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Leveraging Artificial Intelligence for Enhanced Operational Efficiency in the Telecommunications Industry: A Case Study from Zimbabwe

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Abstract

This study uses one telecommunications company as a case study to investigate the potential of artificial intelligence (AI) to enhance operational efficiency in Zimbabwe's telecommunications industry. Despite global advancements in AI adoption, its integration within Zimbabwe remains limited, particularly in addressing inefficiencies such as high operational costs, poor service quality, and outdated infrastructure. The research is grounded in the TOE framework, the RBV model, and the DOI theory. A quantitative approach was adopted, and data were collected from 117 respondents using structured questionnaires. Analysis was conducted using descriptive statistics, factor analysis, Pearson correlation, regression modelling, and ANOVA to assess AI adoption levels, its impact on efficiency, and the barriers to integration. Findings indicate that while AI adoption is still emerging, it has already led to improved service delivery, reduced downtime, and enhanced resource utilisation. However, several barriers persist, including financial constraints, regulatory uncertainty, infrastructure deficits, and limited technical expertise. The study proposes a five-pillar strategic framework focusing on technological readiness, supportive policy, capacity building, financial planning, and stakeholder collaboration to guide sustainable AI implementation. In conclusion, the research underlines that with targeted strategic investments and institutional support, AI can significantly transform operational efficiency in Zimbabwe's telecom sector. The findings offer practical insights for industry leaders, policymakers, and researchers seeking to drive digital transformation in emerging economies for operational efficiency.

Keywords: Artificial Intelligence, operational efficiency, strategic framework, digital transformation.

1. INTRODUCTION

Artificial Intelligence (AI) continues to command every industry worldwide, offering potential solutions to operational challenges faced by developing economies. Telecommunications providers have utilized AI technologies to address various issues [1]. Tools such as machine learning-powered predictive maintenance, network traffic analysis, and automated customer service through

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natural language processing have emerged to improve efficiency and offer high-quality services [2]. In some regions, AI has resulted in operational cost savings of up to 25 percent [2]. AI in Zimbabwe is, however, getting some traction across sectors like banking, agriculture, and insurance [1], [2], while its application in the telecoms sector appears to be relatively dormant. This is quite surprising, given the strategic importance that the industry bears to Zimbabwe's digital economy. With mobile penetration rates at over 90% [3], the telecoms sector has essentially been facilitating connectivity while enabling digital services and economic resilience.

Despite these milestones, operational inefficiencies persist, ranging from power outages, exorbitant energy costs, skills shortage, slow service delivery, and outdated infrastructure [1], [2]. Furthermore, telecom operators face numerous structural and institutional barriers that hamper adoption. These include outdated infrastructure, recurring power outages, and limited investment in technology upgrades [1], [2]. In addition, regulatory uncertainty surrounding emerging technologies such as AI, coupled with a scarcity of technical expertise, makes it difficult for telecom firms to innovate at scale [4]. The result is a sector struggling with high operating costs, inefficient fault resolution processes, and inconsistent service delivery. While these barriers initially hinder AI uptake, the adoption of AI itself can, over time, help mitigate them. For example, AI-driven automation can reduce operational costs, freeing up resources for infrastructure upgrades [2], [5]. Similarly, organizations investing in AI are incentivized to upskill their workforce, gradually addressing the skills gap [1]. Regulatory uncertainty can also be lessened as policymakers observe the tangible benefits of AI, prompting more straightforward guidelines and support [4].

In contrast, the Zimbabwean environment is much more constrained, with economic volatility, policy uncertainty, and infrastructure bottlenecks limiting large-scale AI adoption. While major players like Econet Wireless have taken some significant steps by deploying AI-powered chatbots like Yamurai and EcoChat AI, these AI applications remain somewhat confined to customer support functions and see very little use in core operational areas such as energy management, network optimization, or predictive system maintenance [5].

This study identified the gap between what is potential internationally and what is instantaneously prevalent locally. How can AI technologies be meaningfully and productively adopted to enhance operational efficiency within Zimbabwe's telecommunications industry? Strategic integration focuses on deploying and using AI solutions that best fit the Zimbabwe-specific operational challenges, particularly those related to power disruption management, resource optimization, and automation of routine technical operations.

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Telecom operators in Zimbabwe are still burdened by extended power cuts, sometimes even 12 hours during the day, primarily because hydroelectric power sources like Kariba Dam are underperforming [6]. These power cuts force network operators to lean heavily on backup power solutions, including costly diesel generators, whose operational cost keeps rising. Also, poor infrastructure maintenance has backed over 100,000 unserved connection requests even in areas where physical infrastructure exists [7]. The situation creates bottlenecks in service delivery, grazes customer satisfaction, diminishes profitability, and compromises the sector's sustainability. Contrastingly, over the African continent, AI tools are actively employed by operators such as MTN and Safaricom to proactively monitor network performance, forecast equipment failure, and optimize customer service workflows [8]. Detecting network faults before they become critical and deploying field teams more efficiently in concert with concerns over energy consumption would benefit Zimbabwean telecoms, should these approaches be well localized.

While the study acknowledges AI's enormous potential, it also identifies some special contextual challenges for Zimbabwe. Besides the infrastructural and financial constraints, the regulatory environment misses out on fit policies, let alone incentives for AI innovation; the other is a low availability of AI-skilled personnel, as formal AI and data science programs are still in their infancy within local learning institutions. Without deliberate efforts to develop these digital skills, the sector will continue missing out on AI's opportunities. Thus, in response to this urgent need, the study will undertake an in-depth exploration into (i) the assessment of AI adoption status in Zimbabwe's telecommunications sector, and (ii) the effect of AI technologies on operational efficiencies. These two objectives are paramount and directly relate to the technological and organizational landscape. By narrowing the scope of investigation, the study seeks to provide a more in-depth and actionable understanding of how AI can be harnessed in practical, scalable, and contextually appropriate ways.

The study has two theoretical considerations: the Technology–Organization–Environment (TOE) framework and the Resource-Based View (RBV). The TOE framework allows for exploring technology adoption in a multidimensional fashion, including technological capabilities, organizational readiness, and environmental pressures. RBV, on the other hand, facilitates explaining how AI can be a valuable organizational resource, conferring competitive advantage if it is implemented strategically and backed by complementary assets such as skilled labor and robust infrastructure.

Moreover, this study aligns with Zimbabwe's national development aspirations, notably Vision 2030, which sees technological innovation as an engine of inclusive socio-economic transformation [9]. By exploring AI through the lens of

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telecommunications, this study aims to provide industry and policy leaders with a knowledge base to develop an evidence-based approach to AI integration.

The key research question drives this inquiry: How can Artificial Intelligence be effectively leveraged to increase operational efficiency in the Zimbabwean telecommunications industry? Two other research questions support these:

1) What is the state of AI adoption in Zimbabwe's telecommunications sector?
2) How are AI technologies affecting operational efficiency in the Zimbabwean telecom industry?

The rest of the paper is structured as follows: Section 2 focuses on the research method and design adopted in the research study; Section 3 presents the research findings and the discussion, and Section 5 gives the study conclusion.

2. METHODS

To further elaborate on Figure 1, this research adopted the quantitative methodology to analyze the impact of AI on operational efficiency in the telecom industry in Zimbabwe. This research design was based on the positivist philosophy that knowledge can be counted as accurate through observation of phenomena and/or empirical data [10]. In line with this perspective, the study employed a deductive approach, allowing for testing pre-established hypotheses derived from theoretical frameworks, notably the TOE model and the RBV [11].

The survey method was adopted for the collection of data. This method was particularly suitable for getting standardized, quantitative data from a vast population that could be analyzed statistically [12]. The study targeted personnel at one telecommunications company in Zimbabwe, mainly the medium-level management, technical, and customer staff directly involved in the application or use of AI technologies. This was done since it was based mainly on accessibility, its ongoing digitisation efforts, and its representativeness of mid-tier operators in Zimbabwe. From the researchers' view, this makes the findings transferable to similarly positioned telecom firms. The sampling was stratified randomly to ensure a diversity of opinions between managers at different job designations, departments, and experience levels. Using Yamane's formula for finite populations [13], the sample size determined was 212, drawn from a total population of 450 employees, against a 5% margin of error. This sample size supports the generalizability and robustness of findings within the organization.

The tool used for research was divided into five sections: demographics, AI adoption, operational efficiency, barriers to adoption, and perceived benefits. A 5-point Likert scale was used to assess levels of agreement, thus generating

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quantitative data about the respondents' attitudes and experiences. The survey was pilot tested on 15 employees to enable adjustments relating to question clarity and reliability.

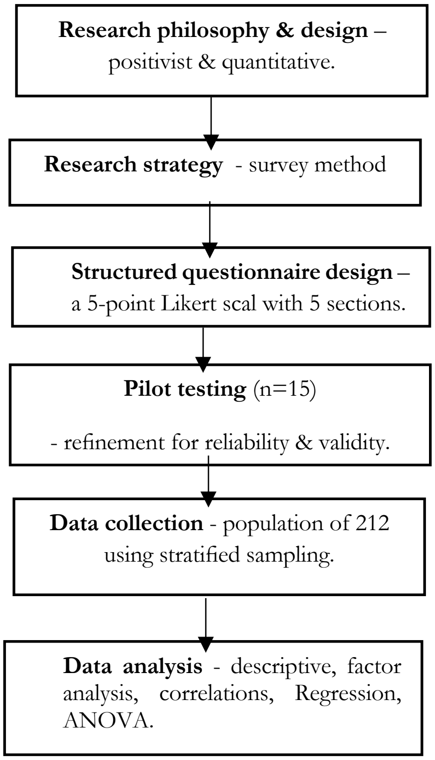

Figure 1. Research process flow diagram

The data was analyzed using both descriptive and inferential statistics. Descriptive statistics were used to summarize variables from demographics to the general trends of AI adoption. Pearson correlation was used to investigate the strength and directions of the association between the use of AI and operational results along dimensions such as cost efficiency, service quality, and network reliability [14]. Multiple regression analysis examined how strongly AI adoption accounted for improvements in operational efficiency while controlling for organizational and infrastructural variables. Exploratory Factor Analysis (EFA) was utilized to discover underlying dimensions amongst the barrier-related survey items, which helped thematically structure the proposed strategic framework.

Reliability was tested by using Cronbach's alpha, with all subscales confirming good internal consistency ($\alpha > 0.70$), as suggested for use in social sciences [15].

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This complemented the pre-test of 15 industry experts whose feedback informed minor refinements to the survey structure and wording, ultimately improving the reliability and validity of the instrument. Content validity-wise, the consultation of experts and prior literature shared in precedents ensured validity. For construct validity, items were drawn from established, well-defined theoretical domains. Finally, criterion validity was established by comparing results from similar studies in related emerging-market contexts [16].

Ethics were of concern throughout the study. All respondents were informed and consented to participate, and all measures for confidentiality and anonymity were adhered to. Participation was voluntary; respondents were briefed on the purpose of the study, the handling of data, and their rights, including the right to withdraw from the study at any point.

3. RESULTS AND DISCUSSION

This section presents and interprets the findings of this research endeavor arising out of two key objectives: (i) the study of the relationship between AI adoption and operational efficiency, and (ii) the identification of barriers that limit effective implementation of AI. Based on the response rate, it was deduced that 117 out of 212 participants responded to the questionnaire, giving an average response rate of 55.2%. Descriptive statistics, correlation, regression, ANOVA, and factor analysis statistically analyze the findings. The findings are discussed critically against the background of the conceptual and theoretical framework of the study.

3.1. Relation between AI adoption and operational efficiency

Descriptive statistics indicated moderate AI adoption, with Likert scales between 2.23 and 2.93. This is depicted in Table 1.

Table 1. Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
B1	117	1	5	2.39	1.122
B2	117	1	5	2.37	1.047
B3	117	1	5	2.23	1.037
B4	117	1	5	2.24	1.127
B5	117	1	5	2.44	1.125
B6	117	1	5	2.93	1.230
C1	117	1	5	2.47	1.047
C2	117	1	5	2.67	1.099
C3	117	1	5	2.68	1.134
C4	117	1	5	2.75	1.090
C5	117	1	5	2.75	1.082
C6	117	1	5	2.74	1.062

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	N	Minimum	Maximum	Mean	Std. Deviation
D1	117	1	5	3.82	1.291
D2	117	1	5	3.53	1.374
D3	117	1	5	2.89	1.331
D4	117	1	5	3.06	1.373
D5	117	1	5	3.29	1.384
D6	117	1	5	2.87	1.290
E1	117	1	5	2.80	1.154
E2	117	1	5	2.73	1.127
E3	117	1	5	2.78	1.130
E4	117	1	5	2.77	1.132
E5	117	1	5	2.89	1.158
E6	117	1	5	2.75	1.129
Valid N (listwise)	117				

Table 2 reflects the relationships among the variables within the study.

Table 2. Correlations

		AI adoption	Operational efficiency	Barriers/ Challenges	Benefits
AI adoption	Pearson Correlation	1	.709**	.100	.536**
	Sig. (2-tailed)		.000	.284	.000
	N	117	117	117	117
Operational efficiency	Pearson Correlation	.709**	1	.302**	.587**
	Sig. (2-tailed)	.000		.001	.000
	N	117	117	117	117
Barriers/ Challenges	Pearson Correlation	.100	.302**	1	.148
	Sig. (2-tailed)	.284	.001		.112
	N	117	117	117	117
Benefits	Pearson Correlation	.536**	.587**	.148	1
	Sig. (2-tailed)	.000	.000	.112	
	N	117	117	117	117

**. Correlation is significant at the 0.01 level (2-tailed).

The study discovered the following relationships:

1) Adopting AI correlates significantly with operational efficiency at $r = .709$ ($p < 0.01$), indicating that the greater the adoption, the greater the operational efficiency.
2) Adoption and benefits from AI correlate at $r = 0.536$ ($p < 0.01$), confirming the participants' perception that they benefit from AI.
3) Operational efficiency and benefits correlate at $r = .587$ ($p < .01$), so perceived benefits could be the basis for operational efficiency.
4) The adoption of AI and challenges do not correlate significantly, and they are at a negligible level at $r = .100$ ($p = .284$), implying that the barriers could not be absolute impediments to adoption.

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The above suggests that the greater use of AI is accompanied by real operational improvements in telecommunication [17]. Multiple regression analysis was conducted, as shown in Table 3, and it further confirmed AI adoption as the strongest predictor of operational efficiency ($\beta = 0.547$, $p < 0.001$). Along with perceived benefits, AI adoption explains more than 60% of the variance in efficiency outcomes ($R^2 = 0.605$). A residual diagnostics and multicollinearity tests revealed no statistical irregularities, confirming the model's validity [18].

Table 3. Regression model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.778[a]	.605	.595	.63016	.605	57.806	3	113	.000	1.829

a. Predictors: (Constant), AI adoption, Barriers/ Challenges, Benefits
b. Dependent Variable: Operational efficiency

Network uptime, cost reductions, and service quality were paramount among the operational key performance metrics. Predictive maintenance, for instance, is an important application as it detects faults ahead of time, thus minimizing downtime, which corresponds with earlier research [19]. AI was not frequently used for energy optimization or customer interaction automation; however, both applications could help represent an opportunity yet to be seized.

3.2. Barriers to the implementation of AI

The factor analysis upheld the validity of the barrier construct, indicated by a high KMO value and a significant Bartlett test. This is summarized in Table 4.

Table 4. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.885
Bartlett's Test of Sphericity	Approx. Chi-Square	414.263
	df	15
	Sig.	.000

While respondents still accepted some of the barriers, correlation analysis indicated that these factors have weak relationships with AI adoption and operational efficiency. Nevertheless, barriers remain relevant for their long-term strategic influence on AI integration. Three major themes came to the fore:

1) Skills and capacity deficits - there is a glaring lack of AI skills. Only a few respondents ever received regular training in AI (see Figure 4.6), with a majority confirming little or no exposure at all. This supports the top finding that AI adoption was significantly higher among those who were involved in training and other AI-related activities ($p < 0.001$) [20].

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2) Regulatory uncertainty - a significant cause of concern continues to be unclear policies on AI. Respondents mentioned the lack of data privacy laws and ethical guidelines as key issues that caused their hesitation. These findings find resonance in broader African contexts, where digital regulatory frameworks are usually in their infancy or appear to exist just on paper [21].
3) Infrastructure constraints - power instability, poor connectivity, and legacy systems were cited frequently as operational constraints. These constraints become particularly serious in emerging markets, as AI depends on real-time data and computing infrastructure [22].

3.3. Group differences and demographic insights

The ANOVA tests were performed to assess the significant differences in the adoption of AI across demographic characteristics of the participants. This is depicted in Table 5. The tests revealed no statistically significant differences in AI adoption by department or years of industry experience. However, three variables were found to influence adoption significantly:

1) Job role - participants in technical roles had higher adoption levels ($p = 0.045$).
2) Involvement in AI initiatives: Those engaged in AI projects reported higher adoption rates ($p = 0.002$).
3) Regular training: Participants receiving frequent training showed significantly greater adoption ($p < 0.001$).

Table 5. ANOVAs

	Sum of Squares	df	Mean Square	F	Sig.
Participant department					
Between Groups	8.792	6	1.465	1.883	.090
Within Groups	85.600	110	.778		
Total	94.392	116			
Job role					
Between Groups	9.071	5	1.814	2.360	.045
Within Groups	85.322	111	.769		
Total	94.392	116			
Experience in telecommunications department					
Between Groups	5.769	4	1.442	1.823	.129
Within Groups	88.623	112	.791		
Total	94.392	116			
Participants' AI technologies experience					
Between Groups	26.848	4	6.712	11.129	.000
Within Groups	67.545	112	.603		
Total	94.392	116			

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Participant involvement in AI initiatives					
Between Groups	15.035	5	3.007	4.206	.002
Within Groups	79.357	111	.715		
Total	94.392	116			
Participant regular training					
Between Groups	22.135	4	5.534	8.578	.000
Within Groups	72.257	112	.645		

These perceptions emphasize that experience and exposure to AI, not job seniority or duration of service, drive adoption, reinforcing the importance of internal capacity-building initiatives.

3.4. Synthesizing the evidence

Statistical findings found that AI adoption significantly contributes towards operational efficiency and that AI-related barriers do not prevent such benefits. This highlights resilience and adaptability within the sector to some degree. While the TOE framework stated that technological, organizational, and environmental readiness should precede adoption, the results showed a heavy dominance of organizational factors, particularly training and involvement. Similarly, trialability and observability are important in the Diffusion of Innovation theory: departments already involved in AI tools will be more inclined to achieve further appreciation for usage. Lastly, the RBV helps understand why the internal capabilities, particularly know-how and technical infrastructure, are important in achieving competitive advantage through AI. Hence, the data speak strongly towards AI being an upgrade in technology and an organizational asset from a strategic point of view.

3.5. Theoretical implications

The research contributes to extant literature concerning technology adoption for achieving operational efficiency in emerging economies. More specifically, the findings affirm the applicability of the TOE framework and RBV in the context of AI diffusion within resource-scarce conditions. The study affirms TOE's stance that organizational and environmental settings greatly influence technology adoption. Organizational readiness, notably training and internal involvement in AI projects, appeared as the main determinants of adoption in the Zimbabwean telecommunications environment. This supports the notion that technological innovations cannot be severed from the socio-organizational context within which it is introduced [23].

Following the contention of the RBV, the co-factors of human capital and digital infrastructure were found to be key contributors to realizing operational efficiency

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through AI. Organizations that focused on knowledge resources, such as training of staff and staff awareness about AI, were in a much better position to reap the rewards of AI performance benefits, thus echoing the fundamental philosophy in RBV that competitive advantage is derived from internal assets that are distinguished from other firms [24]. Finally, a merger between theoretical views and organizational performance was introduced with a statistical model approach that advances the implementations of both TOE and RBV into measurements.

3.6. Discussion

The findings of this study resonate with trends observed in other African contexts where AI is gaining traction as a catalyst for operational transformation. In Kenya, AI telecom applications have significantly improved fraud detection and network monitoring, driven by supportive regulatory environments and active public-private innovation partnerships [25]. Similarly, South Africa has leveraged AI to enhance customer service experiences and optimise infrastructure planning, benefiting from stronger institutional capacity and a skilled digital workforce [26]. Compared to these countries, Zimbabwe's AI adoption is still emergent and largely constrained by economic instability, limited infrastructure investment, and ambiguous policy direction.

Nonetheless, the data suggest that even within this constrained environment, AI has begun to yield meaningful improvements in operational efficiency, particularly in areas such as fault detection, service automation, and customer query resolution. This mirrors [27] and [28] observation that even limited AI deployments can offer tangible operational benefits when aligned with organizational priorities.

From a policy standpoint, this study highlights the urgency for government regulators to develop adaptive frameworks that support responsible AI integration while addressing data governance, skills development, and innovation financing issues [29]. The lack of regulatory clarity continues to deter private-sector investment in AI technologies. For industry stakeholders, the implications are equally significant: AI adoption must be linked not only to cost-cutting but also to strategic capability development that enables long-term resilience and service differentiation in a competitive market.

From a practical perspective, this study offers valuable insights to telecommunications operators, technology managers, and policymakers in Zimbabwe and similar emerging-market settings. First, evidence revealed that operational improvements could be measured with a limited level of AI adoption at the most rudimentary application stages of predictive maintenance, customer service quality, and cost optimization. Telecom firms should, therefore, encourage incremental adoption strategies, prioritizing early opportunities where immediate

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benefits are realized. The second consideration links adoption to capacity-building training, staff involvement in AI-related initiatives, and exposure to AI tools, thus implying that management should invest in the development of human resources as much as it values the technology itself. Building internal knowledge bases on AI, partnerships with academia, and initiatives for on-the-job training could further augment AI readiness. Third, this study stresses the importance of infrastructure and governance alignment. While power supply irregularities and a lack of a clear governance framework for AI do not outright prohibit diffusion, they surely slow it down. Regulations and frameworks curb the disambiguation of data protection, enhance digital infrastructure, and nurture an enabling environment for the responsible deployment of AI. Fourth, based on the revelations of this study, practitioners should consider AI as anything but a one-size-fits-all blanket solution and instead, view it as a modular capability that can be scaled up as internal readiness increases. In essence, the modular-staged integration approach drastically reduces organizational resistance, thereby significantly increasing project success rates.

This study opens the gateway for further academic inquiry into AI adoption in emerging markets. Firstly, further studies ought to be conducted along longitudinal lines to gauge the progression of AI adoption over time, especially vis-à-vis regulatory, economic, and organizational changes. Long-term tracking would offer deeper insights into the sustainability of AI-driven efficiencies. Second, comparative studies between different firms or across sectors (e.g., telecoms versus banking) could illuminate sector-specific barriers and enablers of AI adoption. Such cross-sectional diversity would help build a more nuanced understanding of context-sensitive adoption models. Thirdly, mixed-method approaches could enrich the depth of analyses by juxtaposing quantitative findings with qualitative understanding gained from interviews or case studies. This would provide an enriched contextualization of the causes that spur or deter adoption compared to culture- and environment-induced fears and inhibitions. Researchers might also want to pursue ethical considerations in AI deployment alongside questions on algorithmic transparency, data sovereignty, and stakeholder trust. As technical deployments increasingly overlook AI implications and causes, the commitment to ethics will stand shoulder-to-shoulder with technical developments.

4. CONCLUSION

This study examined how AI can enhance operational efficiency within Zimbabwe's telecommunications industry. The study result demonstrates that while Zimbabwe's telecommunications sector is still in the early stages of AI adoption, even incremental steps towards automation and data-driven decision-making can yield meaningful improvements in operational efficiency. It indicated that although AI adoption is still emerging, its application has already contributed

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to reducing network downtimes, streamlining customer service, and improving resource management, consistent with global findings on AI's transformative potential in telecommunications. The experiences of regional cases such as Kenya and South Africa show that, with the proper support, African telecom operators can successfully leverage AI to enhance service delivery, reduce costs, and foster innovation. However, the pace and scope of adoption remain constrained by financial limitations, infrastructural decay, skills shortages, and policy uncertainty, challenges that have been well noted. These constraints must be addressed systematically if the sector moves beyond pilot deployments toward scalable, strategic integration of AI.

Future studies should consider a longitudinal approach to track AI adoption and the long-term impact of AI adoption in Zimbabwe's telecom sector. Additionally, qualitative investigations into employee attitudes, ethical concerns, and AI governance would offer a more holistic view of readiness and resistance. Expanding the research to include multiple operators and cross-country comparisons within the region would provide a more comprehensive understanding of best practices and context-specific challenges. Furthermore, qualitative research into employee attitudes, ethical concerns, and AI governance would offer a more holistic view of readiness and resistance. More so from the qualitative perspective, exploring organisational culture and change management in AI adoption could yield valuable insights for practitioners and policymakers.

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