Empowering the Current and Future Telecom Network: AI/ML Based Telecom Network Management and Analysis of Critical Factors

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Abstract. The telecommunications sector is undergoing rapid transformation with the rise of 5G, IoT, NFV, and Cloud technologies. However, telecom network management remains largely manual, reactive, and fragmented, limiting cost efficiency and scalability. While Artificial Intelligence (AI) and Machine Learning (ML) promise to modernize this landscape through automation and predictive capabilities, the adoption of such technologies remains inconsistent and poorly understood, particularly within telecom organizations.

This research work intends to overcome a critical shortcoming in the prevailing literature which is characterized by insufficient empirical analysis of telecom-specific elements that impact the use of AI/ML technologies. The study incorporates comprehensive model based on three theoretical frameworks: the Technology-Organization-Environment (TOE) framework, the Diffusion of Innovation (DOI) theory, and the Technology Acceptance Model (TAM). By making use of well-structured cross-sectional survey that includes 198 professionals from major telecom operators and vendors, this research work examines the effects of twelve constructs on decision-making processes related to AI/ML adoption.

The findings indicate that constructs such as Compatibility, Relative Advantage, and Managerial Capability constitute the primary determinants influencing the adoption of AI/ML technologies in the management of telecommunications networks. Interestingly, conventional constructs of the Technology Acceptance Model, such as Perceived Usefulness and Perceived Ease of Use, were determined to lack statistical significance, necessitating a critical reassessment of their applicability within complex and infrastructure-heavy contexts. This investigation provides both theoretical and practical implications by enhancing pre-existing adoption frameworks tailored to the telecommunications sector and pinpointing actionable elements for industry participants. This research work can further be extended by including studies incorporating impact of Organization Size, Regulatory Policies and Vendor Ecosystem on the AIML Adoption strategies.

Keywords: Artificial Intelligence, Benefits, Critical Factors for AI/ML Adoption, DOI Theory, Issues and Challenges, Machine Learning, TAM, Telecom Network Management, TOE Framework

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1 Introduction

The telecommunication network infrastructure is under transformation phase with the adoption of cutting-edge technologies like Software-Defined Wide Area Networking (SD-WAN), Network Function Virtualization (NFV), cloud-native 5G core architectures, and the anticipated 6G framework. These technological innovations are enabling operators to redesign the processes through which services are crafted and delivered thereby transitioning from standard, reactive methodologies to predictive, autonomous, and data-oriented network management [1]   Artificial Intelligence (AI) and Machine Learning (ML) are pivotal in this paradigm shift, facilitating real-time closed-loop automation, enhanced scalability, and superior quality of service across increasingly intricate network systems.

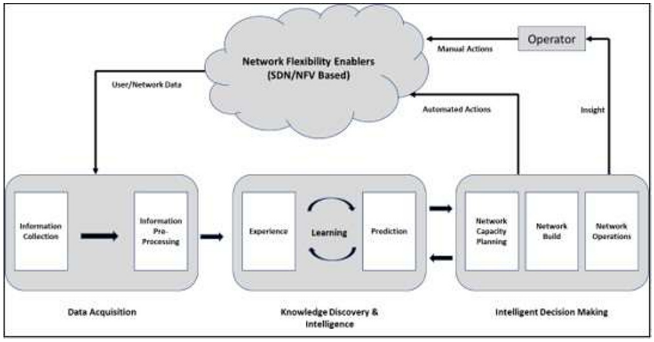

Fig. 1. AI/ML Based Telecom Network Management Approach
Source: Adapted from[1]

AI/ML technologies enable a paradigm shift in network management through three fundamental capabilities: dynamic and predictive network planning [2], automated fault detection and self-healing [3], and near-real-time orchestration of service provisioning and optimization [4][5]. These capabilities are critical for handling the increasing diversity, volume, and velocity of data traffic, while simultaneously reducing operational expenditure and ensuring a high quality of experience for end-users. Predictive analytics powered by ML can proactively identify network bottlenecks or faults [6], facilitating preventive maintenance and optimal resource utilization. Similarly, telemetry-driven network configuration allows dynamic resource optimization without manual intervention, replacing traditional SNMP protocols [7][8].

In spite of the many possibilities of potential use of AI/ML in Telecommunication network, the real application is not that pervasive and is limited and fragmented. Various technical hurdles, such as the integration with pre-existing infrastructure, the scalability of AI models, and the lack of universally accepted standards—particularly within the radio access network (RAN) - hinder widespread adoption [9][10]. Additionally, the speed and the extent of AI/ML adoption are significantly influenced by organizational and strategic factors, such as the readiness of management, the nature of competitive pressures, and compliance to regulations [11][12].

While existing literature has explored general technology adoption, there is a critical lack of empirical research focusing on AI/ML deployment within the telecom sector. Prior studies often apply universal adoption models without fully accounting for telecom-specific operational dynamics, such as real-time control, multi-layer architectures, and domain-specific regulatory constraints. In particular, the influence of constructs like Compatibility with existing systems, Relative Advantage in terms of performance and cost-efficiency, and the role of Managerial Capability in steering innovation initiatives remains under-examined—especially in emerging economies like India, where resource constraints and network heterogeneity are pronounced.

This study intends to bridge the research gap by empirically examining the important technological, organizational, and environmental factors that impact the adoption of AI/ML in the management of telecom networks. It seeks to answer two core research questions:

1. Which constructs significantly influence AI/ML adoption decisions in telecom network management?
2. How strong is the impact of each construct, and what implications does this have for theory and practice?

This research is structured around the integration of three well-established theoretical frameworks: the Technology–Organization–Environment (TOE) framework [13], which assesses organizational preparedness and external pressures; the Diffusion of Innovation (DOI) theory [14], which evaluates the perceived characteristics of innovations such as relative advantage, compatibility, and complexity; and the Technology Acceptance Model (TAM) [15], which captures user-level perceptions of usefulness and ease of use. This integrated framework facilitates a comprehensive examination that includes strategic, operational, and behavioral elements influencing adoption choices.

A quantitative, cross-sectional investigation was carried out employing a structured questionnaire targeting 198 professionals engaged in AI/ML-related roles within prominent Indian telecommunications firms (Reliance Jio, Vodafone Idea, Tata Communications) and technology suppliers (Cisco, Nokia). The collected and collated responses were analyzed through structural equation modeling (SEM) employing AMOS. The responses were additionally verified by confirmatory factor analysis, composite reliability checks, and evaluations of average variance extracted.

The underlying study show that Compatibility, Relative Advantage, and Managerial Capability are the foremost factors impacting AI/ML adoption. It is important to note that the constructs like Perceived Usefulness and Perceived Ease of Use under the Technology Acceptance Model (TAM) has minimal statistical significance within this framework. These findings imply that in extensive, infrastructure-heavy domains like telecommunications, strategic and integration-related aspects supersede individual user perceptions in facilitating adoption. The next sections investigate the theoretical framework, research methodology, empirical outcomes, and implications of this research.

2 Theoretical Framework

Making use of the three well-established theoretical frameworks - Technology Organization Environment (TOE), Diffusion of Innovation (DOI), and Technology Acceptance Model (TAM), this study in a systematic manner evaluates the factors of AI/ML integration in telecom network management. As a result, it delivers a holistic framework for recognizing essential constructs and developing research hypotheses.

The research work included exploring relevant electronic databases such as Elsevier, Scopus, Emerald, Springer, and IEEE, along with reviewing reports and articles from the industry available on internet. This process facilitated the identification of essential constructs pertinent to the adoption of AI/ML technologies within telecommunications environments, which were subsequently aligned with the three selected theoretical frameworks.

2.1 Justification for the Chosen Frameworks

The use of TOE framework in this research work enables a comprehensive, organization-oriented perspective on the adoption of technology, taking into consideration a firm's internal competencies alongside its external environment[13]. In addition, the DOI theory serves as an extra framework, shedding light on the diffusion of innovations based on the perceived features of the relevant technology [16]. Finally, in order to incorporate user-oriented perspective by investigating individual attitudes regarding the use of technology, the use of TAM, which has its origination in Theory of Reasoned Action (TRA) has also been made part of the research work[15]. Integrating all these theoretical frameworks allows for a comprehensive validation of both organizational and individual factors that affect the adoption of AI/ML.

2.2 The TOE Framework

The Technology–Organization–Environment (TOE) framework categorizes the influences on adoption into three domains:

- **Technological Framework:** Highlights technological infrastructure and competencies pre-requisite for the integration of AI/ML. For instance, Technical Capability reflects the organization's capacity to manage substantial data volume, uphold interoperability, and guarantee data integrity.
- **Organizational Framework:** With Managerial Capability and Managerial Support as the major constituting factor, the organizational context provides mechanism to check the internal readiness of the organization. The organizational aspect ascertains if AI/ML initiatives are congruently aligned with strategic objectives, adequately funded, and integrated within a culture of innovation.
- **Environmental Context:** Comprising of factors such as Vendor Partnership, Competitive Pressure, Government Involvement, and Market Uncertainty, the environmental context provides mechanism to gauge the external influences and prospects that impact decisions regarding adoption.

The TOE framework thus enables a systemic evaluation of internal preparedness and environmental dynamics critical to AI/ML adoption in telecom network operations.

2.3 The DOI Theory

The Diffusion of Innovation (DOI) theory brings to focus the aspects like how and why new technologies are adopted over time; based on five key perceived attributes: (1) relative advantage, (2) compatibility, (3) complexity, (4) trialability, and (5) observability [16]. In this study, three attributes are particularly emphasized and have been aligned with the constructs commonly used in empirical studies:

- **Relative Advantage:** The degree to which AI/ML is perceived to offer superior value over existing solutions.
- **Compatibility:** The extent to which AI/ML aligns with existing systems, processes, and organizational norms.
- **Complexity:** The perceived difficulty in understanding, implementing, and managing AI/ML technologies.

These constructs are pivotal in capturing how telecom stakeholders perceive the innovation itself and are essential for understanding adoption decisions at both strategic and operational levels.

2.4 The Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), derived from the Theory of Reasoned Action, focuses on user perceptions and behavioral intentions regarding technology use [15]. Two core constructs are considered:

- **Perceived Usefulness (PU):** The degree to which a user believes that AI/ML will enhance their job performance by improving operational efficiency, enabling real-time monitoring, and supporting predictive decision-making.
- **Perceived Ease of Use (PEOU):** The degree to which the use of AI/ML is perceived to be free of effort. In telecom environments, this includes the availability of intuitive tools, sufficient documentation, and training to support adoption in complex infrastructures.

While TAM typically captures end-user acceptance, its integration here adds value by recognizing that organizational AI/ML initiatives must ultimately be adopted by individual managers, engineers, and decision-makers responsible for implementation.

2.5 Examining Key Constructs

This section synthesizes key constructs identified through a comprehensive literature review and maps them onto the TOE, DOI, and TAM frameworks to assess their influence on AI/ML adoption in telecom network management. Prior research, such as in China[17] and in India[18], provides precedence for combining these models to examine constructs like Managerial Capability, Technical Capability, Compatibility, Relative Advantage, and others across organizational and technological domains. Managerial Capability (MC) is an important factor for AI/ML adoption, as leadership must take charge and bring capabilities for facilitating change, alignment of teams, and lay foundation for technical and non-technical aspects of implementation [19] [20][21]. Managerial Support (MS), at the same time, brings under consideration aspects such as strategic alignment and resource allocation for AI initiatives, encouraging innovation and balancing implementation risks [22] [23][24]. Technical Capabilities (TC) highlights the organization's ability for scalable AI deployment considering factors such as managing data, integrate systems, and secure infrastructure. The AI-CAM model incorporates capabilities across data, skills, technology, and governance dimensions essential for successful integration[25] [26]. Complexity (CX) underscores the difficulties associated with the integration of artificial intelligence into pre-existing systems and operational frameworks, encompassing governance and ethical limitations. Robust governance of artificial intelligence and streamlined decision-making frameworks are essential to alleviating these intricacies [26]. Compatibility (CP), in accordance with the DOI, emphasizes the necessity for artificial intelligence to harmonize with pre-existing systems and user anticipations to facilitate uninterrupted assimilation. Compatibility supports faster adoption and reduces costs [14] [27]. Relative Advantage (RA) constitutes a fundamental determinant within the framework of Diffusion of Innovations (DOI), representing anticipated enhancements in performance. Entities embracing Artificial Intelligence (AI) anticipate quantifiable advantages in terms of cost reduction, operational efficiency, and enhancement of customer service, thereby contributing to the establishment of a competitive advantage [28]. Collaborative Vendor Partnership enhances technical expertise, system integration, and confidence in artificial intelligence solutions. Telecommunications providers depend on strategic collaborations with vendors to successfully execute AI-driven transformations[17][29]. Competitive Pressure (CP) propel technological advancements in the telecommunications sector as organizations strive to align with industry standards. The integration of artificial intelligence emerges as essential to sustain competitiveness in a market characterized by swift technological evolution[30]. Government Involvement (GI) plays a pivotal role in AI adoption through funding, standard-setting, and policy regulation. Supportive governance encourages innovation while ensuring ethical AI usage [31] [32]. Market Uncertainty (MU) often hinders AI adoption due to unclear returns and evolving technology landscapes. Organizations may delay investments until tangible benefits become evident [33]. From TAM, Perceived Usefulness (PU) captures the belief that AI will improve task performance and efficiency, especially in domains like customer relationship management and real-time analytics [34][35]. Perceived Ease of Use (PEOU) reflects the simplicity and effort required to use AI systems. A user-friendly design and seamless integration into telecom networks reduce resistance to adoption [36][11](Castro et al., 2018).

This study integrates these 12 constructs within a unified conceptual model, as illustrated in Figure 2. Notably, constructs such as Compatibility and Complexity appear in both TOE and DOI, emphasizing their dual relevance across organizational and innovation diffusion perspectives.

TOE		DOI	TAM
Organisational Constructs	Managerial Capability	Relative Advantage	Percieved Usefulness
	Managerial Support		
Technological Constructs	Technical Capability	Complexity	Perceived Ease of Use
		Compatibility	
Environmental Constructs	Vendor Partnership		
	Competitive Pressure		
	Government Involvement		
	Market Uncertainty		

Fig. 2. Theoretical Framework with Constructs Used for Research

2.6 Conceptual Framework

The figure below shows the structural model depicting the way the 12 independent constructs viz. "Managerial Capability (MC), Managerial Support (MS), Technical Capability (TC), Complexity (CX), Compatibility (CP), Relative Advantage (RA), Vendor Partnership (VP), Competitive Pressure (CP), Government Involvement (GI), Market Uncertainty (MU), Perceived Usefulness (PU), and Perceived Ease of Use (PE)" are related to the dependent construct "Decision of AI/ML Adoption (DOA)" followed by the brief description of each of the construct.

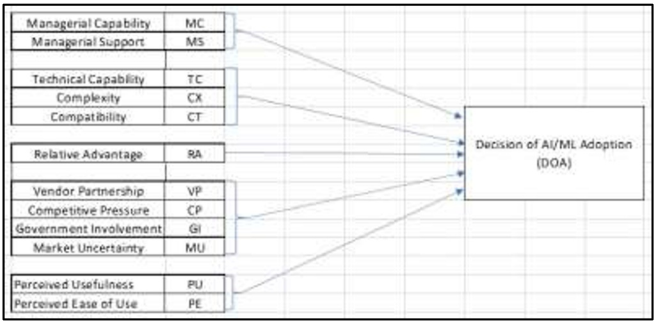

Fig. 3. Conceptual Framework Used for Research
Source: Adapted from [17]

A research instrument (attached as Annexure 1) encompassing all the above constructs was chosen that forms the basis of quantitative cross-sectional study carried out in this paper.

3 Research Model and Hypothesis

The proposed research model as in Figure 4 make use of TOE [37], DOI and TAM Framework to carry out the cross sectional correlation study. As discussed in the Theoretical Framework section, while the constructs under the TOE and DOI framework helps in Organization perspective of technological innovation adoption (AI/ML for Telecom Network Management in this study), the constructs under TAM accommodates views of Technological innovation adoption from the end user perspective.

The relevant constructs under the TOE, DOI and TAM theoretical framework have already been illustrated in the conceptual framework section. Altogether the study considers 12 independent constructs/latent variables (RA, TC, CX, CP, MS, MC, VP, CP, GI, MU, PU, PE) and one dependent variable (DOA).

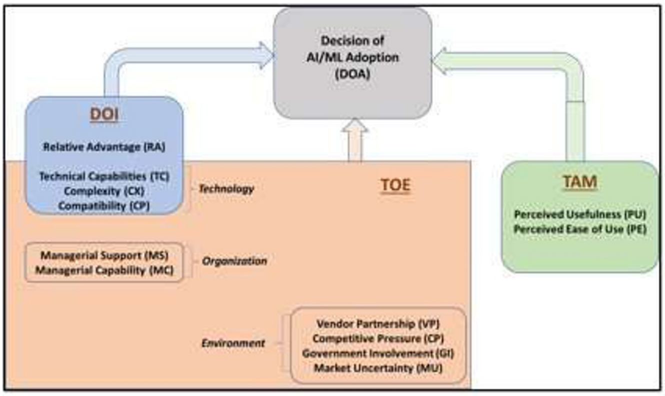

Fig. 4. Proposed Research Model for AI/ML Adoption for Telecom Network Management. Source: Adapted from [18]

Based on the conducted literature review and the theoretical and conceptual framework under examination, the following hypotheses are put forward. Each hypothesis in this study is explicitly grounded in established theoretical frameworks:

- **H1 (Relative Advantage):** Rooted in DOI theory, innovations perceived to offer substantial operational advantages are typically adopted more quickly. Thus, Relative Advantage is hypothesized to positively influence AI/ML adoption.
- **H2 (Technical Capability):** Grounded in TOE theory, Technical Capability encompasses the necessary skills, resources, and infrastructure required to implement AI/ML effectively, thus positively influencing adoption.
- **H3 (Complexity):** Derived from DOI and TOE frameworks, Complexity indicates the perceived difficulty of understanding and implementing AI/ML technology. Higher perceived complexity is hypothesized to negatively affect adoption.
- **H4 (Compatibility):** Also derived from DOI and TOE frameworks, Compatibility indicates the degree of fit with existing values and practices. Higher compatibility significantly facilitates technological integration and adoption.
- **H5 (Managerial Support):** Within the TOE framework, continuous managerial support is essential for providing resources and overcoming resistance, positively influencing adoption.
- **H6 (Managerial Capability):** Within the TOE framework, managerial capability is crucial for technology adoption, as proficient leadership significantly influences effective integration and implementation.
- **H7 (Vendor Partnership):** From the TOE framework, strong vendor partnerships can provide necessary technical support and resources, thus positively influencing AI/ML adoption.
- **H8 (Competitive Pressure):** Rooted in TOE theory, competitive pressure motivates telecom firms to adopt innovative technologies like AI/ML to maintain competitive advantage, positively influencing adoption.
- **H9 (Government Involvement):** From the TOE framework, supportive government policies and regulations significantly encourage technological innovation and adoption, positively influencing adoption.
- **H10 (Market Uncertainty):** Derived from TOE, market uncertainty represents perceived risks and unpredictable market conditions. High uncertainty is hypothesized to negatively influence adoption.
- **H11 (Perceived Usefulness):** Grounded in TAM, perceived usefulness, or the belief that AI/ML will enhance job performance, positively influences adoption intentions.
- **H12 (Perceived Ease of Use):** Within TAM, perceived ease of use relates to how effortless AI/ML systems are perceived to operate, thus positively influencing adoption.

4 Research Methodology

This study employs a quantitative cross-sectional approach to examine the statistical relationship between 12 independent constructs/latent variables and the dependent construct/latent variable "Decision of AI/ML Adoption (DOA)". For quantitative research investigating real-world scenarios, the cross-sectional survey design is deemed most suitable, utilizing participants who meet the necessary criteria for survey involvement. The statistical analysis and hypothesis validation are conducted using the perspectives and feedback gathered from participants through the designed survey.

Besides the Independent and the Dependent Variable, there are 3 control variables that could have been taken into account (Firm Size, Annual Sales and Enterprise Affiliations) but have not been considered here because of the limited nature of the study involving only very big players in the Telecom Domain and with not much of difference amongst them on the 3 mentioned factors.

4.1 About Data and Data Collection Strategy

For the quantitative cross-sectional study, researchers gathered information using a questionnaire as the primary research tool. The survey instrument is derived from a comparable investigation into the implementation of AI technologies among Chinese telecommunications companies.[17]. Additionally, a research study focused on the adoption of Artificial Intelligence in business operations within India's Small and Medium Enterprise Sector[18]. The questionnaire contains items which are adapted from similar earlier studies performed on innovation, deployment, diffusion and adoption of IT/IS innovation.

The research instrument capture responses from the participants to gauge their understanding and views on the 13 latent variables; 12 being the Independent variables viz "Managerial Capability (MC), Managerial Support (MS), Technical Capability (TC), Complexity (CX), Compatibility (CP), Relative Advantage (RA), Vendor Partnership (VP), Competitive Pressure (CP), Government Involvement (GI), Market Uncertainty (MU), Perceived Usefulness (PU), Perceived Ease of Use (PE)"; and one being the Dependent variable viz "Decision of AI/ML Adoption (DOA)".

The research instrument contains 3 to 5 questions linked to each Latent variable/Construct. Participants were asked to respond using a "7-point Likert Scale", with options ranging from 1 ("Strongly Disagree") to 7 ("Strongly Agree"). Annexure 1 includes the constructs and their corresponding questions (observed indicators) used in the survey.

AI/ML being still in the nascent stage of evolution and particularly the use of the AI/ML platform for Telecom Network Management is rare amongst the Telecom Operators and Vendors in India, the study required to collect the input against the research instrument from the Leaders, Managers and Engineers associated with the development and testing of AI related tolls and processes. Accordingly, the participants were chosen from the three major Telecom Operators (Reliance Jio, Vodafone Idea and Tata Communication Limited) and two major Telecom Vendors (Cisco, Nokia).

The request for response to the survey questionnaire was sent to 240+ prospective participants and the response was received from 198 participants. The questionnaire was made available to the participants in the form of Google Form and the responses were collated for the required statistical analysis.

4.2 Quantitative Analysis

Statistical analysis was conducted using responses from 198 survey participants to evaluate the proposed model's fitness and test the hypothesis.

The Measurement Model is used to perform the "Confirmatory Factor Analysis (CFA)" using "Construct Reliability (Cronbach's Alpha)" using SPSS tool[38]; "Composite Reliability and Convergent Validity (Average Variance Extracted - AVE)" using SPSS AMOS Tool [38]. The model (comprising of construct and research indicator) is further modified to get a better Goodness of Model Fit basis the results of CFA. The revised

Measurement Model is used to do the Structural Modelling for testing the proposed Hypothesis.

4.3 Sample Demographics

The Table 1 below captures the sample or respondent demographics. The respondents were selected basis their involvement in the AI/ML related projects/testing/development for the Telecom Network Management.

Table 1. Sample Demographics

Participants Designation	Count of Participants	Participants Age Group	Count of Participants
Director/ Vice President	23	31-40	129
General Manager/ Dy General Manager	74	41-50	58
Senior Manager/ Engineer	101	51-60	11
Total	**198**	**Total**	**198**

5 Data Analysis and Results

This section covers the Quantitative Analysis, Measurement Model and Structural Model data analysis

5.1 Quantitative Analysis

Statistical analysis was conducted using responses from 198 survey participants to evaluate the proposed model's fitness and test the hypothesis.

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5.2 Population Descriptive Statistics

Table 2 is used to validate the sample data both from" PermissibleValues" and "Missing Values" perspective. The standard deviation being greater than 0.25 for each of the research indicators shows the conscious responses from the particpants.

Table 2. Descriptive statistics of the sample population

Construct	Indicator	Mean	Std. Deviation	Sample Count (N)
Market Uncertainty (MU)	MU1	6.19	1.104	198
	MU2	6.4	0.676	
	MU3	6.6	0.605	
	MU4	6.6	0.579	
Competitive Pressure (CP)	CP1	6.31	0.891	
	CP2	5.81	1.145	
	CP3	6.34	0.978	
	CP4	6.54	0.682	
Vendor Partnership	VP1	5.34	1.225	

(VP)	VP2	5.73	1.123	
	VP3	5.12	1.2	
	VP4	5.73	0.898	
	VP5	5.42	1.281	
Managerial Capability (MC)	MC1	5.48	1.33	
	MC2	6.07	1.02	
	MC3	6.57	0.743	
	MC4	6.36	0.916	
Managerial Support (MS)	MS1	5.79	1.297	
	MS2	5.54	1.235	
	MS3	5.85	1.258	
	MS4	5.97	1.154	
	MS5	5.54	1.283	
Technical Capability (TC)	TC1	5.72	1.178	
	TC2	5.51	1.272	
	TC3	5.88	1.023	
	TC4	6.27	0.931	
Compatibility (CT)	CT1	5.7	1.168	
	CT2	5.55	1.158	
	CT3	5.37	1.112	
	CT4	5.4	1.219	
	CT5	5.82	0.984	
Relative Advantage (RA)	RA1	6.33	0.746	
	RA2	6.24	0.854	
	RA3	6.51	0.704	
	RA4	6.48	0.725	
	RA5	6.3	0.798	
Complexity (CX)	CX1	5.07	1.47	
	CX2	5.1	1.281	
	CX3	4.45	1.69	
	CX4	5.04	1.58	
Government Involvement (GI)	GI1	5.63	1.112	
	GI2	4.18	1.325	
	GI3	4.48	1.307	
	GI4	5.9	1.22	
	GI5	5.75	1.491	
Perceived Usefulness (PU)	PU1	6.36	0.773	
	PU2	6.31	0.82	
	PU3	6.48	0.612	
Perceived Ease of Use (PE)	PE1	5.01	1.43	
	PE2	5.01	1.571	
	PE3	6.25	0.927	
Decision of AI/ML Adoption (DOA)	DOA1	4.96	1.319	
	DOA2	4.85	1.384	
	DOA3	4.73	1.238	
	DOA4	5.57	1.246	
	DOA5	6.24	0.818	

Following observations are drawn observing Mean and Standard Deviation of the construct.

- The construct Perceived Usefulness (PU) has the highest mean (6.5), indicating participants strongly perceive AI/ML technologies as valuable for increasing productivity and revenue. Constructs like “Compatibility (CT)” and Decision of AI Adoption (DOA) also score high (6.3), suggesting readiness for adoption and alignment with existing systems.

Vendor Partnership (VP) has a relatively lower mean (5.6), reflecting moderate perceptions of vendor support.

- Vendor Partnership (VP) and Perceived Ease of Use (PE) exhibit higher variability (0.9), indicating diverse opinions among participants regarding vendor reliability and the ease of adopting AI/ML. Constructs like Relative Advantage (RA) and Compatibility (CT) have lower standard deviations (0.3 and 0.4, respectively), reflecting consensus among participants on the benefits and alignment of AI/ML technologies.

The Figure 5 below presents the model created in SPSS AMOS for Structural Equation Modelling Analysis

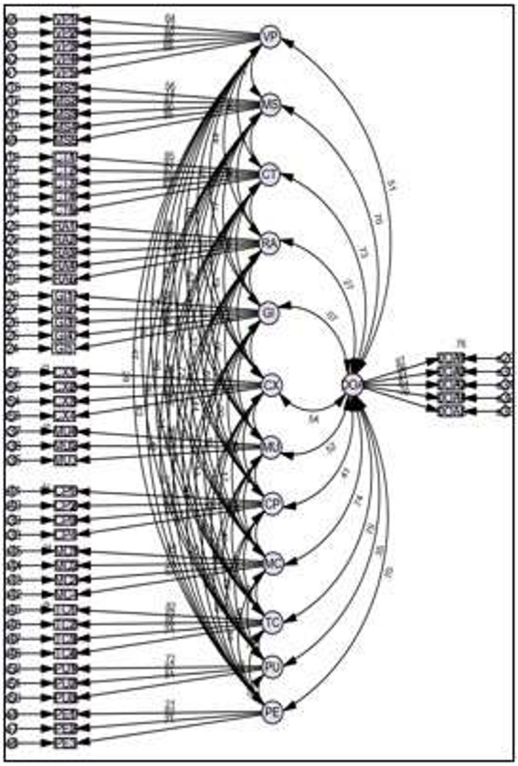

Fig. 5. Initial Model used for Confirmatory Factor Analysis

5.3 Reliability

The internal consistency of a construct within a research investigation is evaluated through its reliability. The dependability of a construct is validated when its Alpha (α) coefficient surpasses the threshold of 0.7[39]. The construct reliability was evaluated employing Cronbach's Alpha through the SPSS software. The findings related to reliability are encapsulated in Table 3 presented below.

Table 3. Cronbach's Alpha for Constructs

Construct	Cronbach Alpha(>0.7)	Research Indicator	Corrected Item - Total Correlation(>0.3)	Cronbach's Alpha (if Item Deleted)
MU	0.544	MU1	0.396	0.460
		MU2	0.438	0.394

		MU3	0.184	0.572
		MU4	0.404	0.439
CP	0.577	CP1	0.347	0.515
		CP2	0.391	0.487
		CP3	0.479	0.400
		CP4	0.242	0.584
VP	0.811	VP1	0.570	0.784
		VP2	0.677	0.751
		VP3	0.661	0.754
		VP4	0.532	0.795
		VP5	0.578	0.783
MC	0.662	MC1	0.571	0.505
		MC2	0.530	0.535
		MC3	0.245	0.700
		MC4	0.475	0.579
MS	0.862	MS1	0.492	0.881
		MS2	0.700	0.828
		MS3	0.783	0.806
		MS4	0.724	0.824
		MS5	0.726	0.821
TC	0.842	TC1	0.686	0.797
		TC2	0.652	0.819
		TC3	0.797	0.752
		TC4	0.612	0.830
CT	0.923	CT1	0.750	0.916
		CT2	0.883	0.889
		CT3	0.797	0.907
		CT4	0.818	0.903
		CT5	0.769	0.913
RA	0.894	RA1	0.739	0.871
		RA2	0.780	0.862
		RA3	0.768	0.866
		RA4	0.783	0.862
		RA5	0.647	0.892
CX	0.623	CX1	0.213	0.680
		CX2	0.522	0.484
		CX3	0.452	0.516
		CX4	0.463	0.507
GI	0.721	GI1	0.328	0.726
		GI2	0.513	0.661
		GI3	0.640	0.607
		GI4	0.396	0.705
		GI5	0.534	0.652
PU	0.817	PU1	0.624	0.798
		PU2	0.715	0.707
		PU3	0.707	0.737
PE	0.413	PE1	0.236	0.343
		PE2	0.339	0.113
		PE3	0.195	0.415
DOA	0.819	DOA1	0.656	0.770
		DOA2	0.756	0.735
		DOA3	0.726	0.748
		DOA4	0.569	0.796
		DOA5	0.361	0.842

In the evaluation of the constructs' reliability, it became clear that specific constructs showcased Cronbach’s Alpha coefficients that were lower than the generally accepted benchmark of 0.7, which includes Competitive Pressure (CP), Complexity (CX), Managerial Capability (MC), and Perceived Ease of Use (PE). This implies possible issues pertaining to the internal coherence of these constructs. Furthermore, certain research indicators encompassed within these constructs exhibited Corrected Item-Total Correlations that fell below 0.3, signifying diminished contributions of these items to their corresponding constructs. This raises questions about their ability to effectively capture the underlying dimension they are intended to measure.

Still, the choices about incorporating or leaving out these constructs and indicators are not entirely dependent on Cronbach’s Alpha. A more extensive methodology was utilized by integrating assessments of “Composite Reliability (CR)” and “Convergent Validity,” including “Average Variance Extracted (AVE).” “Composite Reliability” assesses the cumulative reliability of the construct by considering the variance contributed by all indicators, thereby offering a more rigorous measure of internal consistency. Similarly, Convergent Validity analyzes how various indicators of a construct align to measure the same underlying dimension, with Average Variance Extracted (AVE) values higher than 0.5 reflecting suitable convergence.

This multidimensional assessment ensures that constructs are evaluated holistically, balancing internal consistency with their theoretical relevance and measurement validity. Constructs or indicators demonstrating a low Cronbach’s Alpha yet satisfying the criteria for Composite Reliability and Convergent Validity may still be preserved, provided they are consistent with theoretical postulations and significantly enhance the model[40]. Conversely, indicators with low reliability and validity may be revised, refined, or excluded based on their performance in pilot tests or theoretical considerations. This approach reflects a rigorous methodology that prioritizes both statistical robustness and conceptual clarity.

Factor Loading

The Table 4 below captures the Factor loading for each of the indicator belonging to a construct as worked out using SPSS AMOS tool.

Table 4. Factor Loading between Constructs and the Research Indicators

Standardized Regression Weights			
Research Indicator		Construct	Estimate
VP5	<---	VP	0.692
VP4	<---	VP	0.656
VP3	<---	VP	0.802
VP2	<---	VP	0.731
VP1	<---	VP	0.637
PE3	<---	PE	0.706
PE2	<---	PE	0.818
PE1	<---	PE	0.215
MS5	<---	MS	0.848
MS4	<---	MS	0.899
MS3	<---	MS	0.871
MS2	<---	MS	0.744
MS1	<---	MS	0.556
CT5	<---	CT	0.831
CT4	<---	CT	0.875

CT3	<---	CT	0.865
CT2	<---	CT	0.935
CT1	<---	CT	0.847
RA5	<---	RA	0.713
RA4	<---	RA	0.818
RA3	<---	RA	0.85
RA2	<---	RA	0.843
RA1	<---	RA	0.808
GI5	<---	GI	0.458
GI4	<---	GI	0.269
GI3	<---	GI	0.954
GI2	<---	GI	0.727
GI1	<---	GI	0.376
DOA1	<---	DOA	0.873
DOA2	<---	DOA	0.961
DOA3	<---	DOA	0.911
DOA4	<---	DOA	0.645
DOA5	<---	DOA	0.391
MU3	<---	MU	0.218
MU2	<---	MU	0.643
MU1	<---	MU	0.737
CP4	<---	CP	0.189
CP3	<---	CP	0.55
CP2	<---	CP	0.778
CP1	<---	CP	0.506
MC4	<---	MC	0.529
MC3	<---	MC	0.212
MC2	<---	MC	0.771
MC1	<---	MC	0.842
TC4	<---	TC	0.741
TC3	<---	TC	0.85
TC2	<---	TC	0.817
TC1	<---	TC	0.822
PU3	<---	PU	0.835
PU2	<---	PU	0.871
PU1	<---	PU	0.72
CX4	<---	CX	0.886
CX3	<---	CX	0.642
CX2	<---	CX	0.594
CX1	<---	CX	0.26

The factor loadings indicate the strength of the relationship between constructs and their respective research indicators. Most constructs exhibit strong loadings, with values exceeding the acceptable threshold of 0.7, demonstrating good indicator-construct relationships. Constructs such as "Vendor Partnership (VP), Compatibility (CT), Relative Advantage (RA), and Technical Capability (TC)" consistently show strong loadings across all indicators, requiring no further modifications. However, certain indicators, including PE1 (0.215), GI4 (0.269), MU3 (0.218), CP4 (0.189), MC3 (0.212), and CX1 (0.26), have significantly low loadings, falling below the threshold of 0.3. These items do not effectively represent their respective constructs and warrant revision or removal. Constructs such as "Managerial Support (MS), Decision of AI/ML Adoption (DOA), and Government Involvement (GI)" exhibit mixed performance, with a few weaker indicators like DOA5 (0.391) and GI1 (0.376) that could be revised for better alignment.

5.4 Composite Reliability and Convergent Validity

Assessing composite reliability facilitates understanding of how effectively a variable or a collection of variables consistently fulfills its measurement objectives [41]. Convergent validity assesses how well different measures of a theoretical concept, which are expected to be related, actually show a correlation[41].

Convergent validity is evaluated using the "Average Variance Extracted (AVE)" metric, which measures how much of the variance in the indicators is due to the latent variable they represent. Empirical support for convergent validity is established when the AVE exceeds 0.50, indicating that a substantial portion of the indicator variance is explained by the unobserved construct [42].

The table 5 below captures the analysis of each of the construct using Composite Reliability and Convergent Validity.

Table 5. Composite Reliability and Convergent Validity of Constructs

Construct	Composite Reliability (>0.7)	Convergent Validity (>0.5)	Remarks
MU	0.561	0.334	Requires reconsideration on Construct and associated Indicators
CP	0.593	0.299	Requires reconsideration on Construct and associated Indicators
VP	0.831	0.49	OK
MC	0.7	0.407	Requires reconsideration on Research Indicators
MS	0.892	0.629	OK
TC	0.882	0.653	OK
CT	0.94	0.759	OK
RA	0.9	0.652	OK
CX	0.704	0.404	Requires reconsideration on Research Indicators
GI	0.711	0.372	Requires reconsideration on Research Indicators
PU	0.851	0.658	OK
PE	0.628	0.4	Requires reconsideration on Research Indicators
DOA	0.881	0.616	OK

The analysis of “Composite Reliability (CR) and Convergent Validity (AVE)” reveals mixed results across constructs. High-performing constructs, including “Managerial Support (MS), Technical Capability (TC), Compatibility (CT), Relative Advantage (RA), and Decision of AI/ML Adoption (DOA)” demonstrate strong reliability (CR > 0.7) and convergent validity (AVE > 0.5), indicating robust measurement quality. Conversely, constructs such as Market Uncertainty (MU) and Competitive Pressure (CP) exhibit poor reliability (CR < 0.7) and validity (AVE < 0.5), requiring significant reconsideration of their indicators. Constructs like Managerial Capability (MC), Complexity (CX), and Government Involvement (GI) have acceptable reliability but weak convergent validity, with AVE values below the threshold of 0.5, highlighting the need for indicator refinement. The construct Perceived Ease of Use (PE) demonstrates both low reliability and validity, necessitating a comprehensive review or redefinition. It is to note that Research Indicator MU4 has to be dropped during the Initial SEM exercise as it was leading to high errors and non-convergence.

5.5 Model Fit

The assessment of model fit determines whether the estimated covariance matrix accurately represents the observed covariance matrix derived from the data. Tables 6 present the initial model fit results

Table 6. Initial Model Fitness

Statistics	Initial	Recommended Values
Chi-square (Chi)	2717.929	
Degrees of freedom (df)	1353	
Chi/df	2.0088	<3
RMSEA	0.124	<0.08
CFI	0.522	>0.9

The research indicators not found adequate for consideration after the CFA were removed from the respective constructs and the revised structural equation modelling was done. The Final Model Fit Summary is presented in Table 7 that shows only incremental improvement from the Initial Model Fit Summary and that may be attributed to the insufficient sample size (limited to 198 samples) taken for this study.

Table 7. Final Model Fitness

Statistics	Initial	Recommended Values
Chi-square (Chi)	1933.578	
Degrees of freedom (df)	1003	
Chi/df	1.927794616	<3
RMSEA	0.119	<0.08
CFI	0.613	>0.9

The research indicators not found adequate for consideration after the CFA were removed from the respective constructs and the revised structural equation modelling was done. The Final Model Fit Summary shows only incremental improvement from the Initial Model Fit Summary and that may be attributed to the insufficient sample size (limited to 198 samples) taken for this study.

The figure 6 captures the revised Structural Equation Modelling basis the consideration on the Construct Reliability, Composite Reliability and Convergent Validity outcomes for different Constructs. The revised SEM model is used to capture the Final Model Fit Summary as well as carrying out the Structural Model Analysis.

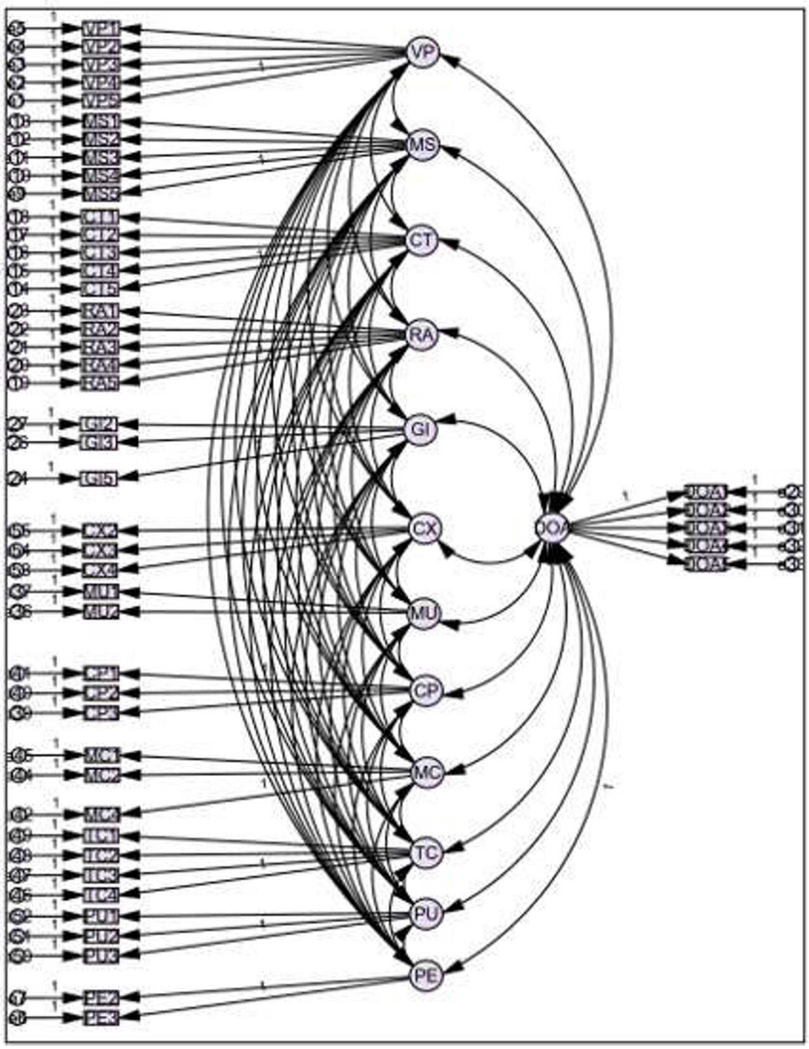

Fig. 6. Revised SEM Model after Confirmatory Factor Analysis

6 Structural Model and Results

The structural model's final version is depicted in Figure 7, while Table 8 presents the outcomes of the structural model analysis.

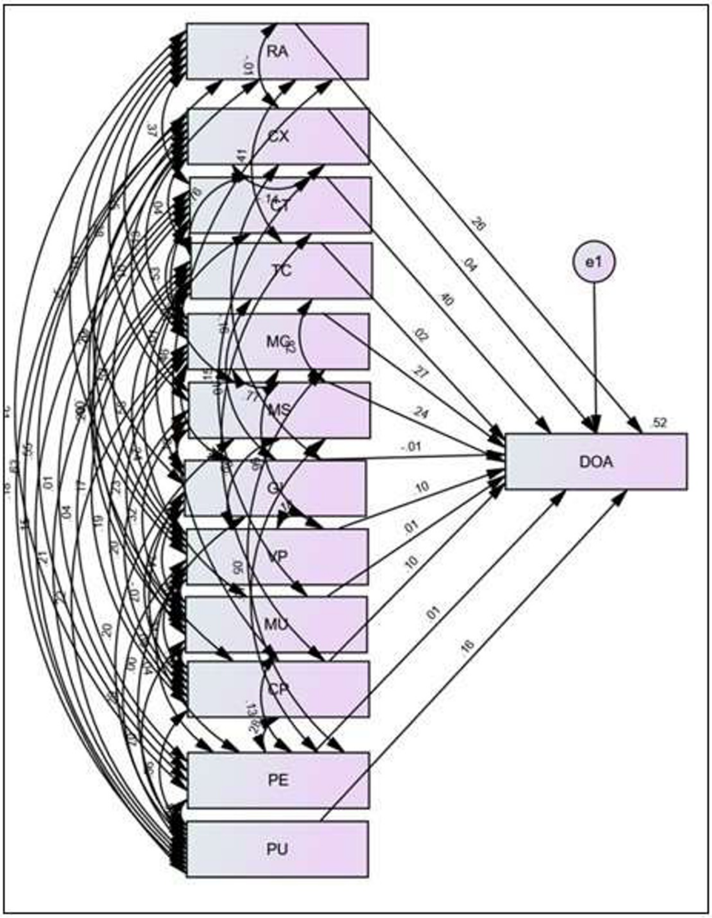

Fig. 7. Final Structural Model

Table 8. Structural Model Analysis

Independent Variable	Dependent Variable	R^2	Standard Path Coefficient	p Value	Significance Level	Hypothesis	Remarks
RA	DOA	0.52	0.255	0.041	***	Hypothesis 1	Supported
TC			0.022	0.908		Hypothesis 2	Not Supported
CX			0.041	0.712		Hypothesis 3	
CT			0.4	0.004	***	Hypothesis 4	Supported
MS			0.244	0.207		Hypothesis 5	Not Supported
MC			0.268	0.056	*	Hypothesis 6	Supported
VP			0.099	0.45		Hypothesis 7	Not Supported
CP			0.101	0.354		Hypothesis 8	
GI			-0.008	0.934		Hypothesis 9	
MU			0.006	0.951		Hypothesis 10	
PU			0.157	0.237		Hypothesis 11	
PE			0.011	0.926		Hypothesis 12	

The Table 8 above captures the R^2, Path Coefficient values between independent constructs and the Dependent Construct (DOA), p Values and the remarks capturing the validity of the Hypothesis basis the significance level measured through p Value.

The R^2 value is interpreted as follows: 0.670 indicates a strong relationship, 0.333 suggests a moderate association, and 0.190 represents a weak connection [43]. In this study, the research model yielded an R^2 value of 0.52. This suggests that the model has a moderate-to-strong explanatory power, suggesting that the constructs included provide meaningful insights into the adoption decision. Among the tested hypotheses, three were supported: Relative Advantage (RA), Compatibility (CT), and Managerial Capability (MC). These constructs were found to have significant positive influences on DOA, with varying levels of significance.

Compatibility (CT) emerged as the most influential construct (Standard Path Coefficient = 0.4, $p = 0.004$), highlighting that the alignment of AI/ML technologies with existing systems and processes plays a critical role in adoption decisions. This finding reinforces the significant requirement of ensuring that artificial intelligence and machine learning solutions are cohesively integrated with established workflows, systems, and institutional strategies. Relative Advantage (RA) exhibited a notable positive correlation (Standard Path Coefficient = 0.255, $p = 0.041$), thereby substantiating that the perceived advantages associated with the adoption of AI/ML, such as enhanced productivity and operational efficiency, exert a favorable influence on decision-making processes. With Standard Path Coefficient as 0.268 and p as 0.056 for the Managerial Capability highlights the aspects of strategic planning and execution by Managers as important aspect of AI/ML adoption.

Conversely, a number of constructs, such as Technical Capability (TC), Complexity (CX), Vendor Partnership (VP), and Perceived Usefulness (PU), were determined to exert no statistically significant effect on DOA, as indicated by their elevated p-values (all exceeding 0.1). This suggests that these factors may not directly drive adoption decisions in the context of this study. Technical Capability (TC), despite being an essential prerequisite for AI/ML implementation, might be perceived as a baseline requirement rather than a differentiating factor influencing adoption. Similarly, Perceived Usefulness (PU) and Perceived Ease of Use (PE), which are central to the Technology Acceptance Model (TAM), did not exhibit significant relationships, potentially due to practical barriers such as cost, organizational readiness, or cultural resistance overshadowing their perceived benefits.

External factors, including Government Involvement (GI) and Market Uncertainty (MU), also showed negligible effects, with path coefficients close to zero and high p-values (GI: -0.008, $p = 0.934$; MU: 0.006, $p = 0.951$). These findings suggest that external pressures or uncertainties may not be significant determinants in the current context, possibly because organizations focus more on internal readiness and strategic alignment when making adoption decisions.

Overall, the results highlight the critical importance of organizational factors like compatibility and managerial capability while indicating potential gaps in the measurement or influence of non-significant constructs. The observed non-significant constructs would get a better validation when the same study is performed with an adequately large sample size.

7 Contribution to Body of Knowledge and Practitioners

This study advances theory by integrating DOI, TOE and TAM into a single, empirically validated model tailored to telecom network management. The findings confirm Compatibility (CP), Relative Advantage (RA) and Managerial Capability (MC) as the strongest predictors of AI/ML adoption, underscoring the primacy of organizational readiness and executive competence. Equally important, the non-significance of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) challenges the universal applicability of TAM in complex, infrastructure-intensive settings, signaling boundary conditions that future research must accommodate. Methodologically, the use of SEM-AMOS, composite reliability and AVE establishes a replicable benchmark for multi-framework adoption studies.

For practitioners, the results translate into three actionable imperatives:

- Align before you deploy – ensure new AI/ML applications interoperate smoothly with legacy OSS/BSS and operational processes to minimize disruption and resistance;
- Invest in managerial capability – cultivate leaders who can steer cross-functional AI initiatives, manage change and articulate a compelling AI vision;
- Quantify and communicate relative advantage – build a clear business case that links AI investments to tangible KPIs in cost, uptime and customer experience. Addressing complexity through phased pilots, robust data governance and vendor partnerships will further smooth the adoption path.

Policymakers have the capacity to improve sector preparedness by revising artificial intelligence standards, providing specific financial assistance for interoperability assessments, and facilitating training initiatives that cultivate both managerial and technical skill development pathways. Collectively, these insights equip telecom stakeholders with a clear roadmap: prioritize internal compatibility and leadership capacity, temper TAM-based assumptions, and focus on measurable value creation to realize AI/ML's transformative potential.

8 Study Limitation and Suggestion for Further Research

This investigation, although yielding important insights into the fusion of AI and machine learning within telecommunications network governance, possesses specific limitations that require acknowledgment. First and foremost, the sample is predominantly made up of respondents associated with significant telecom operators and vendors. To increase generalizability, future investigations ought to take a more inclusive stance by integrating small, medium, and large organizations across the telecom ecosystem. This broader representation would enable a more nuanced understanding of the diverse perceptions, challenges, and enablers of AI/ML adoption. Second, although the study evaluates twelve critical constructs derived from TOE, DOI, and TAM frameworks, other potentially relevant constructs within these theoretical models remain unexplored. Future studies may consider extending the model to include additional factors, such as organizational culture, regulatory compliance, or perceived risk, to develop a more holistic view of the adoption landscape. Third, while the current research employs a cross-sectional quantitative design and uses Structural Equation Modelling (SEM) to analyze relationships among latent variables, the sample size of 198, though acceptable, falls short of the recommended minimum of 500 for complex models involving more than seven latent variables [39]. A larger and more geographically or functionally diverse sample would increase statistical power and improve model stability. Finally, this study offers a conceptual model that has been empirically tested. However, its external validity can be further strengthened through longitudinal studies or mixed-method approaches that incorporate qualitative insights. Such approaches would enable researchers to examine the dynamic nature of technology adoption over time and capture organizational learning and behavioral changes.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

9 Annexures

Annexure I: Part A of the Questionnaire

Name of the Respondent	
Organization	
Designation	
Gender	Male ☐ Female ☐
Age range (In Years)	21-30; 31-40; 41-50; 51-60; 61-70
Email ID	

Annexure I: Part B of the Questionnaire

		1 - Strongly Disagree | 2 - Disagree | 3 - Somewhat Disagree | 4 - Neither Agree Nor Disagree | 5 - Somewhat Agree | 6 - Agree | 7 - Strongly Agree							
		Questionnaire	1	2	3	4	5	6	7
Government Involvement	GI-1	"The specification and stability of government policies are beneficial for business operation"							
	GI-2	"The government provides financial aid"							
	GI-3	"The government supplies related information"							
	GI-4	"We should maintain good relationship with local government"							
	GI-5	"The government support and help are very important for us to innovate"							
Market Uncertainty	MU-1	"There is a trend in our principal industry to utilize more AI technologies for business development and applications"							
	MU-2	"AI has broad application prospects in our principal industry"							
	MU-3	"Only innovative technologies can help our company to provide perfect products and services to meet the growing personalized needs of consumers"							
	MU-4	"AI can help our company to gain competitiveness"							
Competitive Pressure	CP-1	"The rate of innovation of new operating processes and new products or services in our principal industry has increased dramatically"							
	CP-2	"An industry moves to utilize the AI technologies for innovation would put pressure on our company to do the same"							
	CP-3	"Tough price competition in our industry"							
	CP-4	"Tough competition on product/service quality"							
Vendor Partnership	VP-1	"We have had no difficulty in obtaining assistance or reliable services from our vendors/partners."							
	VP-2	"Our vendors/partners are trustworthy."							
	VP-3	"Vendor makes decisions beneficial to my organization."							
	VP-4	"We have very close relationships with vendors/partners."							
	VP-5	"Our vendors/partners are knowledgeable for AI technologies"							
Managerial Capability	MC-1	"We have clear goals and objectives to adopt AI technologies innovation"							
	MC-2	"We have great project management team."							
	MC-3	"The inter-department cooperation is very important to adopt AI technologies innovation"							
	MC-4	"Formal education and training programs can be developed to include all classes of users ranging from managers to shop floor controllers"							
Managerial support	MS-1	"The managers explicitly demonstrate to support the adoption of AI"							
	MS-2	"Managers are willing to take risks involved in the adoption of AI"							
	MS-3	"Our managers have the ability to exploit new technologies before our competitors."							
	MS-4	"Our managers have the ability to leverage IT new technologies as a strategic core competence"							
	MS-5	"Our managers have a strong understanding of how AI technology can be used to increase business performance"							
Technical capability	TC-1	"We have standardized process for IT innovation."							
	TC-2	"We have the ability to quickly integrate new AI technologies into our existing infrastructure."							
	TC-3	"Our IT strategies support our business strategies."							
	TC-4	"We have suitable hardware/software to protect the security and privacy of our systems and networks."							
Compatibility	CT-1	"AI application is compatible with our current communication/network environment."							
	CT-2	"AI application is compatible with our current software environment."							
	CT-3	"AI application is compatible with our current hardware environment."							
	CT-4	"AI application is compatible with our infrastructure."							
	CT-5	"AI application is compatible with computerized data resources."							
Relative advantage	RA-1	"AI application can increase revenues and profitability."							
	RA-2	"AI application can get higher employee productivity."							
	RA-3	"AI application can improve customer service."							
	RA-4	"AI application can better utilize IT resources."							
	RA-5	"AI application can promote flexibility and integration."							
Complexity	CX-1	"Adopting AI innovation lacks application maturity."							
	CX-2	"There has been a high cost for AI application and migration."							
	CX-3	"Adopting AI innovation is time consuming."							
	CX-4	"Inappropriate staffing and personnel shortfalls are a big issue for adopting AI innovation."							
Perceived Usefulness	PU-1	"Artificial intelligence can increase revenue and profitability."							
	PU-2	"Artificial intelligence can increase employee productivity."							
	PU-3	"Artificial intelligence can improve customer service."							
Perceived Ease of Use	PE-1	"Adopting Artificial Intelligence innovation lacks application maturity."							
	PE-2	"Inappropriate staffing and personnel shortfalls are big challenges for Artificial Intelligence adoption."							
	PE-3	"Artificial intelligence can better utilize IT resources and applications."							
Decision of AI Adoption	DOA-1	"A timely AI technical implementation and application migration plan has been developed".							
	DOA-2	"The plan has already been endorsed by managers."							
	DOA-3	"A financial budget and a migration schedule have been approved."							
	DOA-4	"Our customers highly accept new products and services using AI innovations."							
	DOA-5	"We get improvement in the competitive position after adopting AI innovation."							

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