminant validity of the measurement model. This was done in light of the fact that the indicators were defined in a reflective manner. Following the analysis of path coefficients, t-statistics, and p-values, we determined whether or not the hypotheses were correct. For the purpose of obtaining t-statistics and p-values, the process also included bootstrapping method.

Data Analysis

Assessment of Measurement Model

A number of different types of validity tests were performed on the measurement models, including construct validity, reliability, convergent validity, and discriminant validity. A factor loading that is larger than 0.70 is regarded to be substantial, as stated by Hair *et al.* (2020). As can be seen in Table 2, all of the items that were included in the research had loadings that were more than the recommended threshold of 0.7. All of the Cronbach’s alpha (CA) values in this investigation were higher above the recommended threshold of 0.7 as recommended by Kline (2023), each composite reliability (CR) and Rho_A components have a value that falls somewhere in the range of 0.714 to 0.914. Because both CR, Rho_A, and Cronbach's Alpha were largely free from mistakes for all of the constructions, it may be concluded that build reliability test has been established, as stated in Table 2.

According to Hair *et al.* (2017), the AVE values used in this study varied from 0.541 to 0.783, which is higher than the recommended threshold of 0.50. Table 2 demonstrates that all of the constructs have successfully demonstrated convergent validity after being tested.

Table 2: Measurement Assessment Results

Construct	Item	Outer Loading	rho_A	CA	CR	AVE
Chatbot Adoption	CA2	0.721	0.758	0.753	0.812	0.591
	CA4	0.768				
	CA5	0.815				
Competitive Environment	CE1	0.781	0.825	0.82	0.881	0.65
	CE10	0.851				
	CE2	0.784				
	CE9	0.807				
Complexity	CO15	0.714	0.799	0.786	0.861	0.609
	CO4	0.747				
	CO5	0.846				
	CO6	0.808				
Compatibility	CP11	0.855	0.736	0.736	0.846	0.733
	CP3	0.858				
Government Involvement	GI1	0.835	0.878	0.874	0.909	0.667
	GI2	0.867				
	GI3	0.845				
	GI4	0.781				
	GI5	0.748				
Managerial Support	MS5	0.775	0.79	0.788	0.863	0.613
	MS6	0.813				
	MS7	0.81				
	MS8	0.73				
Market Uncertainty	MU1	0.876	0.737	0.705	0.798	0.665
	MU3	0.75				
Relative Advantage	RA1	0.748	0.753	0.751	0.811	0.589

	RA4	0.778				
	RA9	0.775				
Technical Capability	TC14	0.78	0.745	0.745	0.84	0.568
	TC16	0.71				
	TC18	0.779				
	TC9	0.743				

Note: *CA=Chatbot Adoption, CE=Competitive Environment, CO=Complexity, CP=Compatibility, GI=Government Involvement, MS=Managerial Support, MU=Market Uncertainty, RA= Relative Advantage, TC=Technical Capability*

As a consequence of applying the Fornell-Larcker criteria, the findings for discriminant validity are shown in Table 3. According to Fornell and Larcker (1981), the square roots of the Average Variance Extracted (AVE) on the diagonals were found to be larger than the correlations among constructs. This suggests that there are strongly correlated relationships between constructs and their indicators in comparison to other constructs in the model. The findings of Hair *et al.* (2020) indicate that this displays a high level of discriminant validity. Successfully meeting the criterion for discriminant validity was achieved by each and every construct.

The Fornell-Larcker criteria are debated due to their limited capacity to accurately identify the lack of discriminant validity in typical research settings (Sarstedt *et al.*, 2019). Another suggested strategy in this study is the use of HTMT ratios of correlations for testing discriminant validity. Discriminant validity concerns arise when HTMT values exceed 0.90 or the 0.85 threshold (Kline, 2023). In accordance with the discriminant validity criterion, all of the HTMT values are found to be lower than 0.85, as demonstrated in Table 4.

Table 3: Fornell-Larcker criteria

	CA	CE	CO	CP	GI	MS	MU	RA	TC
CA	**0.769**								
CE	0.493	**0.806**							
CO	0.45	0.718	**0.781**						
CP	0.48	0.731	0.678	**0.856**					
GI	0.491	0.68	0.624	0.565	**0.816**				
MS	0.45	0.663	0.632	0.629	0.572	**0.783**			
MU	0.435	0.594	0.57	0.532	0.512	0.451	**0.815**		
RA	0.457	0.675	0.632	0.584	0.519	0.494	0.575	**0.767**	
TC	0.421	0.766	0.731	0.719	0.621	0.69	0.572	0.631	**0.753**

Note: *CA=Chatbot Adoption, CE=Competitive Environment, CO=Complexity, CP=Compatibility, GI=Government Involvement, MS=Managerial Support, MU=Market Uncertainty, RA= Relative Advantage, TC=Technical Capability*

Table 4: HTMT ratios of correlations

	CA	CE	CO	CP	GI	MS	MU	RA	TC
CA									
CE	0.671								
CO	0.621	0.898							
CP	0.745	8.011	0.861						
GI	0.647	0.799	0.763	0.756					
MS	0.627	0.825	0.808	0.889	0.688				
MU	0.743	0.813	0.692	0.839	0.75	0.696			
RA	0.701	0.819	0.883	0.804	0.685	0.687	8.006		
TC	0.604	0.878	0.58	8.044	0.768	0.801	0.827	0.803	

Note: *CA=Chatbot Adoption, CE=Competitive Environment, CO=Complexity, CP=Compatibility, GI=Government Involvement, MS=Managerial Support, MU=Market Uncertainty, RA= Relative Advantage, TC=Technical Capability*

Table 5 displays the outer loadings of several indicators on the construct, which are higher than any cross-loadings with other constructs. The cross-loading criteria meets the requirements.

Table 5: Cross Loadings

	CA	CE	CO	CP	GI	MS	MU	RA	TC
CA2	0.721	0.381	0.31	0.385	0.325	0.359	0.305	0.345	0.344
CA4	0.768	0.339	0.363	0.325	0.401	0.302	0.345	0.349	0.288
CA5	0.815	0.416	0.363	0.397	0.404	0.376	0.351	0.36	0.34
CE1	0.391	0.781	0.495	0.601	0.521	0.515	0.421	0.464	0.588
CE10	0.429	0.851	0.689	0.656	0.576	0.6	0.519	0.646	0.698
CE2	0.351	0.784	0.552	0.571	0.483	0.549	0.521	0.562	0.598
CE9	0.414	0.807	0.569	0.527	0.603	0.475	0.458	0.503	0.583
CO15	0.299	0.558	0.714	0.483	0.563	0.478	0.479	0.462	0.527
CO4	0.316	0.596	0.747	0.562	0.477	0.496	0.469	0.494	0.597
CO5	0.374	0.6	0.846	0.562	0.484	0.527	0.486	0.557	0.619
CO6	0.402	0.507	0.808	0.516	0.449	0.48	0.369	0.464	0.547
CP11	0.409	0.629	0.54	0.855	0.469	0.51	0.459	0.462	0.577
CP3	0.413	0.623	0.62	0.858	0.498	0.567	0.453	0.538	0.654
GI1	0.388	0.56	0.504	0.486	0.835	0.478	0.454	0.413	0.526
GI2	0.442	0.604	0.551	0.498	0.867	0.507	0.492	0.466	0.548

GI3	0.393	0.543	0.487	0.46	0.845	0.483	0.389	0.36	0.501
GI4	0.417	0.534	0.506	0.433	0.781	0.459	0.353	0.457	0.497
GI5	0.356	0.531	0.497	0.424	0.748	0.401	0.398	0.418	0.458
MS5	0.334	0.494	0.513	0.466	0.439	0.775	0.346	0.36	0.502
MS6	0.36	0.484	0.469	0.479	0.438	0.813	0.337	0.385	0.502
MS7	0.365	0.505	0.487	0.456	0.453	0.81	0.339	0.395	0.544
MS8	0.348	0.592	0.513	0.569	0.461	0.73	0.39	0.406	0.613
MU1	0.404	0.536	0.527	0.453	0.491	0.436	0.876	0.479	0.498
MU3	0.294	0.423	0.389	0.418	0.326	0.281	0.75	0.466	0.433
RA1	0.332	0.427	0.407	0.366	0.363	0.338	0.347	0.748	0.399
RA4	0.349	0.574	0.546	0.505	0.38	0.385	0.572	0.778	0.566
RA9	0.37	0.548	0.498	0.47	0.449	0.411	0.403	0.775	0.485
TC14	0.312	0.614	0.536	0.577	0.5	0.58	0.395	0.436	0.78
TC16	0.322	0.57	0.582	0.494	0.488	0.476	0.393	0.469	0.71
TC18	0.316	0.545	0.556	0.54	0.467	0.551	0.385	0.419	0.779
TC9	0.316	0.579	0.526	0.555	0.414	0.473	0.549	0.577	0.743

Note: *CA=Chatbot Adoption, CE=Competitive Environment, CO=Complexity, CP=Compatibility, GI=Government Involvement, MS=Managerial Support, MU=Market Uncertainty, RA= Relative Advantage, TC=Technical Capability*

Assessment of Structural Model

The structural model assessment includes hypothesis testing as shown in Table 6. The test findings confirmed the 8 hypotheses developed for this research. It has been confirmed that MS has a favourable impact on CA. H1 is acceptable based on the statistical values ($\beta = 0.147$, $t = 2.528$, $p < 0.05$). TC was found to negatively affect CA, and the test results confirm this relationship. Therefore, H2 is supported with statistical values ($\beta = -0.157$, $t = 2.221$, $p < 0.05$). CO was discovered to directly impact CA. Hence, H3 was accepted ($\beta = 0.188$, $t = 3.096$, $p < 0.05$). Similarly, CP does not have a significant impact on CA, which is shown by the results ($\beta = 0.004$, $t = 0.058$, $p = 0.954$). Therefore, H4 is not supported. RA has a favourable impact on CA, and the test findings confirm this relationship. Thus, H5 is accepted with ($\beta = 0.119$, $t = 1.932$, $p < 0.05$). MU was seen to directly influence CA, and the hypothesis is supported with ($\beta = 0.134$, $t = 2.321$, $p < 0.05$). However, GI was not found to significantly influence CA, as shown by the results ($\beta = 0.288$, $t = 1.396$, $p = 0.163$). Therefore, H7 is not supported. Similarly, CE does not show a significant impact on CA, and the test results do not validate this hypothesis ($\beta = 0.069$, $t = 0.851$, $p = 0.395$). Thus, H8 is not supported.

Table 6: Results of Path coefficient analysis

Hypotheses	Relationship	Std Beta	SM	SD	t value	P Values	Decision
H1	MS -> CA	0.147	0.147	0.058	2.528	0.012	Supported
H2	TC -> CA	-0.157	-0.154	0.071	2.221	0.027	Supported
H3	CO -> CA	0.188	0.185	0.061	3.096	0.002	Supported
H4	CP -> CA	0.004	0.014	0.076	0.058	0.954	Not Supported
H5	RA -> CA	0.119	0.118	0.062	1.932	0.040	Supported
H6	MU -> CA	0.134	0.132	0.058	2.321	0.021	Supported
H7	GI -> CA	0.288	0.27	0.206	1.396	0.163	Not Supported
H8	CE -> CA	0.069	0.066	0.081	0.851	0.395	Not Supported

Note: *CA=Chatbot Adoption, CE=Competitive Environment, CO=Complexity, CP=Compatibility, GI=Government Involvement, MS=Managerial Support, MU=Market Uncertainty, RA= Relative Advantage, TC=Technical Capability*

Discussions

The findings of this study provide important insights into the adoption of AI chatbot technology in the Sri Lankan telecom industry. Results from the structural model reveal that MS, TC, CO, relative advantage (RA), and market uncertainty (MU) significantly influence chatbot adoption, while compatibility (CP), GI, and CE do not demonstrate significant effects. This section discusses these results in detail, compares them with previous research Golubev *et al.*, 2021; Thoutam & Jalasri, 2024; Nyongesa *et al.*, 2025, and outlines implications for telecom firms.

MS was found to have a significant and positive impact on chatbot adoption. This highlights that when organizational leaders provide clear direction, allocate resources, and actively champion AI adoption initiatives, customers are more likely to perceive chatbots as trustworthy and reliable. Prior studies have consistently emphasized the central role of leadership commitment in technology adoption (Livera & Bandara, 2024; Golubev *et al.*, 2021; Thoutam & Jalasri, 2024; Nyongesa *et al.*, 2025). In the context of telecom services, management involvement ensures that chatbots are not merely deployed as a technological tool but are strategically integrated into customer service delivery. Customers interpret this visible commitment as an assurance of quality and continuity, which, in turn, encourages adoption.

This finding implies that companies need to create strong managerial frameworks to support chatbot initiatives, thereby reinforcing trust and enhancing customer readiness.

In contrast, TC displayed a significant but negative influence on chatbot adoption. This finding is counterintuitive but meaningful. It suggests that weak infrastructure, insufficient IT expertise, and integration challenges hinder adoption rather than enabling it. CP in system integration and the perception that chatbots require high technological sophistication may create barriers for both organizations and customers. These results align with studies emphasizing that the absence of strong technical foundations undermines successful IT adoption (Nyongesa *et al.*, 2025; Golubev *et al.*, 2021; Chen, 2019). In the telecom context, technical shortcomings such as slow response times, frequent errors, or limited natural language processing capacity can frustrate customers and discourage continued use. Therefore, enhancing technical readiness and ensuring robust backend support are essential for encouraging positive adoption outcomes.

The study further found that CO significantly affects chatbot adoption in a negative way. When customers perceive chatbot systems as difficult to use, confusing, or requiring excessive effort to obtain satisfactory answers, their willingness to adopt them decreases. This aligns with Rogers' DOI theory, which identifies CP as a critical barrier to adoption (Rogers, 1995). Previous research (Golubev *et al.*, 2021; Thoutam & Jalasri, 2024; Nyongesa *et al.*, 2025) also supports the idea that ease of use is fundamental for successful adoption of emerging technologies. Within the Sri Lankan telecom industry, many customers still expect simple, human-like interactions, and when chatbots fail to meet this standard, they are perceived as frustrating substitutes for human agents. Reducing CO through intuitive design, user-friendly interfaces, and advanced AI-powered personalization will therefore be crucial for overcoming resistance.

Interestingly, CP was not supported as a significant predictor of adoption. This finding suggests that even if chatbot systems align with existing customer service practices or communication preferences, this alignment alone does not guarantee adoption. Customers may expect more than mere CP; they require evidence of added value and superior performance. This diverges from some prior studies (Thoutam & Jalasri, 2024; Chen, 2019; Golubev *et al.*, 2021), which emphasized CP as a driver of innovation adoption. In the Sri Lankan telecom context, customers appear to prioritize tangible benefits such as efficiency and speed over whether chatbots integrate seamlessly with traditional service channels.

Similarly, GI did not show a significant effect on adoption. Although government policies and regulatory frameworks are often considered enabling factors for technological diffusion

(Golubev *et al.*, 2021), their absence as a driver here suggests that customers do not directly perceive GI when deciding to adopt chatbots. Adoption decisions are shaped more by personal experience and perceived service quality than by regulatory encouragement. Likewise, the CE was not supported, indicating that customers are not strongly influenced by CE in their adoption choices. While telecom firms may view chatbot deployment as a strategic response to industry competition, customers base their adoption on the actual performance and benefits of the service rather than on competitor behavior.

On the other hand, relative advantage (RA) was supported as a significant predictor of chatbot adoption. Customers adopt chatbots when they perceive clear advantages over traditional service channels, such as faster query resolution, 24/7 availability, reduced waiting times, and convenience. This aligns with Rogers' DOI theory, where relative advantage is one of the strongest determinants of adoption (Rogers, 1995). Past studies (Nyongesa *et al.*, 2025) also confirm that when customers identify clear benefits of AI chatbots, adoption increases significantly. In Sri Lanka, where customer dissatisfaction with telecom services is often reported, the ability of chatbots to provide instant and efficient support is perceived as a strong reason to adopt.

Another significant driver identified was MU. This factor positively influenced adoption, suggesting that in a volatile telecom environment characterized by frequent service changes, billing updates, and evolving customer needs, chatbots offer a stable, reliable, and immediate channel of support. Overall, the study's results indicate that adoption is more strongly influenced by internal organizational readiness and technological benefits than by external environmental factors. Out of eight hypotheses tested, five were supported (MS, TC, CO, RA, MU) while three were not (CP, GI, CE). This highlights that the drivers of adoption in Sri Lanka are grounded more in perceived usefulness, ease of use, and organizational support than in regulatory or competitive forces.

Research Implications

Theoretical Implications

This study contributes to the growing body of literature on AI adoption in the service sector by applying the TOE framework and DOI theory in the Sri Lankan telecom industry. While previous studies have emphasized mediating and moderating effects in technology adoption, the present research demonstrates that direct relationships alone can explain significant portions of chatbot adoption behavior. This strengthens the argument that TOE and DOI can be effectively integrated without the need for complex mediation models, particularly in emerging economies where technology adoption is at an early stage.

The findings extend DOI theory by confirming the strong role of relative advantage and the negative influence of CO in chatbot adoption, aligning with Rogers (1995). Moreover, the study highlights that CP, GI, and CE commonly emphasized in prior research may not always be significant in all contexts. This indicates that the relative weight of adoption factors varies depending on local market conditions, customer expectations, and service industry characteristics.

In addition, the significant negative effect of TC provides new insights into adoption theory. Contrary to the general assumption that higher technical readiness facilitates adoption, this study suggests that insufficient infrastructure and technical immaturity can serve as major obstacles. This enriches the TOE perspective by emphasizing the importance of not only the presence of technical resources but also their quality, maturity, and usability.

Finally, the study provides theoretical evidence that internal organizational readiness (MS, TC, and service design) has greater influence on adoption than external environmental factors (GI, competition, or market forces) in the Sri Lankan telecom context. This opens avenues for comparative studies across industries and regions to further test the relative importance of these contexts within the TOE framework.

Industry Implications

From an industry perspective, the results provide actionable insights for telecom operators in Sri Lanka and other developing countries seeking to implement AI chatbot solutions. First, the positive impact of MS highlights the need for top management to take an active role in championing chatbot adoption. Telecom leaders should allocate sufficient resources, create strategic alignment, and communicate the value of chatbot initiatives to customers, signaling that these technologies are reliable and supported at the highest organizational level. Second, the negative influence of TC underscores the importance of investing in robust infrastructure and skilled human capital. Telecom operators must strengthen backend systems, integrate advanced natural language processing, and ensure continuous updates to improve chatbot performance. Without sufficient technical maturity, customers are likely to experience dissatisfaction, which hinders adoption. Third, the significant role of CO suggests that user experience design must be prioritized. Chatbots should be intuitive, provide clear responses, and minimize customer effort during interactions. Simplifying interfaces and offering multilingual support can further reduce adoption barriers in diverse markets like Sri Lanka.

Fourth, the positive effect of relative advantage emphasizes the need to communicate the tangible benefits of chatbot use. Marketing campaigns and customer education should focus on demonstrating how chatbots provide quicker query resolution, reduce waiting times, and enhance service convenience compared to traditional call centers. Finally, the influence of MU indicates that chatbots can act as stabilizing tools during periods of service disruption or rapid technological change. Telecom operators should position chatbots as reliable, always-available service channels that help customers manage billing, technical issues, and account-related queries seamlessly. These implications suggest that telecom companies should focus less on external factors like regulatory policies or competition and instead prioritize internal readiness, system quality, and customer-oriented design to ensure successful chatbot adoption.

Conclusion and Recommendation

This study examined the impact of technological, organizational, and environmental factors on the adoption of AI chatbots in the Sri Lankan telecom industry using the TOE framework and DOI theory. The findings revealed that MS, relative advantage, and MU positively and significantly influence chatbot adoption. Conversely, TC and CO exert negative effects, suggesting that weak infrastructure and high perceived difficulty remain major barriers. On the other hand, CP, GI, and CE were not supported as significant predictors of adoption in this context.

These results underscore that chatbot adoption is driven more by internal readiness and technological benefits rather than by external pressures such as GI or competitor strategies. Customers value speed, convenience, and reliability, but they are discouraged when chatbots are perceived as overly complex or when technical support is insufficient. Theoretically, the study confirms the robustness of the TOE and DOI frameworks while showing that the relative weight of adoption factors differs across industries and regions. Practically, the findings highlight the importance of organizational leadership, simplified user experience, and communication of relative advantages to drive adoption.

The findings of this study provide several important recommendations for the telecom industry in Sri Lanka and similar contexts. First, telecom companies should ensure stronger MS for chatbot initiatives, as leadership commitment and resource allocation are crucial to building customer confidence. Equally important is the need to strengthen TC by investing in infrastructure, advanced AI technologies, and skilled professionals, since weak technical readiness directly reduces adoption. To overcome resistance, firms must also focus on reducing

CO by designing chatbots that are simple, intuitive, and capable of supporting multiple languages and personalized responses. In addition, companies should actively highlight the relative advantages of chatbot use through marketing and customer education campaigns, showcasing benefits such as reduced waiting times, 24/7 service availability, and efficient query resolution. Given the positive role of MU, chatbots should also be positioned as reliable service channels during network disruptions, billing issues, or sudden market changes, thereby reinforcing customer trust and loyalty. Finally, the results suggest that less emphasis should be placed on external pressures such as GI and competitor actions, and instead greater attention should be directed towards internal readiness and customer-centric service design, which are more influential in driving adoption.

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