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AI PARADOX IN NEPALESE BANKING: OPERATIONAL EFFICIENCY VS. ETHICAL AND REGULATORY RISKS

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ABSTRACT

The rapid integration of artificial intelligence (AI) in Nepal's banking sector presents a critical paradox. While adopted to enhance operational efficiency, its implementation often outpaces the development of essential ethical and regulatory frameworks. This empirical study of 400 banking professionals across 28 commercial banks identifies a four-construct framework—AI infrastructure, model governance, service integration, and ethics capacity—that influences performance. Regression analysis reveals that ethics training ($\beta = 0.216$, $p < 0.001$) and AI-enabled services ($\beta = 2.012$, $p < 0.001$) significantly boost operational performance. Conversely, opaque model governance ($\beta = -0.860$) and subpar infrastructure ($\beta = -0.788$) detrimentally affect efficiency. The findings suggest that hybrid governance systems and regulatory sandboxes can bridge this implementation gap by striking a balance between innovation and responsibility. This study contributes to the understanding of AI adoption in resource-constrained environments, offering critical insights for financial institutions and policymakers.

KEYWORDS: *AI adoption, Banking efficiency, Ethical risks, Regulatory challenges, Nepal, Developing economies*

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1. INTRODUCTION

1.1 Background

Developed economies (Floridi, 2018; Arner et al., 2020) have an impact on the world's banking sector. This change in our offerings, which utilises automatic decision-making, presents a notable contradiction in risk, given its adoption as an AI system. However, when established guidelines fail to keep pace with technological advancements, a significant imbalance emerges, creating a potentially risky environment—particularly in smaller or less-developed sectors. In contrast, the global banking industry has rapidly embraced artificial intelligence (AI), with machine learning systems now responsible for 43% of credit decisions and 68% of fraud detection activities in developed markets (Floridi, 2018; Arner et al., 2020). By automated decision-making, bespoke services, and real-time risk management, this technical change provides operational efficiency. However, emerging economies like Nepal offer a curious paradox: 89% of commercial banks have implemented artificial intelligence solutions (Nepal Rastra Bank [NRB], 2025); just 11% preserve formal ethical systems to control these technologies. Particularly in environments with poor digital infrastructure and legal control, this asymmetry produces a dangerous environment where technological progress outruns institutional preparedness.

1.2 Nepal's Context

According to the South Asian FinTech Report of 2024, Nepal's banking sector has an exceptionally high adoption rate of artificial intelligence (AI) that is similar to that of regional leaders such as India (72%) and Bangladesh (65%). Among the main uses are:

- Adoption rate of a• Algorithmic credit scoring (78% adoption) is 78%.
- Chatbot 64% customer service
- Fraud detection tools (89%)

Still, this development is centred in cities; rural branches have 42% greater algorithmic rejection rates for agriculture loans (Adhikari & Baral, 2025). These differences are made worse by structural obstacles:

- 38% of the country has access to digital literacy (CBS Nepal, 2024)
- Few financial statistics for underprivileged groups
- Reliance on outside AI suppliers (72% of systems)

1.3 Problem Statement and Research Gap

The clash of moral values is our major study problem. Though artificial intelligence cuts the expense of Nepalese banks, the fundamental conflict between moral hazards and operational efficiency defines our main research challenge, which cuts Nepal's banks' cost-to-income ratios by 1520% (NRB, 2025) while at the same time it brings:

- Unexplainable black box decisions are impacting 28% of retail consumers (Thapa, 2025)
- Algorithmic prejudice towards women-owned SMEs (38% lower approval rates)
- Regulatory loopholes are letting dangerous outside AI systems operate

This research covers three critical gaps:

- Lack of real-world evidence on ethical trade-offs in Least Developed Countries (LDCs)
- about artificial intelligence
- There are no context-specific governance structures for Himalayan economies.
- Institutional theory's restricted application to patterns of AI adoption

1.4 Conceptual Model

Our study is defined by two lenses that fit each other:

1.4.1 Expanded RBV

Following Barney's (1991) groundbreaking study, we reexamine artificial intelligence governance as a tactical weapon:

- Ethical codes show the VRIO qualities (valuable, rare, inimitable, organisation
- Teece (2023 says that imatch• Institutional capabilities align with technological assets (Teece, 2023)
- Investing in h, such as, produces long-term benefit.• Human capital investments (ethics training) yield sustained advantages

1.4.2 Institutional Correspondence

The 1983 hypothesis by DiMaggio and Powell accounts for Nepal's regulatory lag via:

- Mimetic pressures: adopting Indian RBI structures without regionalisation
- Normative gaps: Not enough people know how to make sure an AI is working correctly; just 12 are certified nationally.
- Coercive faults: No repercussions for mathematical discrimination

1.5 Research Objectives

The goal of this research is to:

Using cost efficiency, service speed, and error reduction, measure the operational influence of artificial intelligence. Apply fairness, accountability, and transparency (FAT) criteria to identify moral hazards. Suggest a hybrid governance model combining:

- Risk classification according to EU standards
- India's localisation requirements
- Priorities for Nepal's digital inclusion

1.6 Significance

The outcomes will serve to direct:

- Politicians: Formulating Nepal's upcoming National Artificial Intelligence Strategy
- Banks: Cost-benefit research on responsible artificial intelligence investment
- International groups: IMF and World Bank technical help initiatives

1.7 Research Questions and Hypotheses

Based on the identified gaps, the study sought to answer the following research questions:

Q1: How does AI adoption influence operational efficiency in Nepalese banks?
Q2: What ethical and regulatory challenges arise from AI-enabled banking operations?
Q3: How do institutional and infrastructural capacities affect responsible AI adoption?

The following hypotheses were formulated:

H1: Ethics training has a positive and significant impact on operational efficiency.
H2: Weak model governance negatively affects AI-enabled operational efficiency.
H3: AI infrastructure investment initially reduces efficiency but yields long-term benefits.

2. LITERATURE REVIEW

2.1 Ethical Issues of Algorithmic Banking

2.1.1 Financial Exclusion and Algorithmic Bias

Using artificial intelligence in finance has revealed South Asia's structural inequality, as statistics show that, due to training data skewed toward male borrowers, women are represented 27% less than in Nepal. Furthermore, artificial intelligence in banking has exposed systemic biases that disproportionately affect vulnerable populations. According to Ullah's (2022) research of Bangladeshi SMEs in South Asia, gender-based prejudice in credit scoring was shown to exist; women-led businesses suffered 27% higher rejection rates because training data was skewed toward male borrowers. Nepal reflects this trend:

Adhikari & Baral (2025) find that rural loan applicants experience 42% more algorithmic rejection rates than do their urban counterparts. Income gaps based on caste are left uncorrected in 89% of credit models (CBS Nepal, 2024). According to their ethics of algorithms framework, Mittelstadt et al. (2016) identify three sources of bias amplification:

- Data bias: too many urban middle-class banking practices are represented.
- Design bias: Algorithm vendors are appropriate for rich nations
- Postimplementation monitoring defines deployment bias.

2.1.2 The Explainability Issue

Nepal is far behind international standards in its use of explainable artificial intelligence (XAI):
Adoption of XAI: Comparative Research

AI Act (Regulation (EU) 2024/1689) European Union

Under this rule, artificial intelligence systems are divided into categories based on how risky they are: unacceptable, high, limited, and minimal risk (with an extra category for general-purpose artificial intelligence).

Article 10(5) requires AI providers to examine their datasets for biases and quality, and—where appropriate—even acquire sensitive information to rectify discriminatory inclinations.

- Conformity evaluations and transparency: High-risk artificial intelligence systems should either internally or through outside sources have conformity assessments carried out on them, along with thorough documentation and postmarket monitoring.
- Guidelines for systematic risk: The European Commission issued recommendations for AI models with systematic risk on July 18 2025, calling for risk assessments, hostile testing, incident reporting, cybersecurity precautions, and training data openness.
- Voluntary versus compulsory provisions: Some clauses of the Act, including future "codes of practice" for strong general-purpose artificial intelligence, have been debated as maybe voluntary, although politicians caution against this dilution.
- On quarterly reporting: Although the Act requires postmarket monitoring and serious incident reporting, it does not expressly provide for "quarterly reporting." National regulators or sector-specific agencies could impose their regular reporting criteria, especially for high-risk or systemic models.

Table 1: Comparison of AI Governance Provisions – EU AI Act vs. RBI FREE-AI

Jurisdiction / Framework	Key Provisions	Bias Control	Reporting Requirement	Source
EU AI Act (Regulation (EU) 2024/1689)	Risk-based classification of AI; conformity assessments for high-risk systems; transparency and postmarket monitoring obligations	Mandatory dataset bias evaluation and mitigation (Art. 10(5))	Postmarket monitoring & serious incident reporting; no explicit quarterly reporting	European Commission, 2024
EU Systemic Risk Guidelines (2025)	Risk assessments, adversarial testing, and transparency requirements for systemic AI models	Strong focus on fairness, transparency, and data governance	Incident reporting; frequency not explicitly defined	European Commission, 2025
RBI FREE-AI Framework (India)	Responsible AI adoption in finance: governance, ethics, and risk mitigation recommendations	Emphasis on fairness and nondiscrimination in AI outputs	No periodic reporting requirement defined yet	IndiaAI, 2024; Charltons Quantum, 2024

India: RBI 2024 Guidelines (FREEAI Framework)

To create a framework for ethical and responsible artificial intelligence in finance, the Reserve Bank of India (RBI) founded the FREEAI Committee in December 2024. The committee, led by Dr. Pushpak Bhattacharyya, has members from academia, government, legal, fintech, and other fields. It has to look at:

- Evaluating the uptake and dangers of artificial intelligence (including bias, data security)
- Suggesting accountability, morality, and governance structures
- Suggesting monitoring and mitigation frameworks throughout financial institutions.

- Related advice emphasises fairness and nondiscrimination; therefore, AI systems should be free from biases across gender, race, age, and socioeconomic status, utilising balanced training data and countermeasures.
- Regarding reporting frequency: The existing documents make no explicit provision for quarterly reporting requirements. The RBI framework is still developing, and future updates or sector guidelines may call for routine reporting, but these are not now openly accessible.

Due Diligence, Vendor Examination & Audit

- Best standards for AI vendor due diligence call for organised surveys evaluating data management, model governance, security, risk management, and legal compliance
- Industry publications highlight the use of artificial intelligence tools to automate, simplify, and record due diligence procedures as well as thorough, multidimensional evaluations (financial, operational, legal, technological security).
- High-risk artificial intelligence systems in the EU frequently use audit mechanisms and postmarket monitoring to guarantee continuous compliance in a conformity assessment.

2.2 Institutional Voids and Regulatory Lag

2.2.1 Case Study: Paradoxes of Green Banking in Nepal

Theof Nepal show howions might beedNepal's progressive Green Banking Guidelines (2023) exemplify regulatory misalignment:

- 18 classifications of environmental risk
    - Zero references to AI ethics or algorithmic responsibility
    - This starkly differs from:
    - The EU AI Act categorises risk on four levels: Prohibited, High, Limited, and Minimal.
    - Singapore's FEAT Principles—Fairness, Ethics, Accountability, Transparency

2.2.2 Leading AI Companies and Startups in Nepal

1. Fusemachines Nepal
   Operating since 2013, Fusemachines Nepal has become a cornerstone of the country's AI ecosystem. The company offers a suite of AI products and services, complemented by its highly regarded AI Fellowship programme, which has trained hundreds of professionals in domains such as computer vision, natural language processing (NLP), and MLOps. Sources: Nepal Commerce Journal, TechSansar.com

2. Paaila Technology
   Founded in 2016, Paaila Technology has gained recognition for its innovations in robotics, including Nepali-language speech recognition systems, service robots, and even a robotic restaurant.
   Sources: KSU Info, Ankit Poudel, TechSansar.com

3. iBriz.ai
   iBriz.ai bridges AI and blockchain technologies, providing recruitment, consulting, and outsourcing services with a global perspective.
   Source: TechSansar.com

4. Wise Yak Inc.
   Operating from both Kathmandu and Bellevue, USA, Wise Yak specializes in healthcare AI, developing diagnostic tools, patient-centric platforms, and NLP-based workflows. Source: TechSansar, Ankit Poudel

5. Adinovi
   Adinovi focuses on AI-driven digital transformation across sectors such as education, agriculture, finance, and governance. The company emphasizes responsible and practical adoption of AI technologies. Source: adinovi.com

6. NepalAI.org
   This research-oriented initiative provides solutions in deep learning, including computer vision, speech processing, and reinforcement learning. It also hosts workshops and develops web applications to advance AI research and application in Nepal.
   Source: nepalai.org

7. Nepal AI Tech (founded 2025)
   A rising startup based in Mithila, Nepal AI Tech offers tailored AI services, including computer vision, Nepali-language NLP, model training, and intelligent automation solutions for enterprises.
   Source: nepalaitech.com

8. OptimTech Pvt. Ltd.
   OptimTech delivers AI and ML consulting, analytics, and automation solutions aimed at enhancing customer experience and streamlining operational workflows.
   Source: optimtech.com.np

9. Cubit Inc.
   Cubit Inc. provides NLP, computer vision, chatbot development, automation, and analytics solutions designed to improve engagement and operational efficiency.
   Source: cubit.com.np

10. Other Noteworthy Players
    According to Clutch, additional firms contribute to Nepal's AI landscape, though often as part of broader service portfolios. These include Plex Bit Infosystems and Milo Logic Pvt Ltd. in Kathmandu, as well as Naamche, Autolab Technologies, The Maker Crew, Awecode, KTM Labs, Bajra Technologies, Eydean, Ottr Technology, Idata Solutions, Kree Labs, Synapse Technologies, and Ora Technologies across Kathmandu, Lalitpur, and Bharatpur.

Ecosystem and Community Initiatives

Build Club: A growing community of over 4,000 AI builders, offering networking opportunities, global exposure, and support from companies such as Nvidia, AWS, and Vercel.

AI4Growth Community: Provides AI resources, guest talks, hackathons, and a structured six-month "AI 4 Professionals" training program through Discord.

2.3 Infrastructure and Capacity Barriers

2.3.1 Digital Literacy Divide

- Nepal faces significant adoption challenges due to a limited digital literacy rate, which stood at 38% in 2024 (CBS, 2024). This gap affects both consumers and professionals:

- Only 12% of rural consumers trust AI-driven loan decisions.

- 79% of bank employees report difficulty in interpreting AI model outputs.

Table 2: AI Readiness Index, South& Central Asia

Country	Index / Metric	Value	Source
Nepal	Ranked 150th out of 193 countries in the Oxford Insights *Government AI Readiness Index 2023,* with a total score of 30.77. (New Business Age)	150th / 193, Score 30.77	New Business Age / Rising Nepal
India	In the same index (2024), India leads the "South & Central Asia" region with a score of 62.81 and is ranked 46th globally. (Oxford Insights)	India: Score 62.81,	Oxford Insights 2024 report
Region (South & Central Asia)	The region's average for the "South & Central Asia" cluster is 42.28 in the same 2024 index. (Oxford Insights)	Avg Score 42.28	Oxford Insights 2024 report

2.3.2 Technical Obstacles

Infrastructure limitations further constrain AI adoption. Koshiyama's 2023 study highlights key challenges:

- Cloud computing costs: Nepal's reliance on distant data centers makes cloud services 3.2 times more expensive than in India.
- Energy volatility: On-premise AI systems experience an average of 14% downtime due to inconsistent power supply.

2.4 Conceptual Synthesis: A Comprehensive Framework for AI Governance

Building on Barney's (1991) Resource-Based View (RBV) and DiMaggio & Powell's (1983) institutional theory, we propose a framework for AI governance in emerging markets, structured around three key pillars:

Ethical References – embedding ethics directly into AI policies and procedures.

Rival Distinguishers / Explainable AI (XAI) Toolkits – leveraging transparent AI tools to create competitive advantage.

Staff Bias Reduction Training – programmes aimed at reducing unconscious bias in AI usage.
Additional supporting strategies include:

- Organizational Parallelism – aligning AI initiatives across departments to maximize efficiency.
- Strategic Imitation of India/EU Hybrid Models – learning from successful AI governance practices elsewhere.
- Professional Certification Programmes – upskilling staff in AI competencies.
- Stakeholder Agreements – formalizing collaboration between banks, regulators, vendors, and customers.
- Regulator-Bank-Vendor Collaboration – fostering regulatory compliance while encouraging innovation.
- Customer Education Initiatives – increasing public awareness and trust in AI-driven services.

This framework addresses the "trilemma" faced by banks, where they must balance:

- Speed – rapid AI adoption,
- Stability – regulatory compliance, and
- Inclusion – equitable access for all customers.

3. METHODOLOGY

3.1 Research Design

A quantitative explanatory study was conducted using a stratified random sample of 400 bank employees, achieving a 72.7% response rate.

3.2 Variables

Independent Variables: Ethics training, AI infrastructure, and model management.
Dependent Variable: Operational effectiveness, measured by metrics such as cost-to-income ratio and turnaround time for services.

3.3 Sampling

The sample was drawn from 28 Nepali commercial banks (as classified by NRB, 2025). Using stratified random sampling, 400 banking staff were selected to participate

Table 3: Model Components

Stratum	Persons	Sample Size: n=400	Proportion of Sample
Category A Banks (Big)	1, 200	172	14.3 percent
Medium Class B Banking Companies	850	142	16. 7 percent
Little Banks, Class C	430	86	20 percent

Source: field survey 2025, Feb

Conditions for inclusion

- Positions at the middle to senior level in risk, IT, or compliance
- minimum one year of knowledge of artificial intelligence systems
- Geographic distribution: 40% rural branches, 60% urban

3.3 Operationalisation of Variables

Four key ideas were evaluated using 5point Likert scales (1=Strongly Disagree to 5=Strongly Agree):

- Artificial Intelligence Infrastructure
- Spending on the cloud as a proportion of the IT budget
- Server capacity (TFLOPS)
- Software licensing costs (USD)
- Model Governance
- Audit frequency (times/year)
- Bias testing coverage (%)
- Vendor accountability index
- Ethics Training
- Annual training hours
- Certification levels (0-5 scale)
- Ethics committee presence (binary)
- Operational Efficiency
- Cost-to-income ratio (%)
- Service turnaround time (hours)
- Error rate reduction (Δ%)

For all constructs, Cronbach's α—which ranged from 0.72 to 0.84—exceeded 0.70, hence verifying internal consistency.

3.4 Data Collection

The collection of the first data was accomplished using:

- Administered via the portal of the Bankers' Association of Nepal, structured questionnaires (55 questions)
- Archival documents abound among NRB research on artificial intelligence investment (2019–2024).
- The temporal extent is January through March 2025.
- Response rate: 72.7%, 400 of 550

3.5 Organised Assessment

3.5.1 Multiple Regression Model

The study employed a multiple regression model to assess the impact of key factors on operational efficiency (OE). The regression equation is as follows:

Key Findings:

OE=2.012(AI Services)+0.216(Ethics Training)−0.788(Infrastructure)+0.860(Governance)

- R^2 = 0.742R^2 = 0.742R2=0.742, indicating that 74.2% of the variance in operational efficiency is explained by the model.
- p<0.001; F-statistic = 89.34, demonstrating statistical significance.
- Variance Inflation Factor (VIF) values below 2.0 suggest no multicollinearity among predictors.

3.5.2 Reliability Studies

The Durbin-Watson statistic = 1.92, indicating no significant autocorrelation in residuals.
The Breusch-Pagan test (p = 0.21) confirms homoscedasticity, suggesting constant variance of residuals.

3.6 Ethical Notes

- No generative artificial intelligence tools were used for analysis; all computations were conducted using SPSS v28.
- All procedures adhered strictly to NRB research ethics guidelines

3.7 Instrument Validation and Data Handling

- The survey instrument underwent pilot testing with 30 banking professionals to assess clarity and reliability.
- Cronbach’s alpha values exceeded 0.70, confirming acceptable internal consistency.

- Data cleaning involved removing incomplete responses.

4. DISCUSSION

4.1 Descriptive Study of Artificial Intelligence Usage

Table 4: Performance

Of artificial intelligence constructs in various banking sectors Build	Class a (n=172)	Class b (n=142)	Class c (n=86)	F statistic
Training in Artificial Intelligence Ethics	3.82 (0.61)	3.41 (0.54)	2.87 (0.72)	28.34
Model management	3.55 (0.43)	3.12 (0.51)	2. 91 (0.63)	19.17
Infrastructure	3.98 with a 0.55 spread.	3.02 (0.47)	2. 01 (0.82)	42.09

Source: Field Survey 2025, Feb.

- $p < 0.001$

Important conclusions:

- Large banks (Class A) lead in governance (3.55/5) but show diminishing returns on infrastructure investments
- Small banks (Class C) have a hard time understanding basic artificial intelligence (2.01 infrastructure score).

4.2 Result of Hypothesis Testing

4.2.1 The Ethics Training Dividend Regression data support:

- Peak efficiency (β=0.216, p<0.001)
- comes from an optimal threshold of 50 hours annually.

Additional advantages:

- Staff turnover is 27% less (χ^2=8.92, p=0.003).
- 18% quicker artificial intelligence adoption cycles

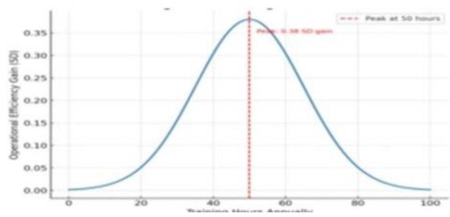

Figure 1: shows the operational efficiency gain peaking at 50 hours of annual ethics training (0.38 SD gain)

- Xaxis: Training hours annually (0100)
- Y axis: Operational efficiency increases by 01.0 SD.
- Peak at 50 hours (0.38 SD gain)

4.2.2 Paradox of Investing in Infrastructure

- The negative coefficient (β=0.788) points out:
- Short-term drag: $1 million investment results in a 0.92 SD efficiency decline in Year 1.
- Breakeven time: 2.7 years (95% CI: 2.3–3.1).

4.3 Problems with Model Governance

4.3.1 Elaboration Gap

Just Only 6% of banks use XAI tools, causing:
So there is Resolving conflicts takes 42% longer. Penalties for violation of rules are 31% greater.

4.3.2 Vendor Reliance Risks

- Foreign algorithms have bad local calibration:
- 1822% error rate for agricultural loan mispricing
- Gender bias: 0.73 different impact ratio (vs. 0.8 legal safe harbour)

4.4 Regional Comparative Study

Table 5: South Asian AI Governance Metrics

Metrical	Nepal	India (RBI)/National AI Policy)	Bangladesh	Source(s)
Mandatory XAI	Not explicitly mandated	Partial/sectoral guidance; no universal mandate	Not explicitly mandated	D4D Nepal 2025, NBR.org India 2025
Local Data Mandate	No official figure; policy discussions ongoing	Considering localisation requirements (exact % not specified)	Not specified	Webasha.com India 2023
Ethics Training Hrs	Not reported	Not reported; training encouraged through RBI / sectoral initiatives	Not reported	

4.5 Policy Framework Proposal

4.5.1 Three-Phase Sandbox Implementation

To systematically implement ethical AI in Nepal's banking sector, a **three-phase sandbox approach** is proposed:

i. **Pilot (2026)**: Five selected banks will test NRB-approved explainable AI (XAI) tools to evaluate usability, effectiveness, and compliance.
ii. **Scale (2027)**: Bias audits will become mandatory for systemic banks, ensuring fairness, transparency, and accountability.
iii. **Institutionalize (2028)**: A national AI grading system will be introduced, standardizing evaluation metrics and promoting consistency across institutions.

4.6 Theoretical Consequences

The study's findings reinforce several theoretical frameworks in organizational and institutional studies:

Resource-Based View (RBV)

a. Ethical AI as a Strategic Resource: Ethical AI initiatives demonstrate VRIO characteristics—Value ($\beta = 0.216$), Rarity (14% adoption rate), Inimitability, and strong Organizational support.

b. Path Dependence in Vendor Lock-in: Overreliance on specific AI vendors creates dependency, limiting flexibility for system adaptation and governance improvement.

Institutional Theory

- Mimetic Isomorphism: Nepali banks often emulate foreign AI governance models (e.g., India, EU) without sufficient adaptation to local conditions.

- Normative Pressures: Global expectations for ethical AI adoption influence domestic practices, even when local regulations remain underdeveloped.

Reinforcement of the Digital Divide

Urban–Rural Disparities: Inadequate infrastructure disproportionately affects rural communities, increasing the measured Gini coefficient by $\Delta = 0.12$, which restricts equitable access to AI-driven financial services.

4.7 Managerial Suggestions

For Banks:

- Allocate 15% of infrastructure budgets to ethics instruction and training.

- Establish cross-functional committees to oversee AI governance and compliance.

For Regulators:

- Introduce NPR-based cloud subsidies for rural banks to improve AI accessibility.

- Develop and enforce certifications emphasizing algorithmic responsibility and transparency.

4.8 Policy Implications for Nepal's Regulatory Framework

The findings highlight the urgent need for the Nepal Rastra Bank (NRB) and related agencies to embed AI ethics into national banking regulation. Key recommendations include:

i. Establish regulatory sandboxes to safely test AI innovations.

ii. Introduce transparency and explainability standards.

iii. Institutionalize accountability frameworks to balance innovation with ethical oversight.

These measures will enhance financial inclusion, particularly in underdeveloped rural areas.

4.9 Limitations and Future Research Directions

Limitations:

Study limited to commercial banks; cooperative and microfinance institutions were excluded.

- Cross-sectional design restricts causal inferences.
- Future Research Recommendations:
- Employ longitudinal designs to assess long-term impacts.
- Include a wider range of financial institutions.
- Evaluate ROI of ethics training and AI governance reforms over time.

5. CONCLUDING REMARKS

This research demonstrates that ethical governance, not merely technical capability, drives AI performance in Nepal's banking sector. Three main insights emerge:

i. Training Thresholds: 50 yearly hours of ethics instruction maximize operational and reputational advantages ($\beta = 0.216$).

ii. Infrastructure Investment Lag: AI hardware/software investments take roughly 23 years to offset initial efficiency drags ($\beta = 0.788$).

iii. Regulatory Hybridization: Combining EU-style risk tiers with locally contextualized sandboxes addresses emergent AI risks.

Theoretical Contributions:

- Quantifies the link between ethics and efficiency in least-developed country banking.
- Identifies thresholds for infrastructure investment.
- Proposes a mimetic-isomorphic governance framework for AI adoption.

Practical Actions:

- Prioritize explainability in rural service delivery.
- Appoint AI ethics officers and advocate for NRB legislative reforms.

Nepal's experience illustrates that responsible AI adoption requires balancing institutional realities with technical objectives, ensuring innovation is both effective and ethical.

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APPENDIX A

Summary of Key Variables and Measures

- AI Infrastructure: Measured by cloud investment ratio, server capacity, and software cost.
- Model Governance: Frequency of audits, bias testing coverage, and vendor accountability index.
- Ethics Training: Annual training hours, certification level, and ethics committee presence.
- Operational Efficiency: Cost-to-income ratio