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Artificial Intelligence Adoption and Governance in Telecommunications: A Literature Review of Drivers, Ethical Risks, and Governance Models in Emerging Markets

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Abstract
Telecommunications operators were among the earliest adopters of artificial intelligence (AI) in network operations, and the sector now offers one of the richer empirical literatures on what drives AI adoption and how its governance is beginning to be formalised. This review synthesises twenty peer-reviewed studies to examine four questions: what factors drive AI adoption in telecommunications firms, particularly in emerging markets; where AI is applied within network operations, including the specific and commercially consequential case of customer churn prediction; what risks accompany AI's expansion into 5G network management specifically; and what governance and ethical risk frameworks the literature proposes for managing AI's expansion into safety, privacy, and competition-sensitive functions. Using the Technology–Organisation–Environment (TOE) framework that recurs across studies from China, Indonesia, Sri Lanka, and India, the review finds that managerial support and organisational readiness are consistently stronger predictors of adoption than external market pressure. AI is most mature in predictive maintenance, churn prediction, and customer-facing analytics, and least mature in autonomous network management, where governance frameworks are still emerging, notably an ambidextrous COBIT-based model tested in an Indonesian operator, a set of 5G-specific risk and governance frameworks, and a series of ethical leadership frameworks proposed for AI-enabled service industries generally. The review closes by considering what these findings imply for AI governance in Somalia's telecommunications sector, a sector with unusually mature mobile money regulation but, on current evidence, no documented AI-specific governance framework of its own.

Keywords: Artificial intelligence, Telecommunications, Technology adoption, Churn prediction, AI governance, Ethical leadership, Emerging markets, Somalia

1. Introduction

Telecommunications operators were early and, in several markets, enthusiastic adopters of artificial intelligence (AI), using machine learning models for network optimisation, predictive maintenance, and customer analytics well before AI entered mainstream public sector or financial services discourse (Balmer et al., 2020). The scale of the ambition has grown accordingly: Ismail et al. (2026) project that large-scale AI adoption in Indonesian telecommunications alone could contribute approximately 285.4 trillion Indonesian rupiah to national GDP by 2035, positioning AI-enabled telecommunications as a strategic pillar of that country's digital economy transformation, and comparable ambitions are visible across

operators in China, India, Sri Lanka, and Vietnam (Chen et al., 2020; Sohoni et al., 2025; Sanjeetha et al., 2026; Nguyen et al., 2026).

The governance side of this expansion has moved more slowly. Balmer et al. (2020), interviewing senior AI executives at telecommunications, electricity, gas, and water companies across North America and Europe, find that while applications such as predictive maintenance are already mainstream, more complex applications, traffic management AI for 5G networks among them, are still confined to a handful of large operators, and that regulatory engagement with AI in network industries is, in their words, only beginning to emerge. Asadi (2025) frames the resulting gap directly: AI and machine learning are becoming central to the future of telecommunications, but realising their benefit sustainably requires balanced investment across technology, expertise, and governance together, not technology investment alone. Garg et al. (2023) sharpen this concern for the specific case of 5G, arguing that AI embedded directly into radio access networks and core network orchestration introduces a governance problem qualitatively different from earlier, more contained applications such as customer service chatbots, because a misconfigured or compromised AI system managing live network infrastructure can degrade service, expose subscriber data, or be manipulated by malicious actors at a scale and speed that traditional network operations centres, staffed and organised for human-paced decision-making, are not designed to catch in real time.

Somalia's telecommunications sector is a distinctive setting against which to read this literature. Operators such as Hormuud Telecom, Telesom, and Somtel built extensive mobile network and mobile money infrastructure largely in the absence of a strong central regulatory authority during the country's long period of state fragmentation, producing a sector that is, by most measures of mobile penetration and mobile money usage, among the most developed in East Africa, even as the wider Somali economy remains characterised by limited formal financial infrastructure and a still-consolidating federal regulatory system. This combination, commercial and technical maturity alongside comparatively young formal governance institutions, discussed further in Section 7, mirrors at a sectoral level the broader pattern documented in the companion review of AI governance in Somalia's public sector: the technology and the institutional capacity to govern it are not developing at the same pace, and the direction of that gap, capacity lagging capability rather than the reverse, has direct implications for how AI adoption in this specific sector should be sequenced.

This review asks four questions: what drives AI adoption in telecommunications firms, with particular attention to emerging-market evidence; where within network operations AI is actually deployed, including in the specific and commercially important case of customer churn prediction; what risks are specific to AI's extension into 5G network management; and what governance and ethical risk frameworks the literature proposes as adoption moves into functions with direct safety, privacy, and competition implications. It draws together adoption-focused studies, largely grounded in the Technology–Organisation–Environment (TOE) framework, with a separate but overlapping literature on AI governance and ethical leadership in service industries, and with the more technical literature on churn prediction and 5G-specific AI risk. The remainder of the review proceeds as follows. Section 2 sets out the methodology. Section 3 examines adoption drivers. Section 4 reviews AI applications in network operations, including churn prediction. Section 5 addresses 5G-specific governance risk. Section 6 reviews the broader AI governance and ethics literature. Section 7 discusses implications for Somalia, Section 8 sets out limitations, and Section 9 concludes.

2. Review Methodology

This is a narrative and integrative review rather than a formally registered systematic review. Peer-reviewed articles, dissertations, and conference proceedings published between 2019 and 2026 were located through academic literature search using combinations of the terms

"artificial intelligence adoption," "machine learning," "telecommunications," "telecom," "churn prediction," "5G," "AI governance," and "ethical AI," together with "emerging markets" and named country terms. Studies were included where they addressed AI adoption, application, or governance specifically within telecommunications, or, for the governance-focused subset, within AI-enabled service industries broadly enough to be directly applicable to telecommunications operators, and excluded where the telecommunications setting was incidental to a study whose primary focus lay elsewhere. Twenty studies met the inclusion criteria. Of these, seven are structural equation modelling or survey-based adoption studies, five are governance or ethics framework papers, four are single-operator or single-country case studies, three are systematic reviews, and one is a large-scale computational study of adoption diffusion. The adoption-focused literature is dominated by structural equation modelling studies applying the TOE framework (Chen et al., 2020; Fernaldy et al., 2026; Sanjeetha et al., 2026), which is why that framework organises Section 3; the governance-focused literature is more conceptual and framework-building in character (Birkstedt et al., 2023; Brendel et al., 2021; Sposato et al., 2026), reflecting the comparative youth of that strand relative to the adoption literature, while the churn prediction and 5G risk literatures reviewed in Sections 4 and 5 are more technical and methods-focused in orientation (Jain et al., 2026; Garg et al., 2023).

3. Drivers of AI Adoption in Telecommunications: A TOE Perspective

The Technology–Organisation–Environment (TOE) framework, often paired with Diffusion of Innovation (DOI) theory, structures most of the empirical adoption literature reviewed here, and a consistent pattern emerges across markets with otherwise very different telecommunications sectors.

3.1 Technology factors

Chen et al. (2020; see also Chen, 2019), surveying telecom firms in China and analysing the results with structural equation modelling, find that compatibility, relative advantage, and complexity of the AI technology itself are all significantly related to adoption, consistent with classical diffusion of innovation predictions. Sanjeetha et al. (2026), studying AI chatbot adoption specifically in Sri Lanka's telecommunications sector with 368 respondents, find that technical capability is among the strongest direct predictors of adoption, while compatibility, significant in the Chinese study, is not significant in the Sri Lankan one, a divergence the authors attribute to differences in prior digital infrastructure between the two markets.

3.2 Organisational factors

Organisational factors are where the literature is most consistent across countries. Chen et al. (2020) find managerial support significantly related to adoption in China; Sanjeetha et al. (2026) find the same in Sri Lanka; Sohoni et al. (2025), examining a top-three Indian telecom operator's AI/ML rollout empirically, identify leadership drive as the first listed enabler, alongside a robust data management strategy, investment in technological infrastructure, and organisation-wide training on digital skills. Fernaldy et al. (2026), surveying 231 managerial and technical professionals in Indonesian telecommunications firms with structural equation modelling, extend this picture by showing that organisational readiness combines with trust in AI and data privacy assurance to shape adoption intention, and that adoption intention in turn predicts actual AI use behaviour, which then predicts corporate sustainability performance across economic, operational, and environmental dimensions. Nguyen et al. (2026), studying 710 employees across Vietnamese telecommunications and IT firms, find that AI adoption's effect on productivity is mediated by employee engagement, wellbeing, and knowledge sharing, and moderated in opposite directions by digital literacy, which strengthens the effect,

and employee resistance, which weakens it, evidence that organisational adoption outcomes depend on workforce factors that extend beyond leadership support alone.

3.3 Environmental factors

Environmental factors produce the least consistent findings across studies, which is itself informative. Chen et al. (2020) find that market uncertainty and competitive pressure are not significantly related to AI adoption in China, though external environmental factors do positively influence managerial capability indirectly. Sanjeetha et al. (2026) find a similar pattern in Sri Lanka: market uncertainty is significant, but government involvement and competitive environment are not, leading the authors to conclude that internal organisational readiness and customer perceived value are stronger adoption catalysts than external pressure. Dahlke et al. (2024), taking a very different empirical approach, training a transformer language model to detect AI adoption signals across more than 1.1 million firm websites and 380,000 firms in Germany, Austria, and Switzerland, find that AI adoption is highly clustered around existing regional and industrial knowledge hubs, a pattern the authors describe as an epidemic-like diffusion process that is likely to hinder broader diffusion beyond those clusters without deliberate policy intervention. Applied to telecommunications specifically, this raises a caution for operators outside established AI knowledge hubs, including those in Somalia and the wider Horn of Africa, that adoption may lag not for lack of organisational will but for lack of proximity to the knowledge networks the Dahlke et al. (2024) findings identify as central to diffusion.

4. AI Applications in Network Operations

Within network operations specifically, Balmer et al. (2020) identify predictive maintenance as the most mature and widely deployed AI application among the operators and equipment suppliers interviewed, followed by customer service and engagement applications, with genuinely autonomous network management functions, dynamic traffic management for 5G networks in particular, still under consideration by only a few large operators. Ismail et al. (2026), benchmarking Indonesian operators against fifteen international peers, find a similar maturity gradient: strategic leadership and foundational AI deployment are relative strengths, while talent readiness, data governance, technology integration, and autonomous network capability remain persistent gaps, prompting the authors to propose a five-phase implementation roadmap linking readiness assessment to policy action and staged operational scaling.

Customer-facing applications occupy an intermediate position in this maturity gradient. Sanjeetha et al. (2026) find AI chatbot adoption already well established in Sri Lankan telecommunications, driven by persistent customer dissatisfaction with conventional service channels, while Sohoni et al. (2025) document a similarly mature deployment in India aimed at operational efficiency and consumer experience improvement.

4.1 Customer churn prediction as a mature, commercially central application

Churn prediction, forecasting which subscribers are likely to leave an operator for a competitor, deserves treatment as its own case within this maturity gradient because it sits closest to full commercial deployment and because it has attracted its own dedicated methodological literature. Jain et al. (2026), conducting a systematic review of 199 peer-reviewed studies published between January 2010 and December 2024, trace the field's evolution from classical machine learning approaches such as logistic regression and decision trees toward deep learning architectures and, more recently, explainable AI methods that attempt to show not only which customers are likely to churn but why, a shift motivated by the practical observation that a churn prediction a retention team cannot interpret is difficult to act on. Their review situates this technical evolution within a straightforward commercial logic that recurs

throughout the telecommunications literature: retaining an existing subscriber is consistently cheaper than acquiring a new one, which gives churn prediction an unusually direct and easily quantified return on investment relative to other AI applications discussed in this review, and plausibly explains why it has matured faster than governance-dependent applications such as autonomous network management. At the same time, Jain et al. (2026) note that churn models trained on historical subscriber data can encode the same kind of bias risk documented in the credit scoring literature reviewed in the companion review of AI in Islamic finance, for instance by systematically under-predicting churn risk among customer segments underrepresented in the training data, a risk that has received comparatively little attention in the telecommunications-specific literature to date.

Asadi (2025) situates both ends of the network operations maturity gradient, mature customer-facing applications such as churn prediction and chatbots, and immature autonomous network management, within a single framework, arguing that realising AI's full potential in telecommunications requires closing data privacy, cost, regulatory, and skills gaps concurrently rather than sequentially.

5. AI in 5G Network Management: A Distinct Governance Risk

The extension of AI from customer-facing and predictive maintenance functions into direct, real-time management of network infrastructure, the least mature application in the maturity gradient discussed in Section 4, warrants separate treatment because the governance literature treats it as qualitatively rather than merely incrementally more demanding. Garg et al. (2023) document AI applications across radio access networks, core network orchestration, customer service, and fraud detection, and argue that the risks associated with each differ sharply in kind. A fraud detection or customer service AI system that fails produces an inconvenience or a financial loss that can usually be reversed; an AI system with direct control over radio access network parameters or core network orchestration that fails, or is manipulated, can degrade service for large subscriber populations simultaneously, expose the kind of aggregated location and usage data that only a network-level system can see, or create a single point of failure that a malicious actor has a strong incentive to target precisely because of its scale of impact. The authors propose a multi-layered approach to responsible AI adoption in telecommunications that treats network-level AI as requiring a materially higher governance standard, including more rigorous testing before deployment, continuous monitoring rather than periodic audit, and clearer lines of human accountability for automated network decisions, than customer-facing applications require.

This distinction is directly relevant to how the maturity gradient documented in Sections 3 and 4 should be interpreted. The fact that predictive maintenance and churn prediction are mature and widely deployed, while autonomous network management remains limited to a handful of large operators (Balmer et al., 2020), is not simply a matter of technical difficulty or return on investment; it also reflects, on the Garg et al. (2023) analysis, an appropriately cautious governance response to a materially higher risk category, one that operators and regulators in emerging markets should be careful not to bypass under commercial or competitive pressure to catch up with more advanced peers.

6. Governance and Ethical Risk in AI-Enabled Telecommunications

As AI moves from predictive maintenance toward functions with direct implications for competition, privacy, and safety, the literature's attention shifts from adoption drivers to governance design. Putri et al. (2025) provide the most concrete telecommunications-specific example: using design science research methodology with an Indonesian state-owned telecommunications operator, they develop an ambidextrous AI governance framework combining the COBIT 2019 control framework with DevOps practice, applied across seven

governance components and validated through interviews with operator stakeholders until data saturation was reached. Prioritising the Managed Risk governance objective in response to national regulatory requirements, the resulting framework, which formalises AI governance roles, strengthens AI-related risk training, and implements governance, risk, and compliance automation tools, raised the operator's risk management maturity score from 3.83 to 4.66 on the model's five-point scale, one of the few studies reviewed here to report a measured before-and-after governance outcome rather than a proposed framework alone.

Beyond this telecommunications-specific case, a broader AI governance and ethics literature, developed largely for service industries in general, is directly applicable to telecommunications operators. Birkstedt et al. (2023), conducting a PRISMA-guided systematic review of organisational AI governance research, find the field fragmented, with few explicit definitions, and propose a working definition, AI governance as a system of rules, practices, and processes ensuring an organisation's AI use aligns with its strategy, objectives, values, legal requirements, ethical principles, and stakeholder expectations, organised around four themes: technology, stakeholders and context, regulation, and process. Kerr et al. (2020), combining document analysis with a public survey, identify a significant divergence between societal expectations of ethical AI in communication systems and how AI is actually governed in practice, concluding that closing this gap requires domain appropriate tools, updated professional practice, and robust regulatory and accountability frameworks rather than aspirational ethics statements alone, a finding with direct relevance to telecommunications, itself a communication governance domain (see also Du & Xie, 2021).

Several studies propose frameworks for translating these ethical concerns into organisational practice. Brendel et al. (2021) develop an Ethical Management of AI framework spanning managerial decision-making, ethical considerations, and macro- and micro-environmental dimensions (see also Heyder et al., 2023). Sposato et al. (2026), synthesising the service ecosystem literature, propose an Ethical AI Risk Mitigation model built around four leadership approaches, compliance-oriented, values-based, stakeholder-engaged, and anticipatory, arguing that identical ethical risks operate through different causal mechanisms depending on how human and AI resources are configured, and that no single actor controls ethical outcomes in a multi-actor service ecosystem such as telecommunications. Isiaku et al. (2026), applying a Fuzzy Delphi-DEMATEL approach with twenty experts from Nigeria's public and private service sectors, identify twelve critical enablers of responsible AI adoption, split between six causal enablers, organisational readiness, transparency, leadership support, workforce reskilling, strategic alignment, and data privacy, and six effect enablers, including regulatory compliance and ethical risk awareness, a structure that offers a testable causal ordering for governance interventions rather than a flat checklist.

Figure 1

AI adoption and governance framework for telecommunications operators in emerging markets

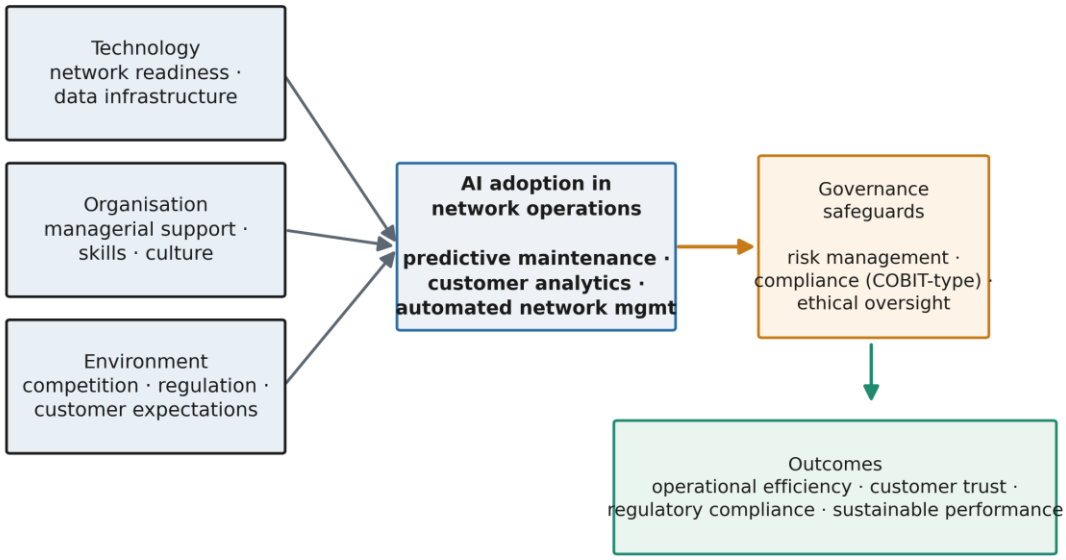


Figure 1. AI adoption and governance framework for telecommunications operators in emerging markets. Technology, organisation, and environment factors drive AI adoption in network operations, which is routed through governance safeguards, risk management, COBIT-type compliance, and ethical oversight, to produce operational, trust, compliance, and sustainability outcomes, with network-level applications such as 5G management subject to a materially higher governance standard than customer-facing applications such as churn prediction.

Table 1 summarises twelve of the twenty studies reviewed, spanning the adoption driver, churn prediction, 5G governance, and broader governance strands discussed above.

Study	Context / Scope	Focus	Key Contribution
Chen et al., 2020	China telecom sector (SEM survey)	TOE/DOI adoption success factors	Compatibility, relative advantage, managerial support, government involvement, and vendor partnership significantly predict AI adoption
Fernaldy et al., 2026	Indonesia telecom (SEM, n = 231)	TOE, trust, and privacy to adoption to sustainability	Adoption intention predicts actual AI use behaviour, which in turn predicts corporate sustainability performance
Ismail et al., 2026	Indonesia (mixed methods, 15-operator benchmark)	National AI roadmap and readiness model	Operators are strong in leadership and deployment but weak in talent, data governance, and integration; projects IDR

			285.4 trillion GDP contribution by 2035
Sanjeetha et al., 2026	Sri Lanka telecom (PLS-SEM, n = 368)	Chatbot adoption (TOE/DOI)	Managerial support and technical capability drive adoption more strongly than external or government factors
Sohoni et al., 2025	India (case study, top-3 operator)	Adoption enablers	Leadership drive, data strategy, infrastructure investment, and organisation-wide training identified as key enablers
Balmer et al., 2020	North America and Europe (executive interviews)	AI applications and regulatory implications	Predictive maintenance is already mainstream; complex applications such as 5G traffic AI remain limited to a few large operators
Jain et al., 2026	Global (systematic review, 199 studies, 2010-2024)	Churn prediction methodology	Traces evolution from classical ML to deep learning and explainable AI; retention is cheaper than acquisition, driving rapid maturity
Garg et al., 2023	Global (conceptual/technical review)	AI in 5G network management	Network-level AI failure or manipulation carries materially higher risk than customer-facing AI; proposes multi-layered responsible AI governance
Putri et al., 2025	Indonesia TelCo (design science research)	COBIT 2019 ambidextrous AI governance	Formalising AI governance roles raised the operator's Managed Risk maturity score from 3.83 to 4.66
Birkstedt et al., 2023	Global (PRISMA systematic review)	AI governance conceptualisation	Defines AI governance and identifies four research themes: technology, stakeholders/context, regulation, and process
Sposato et al., 2026	Literature synthesis (service ecosystems)	Ethical leadership risk mitigation (EAIRM)	Identifies four leadership approaches that mitigate distinct AI ethical risks depending on human-AI resource configuration
Isiaku et al., 2026	Nigeria service industry (Fuzzy Delphi-DEMATEL, 20 experts)	Enablers of responsible AI adoption	Twelve causal/effect factors identified, led by organisational readiness,

			transparency, and leadership support

7. Discussion: Implications for Somalia's Telecommunications Sector

None of the studies reviewed here examines a Somali telecommunications operator, which is a significant omission given the sector's scale and regulatory maturity within the Somali economy; the country's telecommunications and mobile money infrastructure is among its most developed institutional domains, in a market otherwise characterised by weak formal financial infrastructure. The Dahlke et al. (2024) finding that AI adoption clusters around existing knowledge hubs is a relevant caution here: without deliberate investment in local AI capability, Somali operators risk adopting AI more slowly than their scale would otherwise predict, not because of organisational unwillingness, the Chen et al. (2020), Sanjeetha et al. (2026), and Sohoni et al. (2025) findings all suggest organisational leadership support is the more decisive adoption factor in any case, but because of distance from the AI knowledge networks that appear to drive diffusion elsewhere.

Among the applications reviewed, churn prediction is plausibly the most immediately transferable to Somali operators. The Jain et al. (2026) evidence that churn prediction offers a direct, quantifiable return on investment and does not require the network-level access or safety-critical governance apparatus that 5G-specific applications demand, discussed in Section 5, suggests it as a lower-risk, commercially self-justifying entry point for Somali operators building internal AI capability, provided the bias risk the same authors flag, under-prediction of churn among underrepresented customer segments, is addressed at the model design stage rather than after deployment. By contrast, the Garg et al. (2023) analysis of 5G-specific governance risk counsels considerably more caution: a Somali operator considering AI-enabled network management should treat this as a materially different, higher-stakes undertaking than customer-facing analytics, requiring the kind of continuous monitoring and clear human accountability lines the authors specify, rather than assuming that competence built through customer-facing AI projects transfers directly to network control applications.

On governance more broadly, the Putri et al. (2025) case is the most directly transferable structural finding in this review: a COBIT-based ambidextrous governance framework, built around a small number of prioritised governance objectives and validated through operator interviews, produced a measurable improvement in one operator's risk management maturity without requiring a wholly new regulatory apparatus. For Somali telecommunications operators and their regulators, this suggests a practical starting point that does not require waiting for a comprehensive national AI law: prioritising a small number of governance objectives, risk management chief among them, on the Indonesian evidence, and building institutional roles and training around them first. The Isiaku et al. (2026) causal ordering, which places organisational readiness, transparency, and leadership support ahead of regulatory compliance and ethical risk awareness in the enabler sequence, points in the same direction: internal governance readiness can and arguably should precede external regulatory maturity, rather than waiting on it.

7.1 Practical recommendations for Somali telecommunications operators and regulators

Three steps follow directly from the evidence reviewed above. First, operators building initial internal AI capability should prioritise churn prediction and predictive maintenance over network-level automation, both because the Jain et al. (2026) and Balmer et al. (2020) evidence shows these applications are the most technically mature and commercially self-justifying, and because they carry a materially lower governance burden than the 5G-specific applications discussed in Section 5. Second, any churn prediction system should be validated for the under-

prediction bias risk Jain et al. (2026) identify before deployment, ideally by examining model performance separately across customer segments defined by tenure, geography, and service type, given that Somali operators serve a customer base with substantial variation along exactly these dimensions. Third, regulators and operators considering AI-enabled network management should adopt the Garg et al. (2023) recommendation of continuous monitoring and explicit human accountability lines from the outset, rather than extending the governance approach used for lower-risk customer-facing applications, since the consequences of failure in network-level systems, service disruption and data exposure at scale, differ in kind rather than only in degree from the consequences of a misfiring chatbot or churn model.

8. Limitations and Future Research Directions

This review is narrative rather than a formally registered systematic review, and it draws predominantly on evidence from China, Indonesia, Sri Lanka, India, and Vietnam, together with a governance literature developed largely for advanced-economy service industries; the Horn of Africa is entirely absent from the primary studies reviewed, a gap consistent with the pattern observed across the companion reviews of AI in Islamic finance and public sector governance. The adoption literature is also weighted toward large, well-resourced operators, state-owned or market-leading firms in China, Indonesia, and India, leaving open how well its findings generalise to smaller or more resource-constrained operators typical of frontier telecommunications markets. A further limitation is that the churn prediction bias risk identified by Jain et al. (2026) is noted rather than empirically quantified in the reviewed literature, so its practical magnitude in any specific emerging market, Somalia included, remains an open empirical question.

Three directions follow. First, the TOE-based adoption instruments validated in China, Indonesia, and Sri Lanka should be tested directly with Somali telecommunications operators, where no equivalent study currently exists in the peer-reviewed literature. Second, the Putri et al. (2025) COBIT-based governance framework, so far validated in a single Indonesian operator, would benefit from replication in a frontier-market operator to test whether its risk prioritisation approach transfers to lower resource regulatory environments. Third, given the Dahlke et al. (2024) clustering finding and the Garg et al. (2023) 5G risk analysis, research is needed on whether regional AI knowledge sharing arrangements, of the kind proposed for public-sector AI governance more broadly, see the companion review of AI governance and institutional capacity, can substitute for proximity to established AI hubs in building the specialised governance capacity that network-level AI applications require in frontier markets such as Somalia's.

9. Conclusion

The telecommunications sector literature on AI adoption is more mature and more empirically grounded than the corresponding governance literature, which remains largely conceptual outside a small number of applied cases such as the Indonesian COBIT-based framework reviewed here. Across markets as different as China, Sri Lanka, and India, organisational leadership support and readiness consistently outweigh external market pressure as adoption drivers, and AI maturity within network operations follows a consistent gradient, mature in predictive maintenance and churn prediction, intermediate in customer-facing analytics, and immature in autonomous network management, where the risks documented for 5G specifically justify a materially higher governance standard than customer-facing applications require. For Somali telecommunications operators, a sector with unusually mature regulatory infrastructure by the country's own standards but, on current evidence, no documented AI-specific governance framework, churn prediction offers an accessible and commercially self-justifying starting point, while the applied governance models this review identifies, prioritised,

COBIT-based, and built around organisational readiness ahead of external regulation, offer a more immediately actionable path toward network-level AI governance than waiting for comprehensive national AI legislation to arrive.

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