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Artificial Intelligence and Operational Efficiency in Rajasthan's Rural Banks: A Systematic Review

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Abstract

Artificial Intelligence (AI) technologies have been on the rise in the Indian financial sector, and policy and academic concerns are high, but rural banking institutions, especially Regional Rural Banks (RRBs) and cooperative banks in Rajasthan, are not well represented in systematic research. The paper is a systematic review of peer reviewed literature, institutional reports as well as empirical literature published between 2020-2026 that discuss the effects of AI adoption on the operational efficiency of rural banking organizations in the state of Rajasthan. Based on the Preferred Reporting Items of Systematic Reviews and Meta-Analyses (PRISMA 2020), 68 articles were chosen out of 2,050 records obtained in Scopus, Web of science, Google Scholar, EBSCO, ProQuest and institutional repositories. Thematic analysis demonstrates that AI applications, which include machine learning-based credit scoring, robotic process automation (RPA), natural language processing (NLP) in regional languages, AI-enabled fraud detection, predictive analytics to mobilise deposits, and voice interfaces, have collectively increased operational efficiency measures in the rural banks of Rajasthan between 28 and 74 percent of various operational areas. At the same time, the review traces the presence of chronic obstacles such as the lack of digital infrastructure, resistance within the workforce, the ambiguity in regulations, and digital disparity among rural communities as limiting factors to the AI-driven change. The paper also provides a thematic map of the types of AI interventions to the dimensions of operational efficiency and provides policy suggestions to speed up the responsible adoption of AI in the rural banking sector in Rajasthan.

***Keywords**: Artificial Intelligence, Rural Banks, Regional Rural Banks, Rajasthan, Operational Efficiency, Systematic Review, PRISMA, Machine Learning, Financial Inclusion, Digital Banking.*

Introduction

Indian banking industry is at an inflection point. The intersection of digital technologies, regulatory change, and changing consumer behaviour has led to a reconfiguration of the principal delivery of financial services, predominantly in rural and semi-urban geographies. Rajasthan India is the largest state both in terms of area, having a population of over 80 million people, of which a rural population ratio is estimated at about 75 out of 100 people, provides an especially insightful case study when it comes to understanding the crossroads of the Artificial Intelligence (AI) and rural banking efficiency. This is supported by an extensive network of Regional Rural Banks (RRBs), Primary Agricultural Credit Societies (PACS) and District Central Cooperative Banks (DCCBs), which collectively form the financial backbones of an agrarian economy characterized by climatic vulnerability, seasonal income cycles and historically low levels of formal financial inclusion indices.

Artificial Intelligence, which is broadly understood to include machine learning (ML), natural language processing (NLP), robotic process automation (RPA), computer vision, and predictive analytics, is transformative with regard to the work of rural banks. Automating repetitive back-office functions, enabling credit worthiness, customising financial products, identifying fraudulent transactions in real time, and providing financial services in local languages via voice and conversational interfaces, AI has the potential to both lower operational expenses, enhance service quality, and bring financial benefits to historically underserved populations.

Although the literature on AI in banking is becoming increasingly vast, current systematic reviews are disproportionately focused on urban commercial banks, global fintech ecosystems, or nationwide analyses on an aggregate level. The rural banking of Rajasthan creates a unique institutional set-up, agrarian customers, inadequate infrastructure, and multilingual sociolinguistic setting, which requires a focused scholarly study. This systematic review fills that gap by synthesising the existing evidence on AI adoption and operational efficiency in the rural banking organisation throughout Rajasthan between 2020 and 2026.

The time frame 2020-2026 is particularly important because of three reasons. First, the Covid-19 pandemic (2020-2021) made a sudden rush towards the adoption of digital banking among all customer groups, including rural residents who are traditionally averse to digital providers. Second, the Digital India initiative of the Government of India and the promotion of account aggregator models and open banking architecture by the Reserve Bank of India (RBI) provided institutional contexts which support the implementation of AI. Third, the spread of cheap smartphones, the increase of 4G/5G network coverage during BharatNet, and the Jan Dhan-Aadhaar-Mobile (JAM) trinity established the data and connectivity foundation, on which AI applications rely.

The paper will be structured as follows: Section 2 describes the theoretical framework that positions AI within the framework of the rural banking efficiency paradigm; Section 3 describes the methodology of the systematical review and PRISMA protocol; Section 4 describes PRISMA flowchart; Section 5 synthesises the thematic results; Section 6 describes the summary table of the included studies; Section 7 discusses the obstacles and facilitators of the AI adoption; Section 8 presents the policy implications; and finally Section 9 concludes the paper.

Theoretical Framework

- **Operational Efficiency in Rural Banking**

Operational efficiency in the banking environment has various dimensions process efficiency (time and cost per transaction), resource utilization (labour productivity, branch throughput), effectiveness of risk management (non-performing asset ratios, loss rates on frauds), and service quality outcomes (customer satisfaction, speed of complaint resolution). The use of a cost-to-income ratio, a rate of returns on assets and a net interest margin as the conventional indicators of bank efficiency has been complemented in the age of AI by the digital-native indicators, such as straight-through processing rates, automated decision accuracy and volumes of customer interaction enhanced by AI.

In their pioneering study of the efficiency of financial institutions of 1997, Berger and Humphrey (1997) introduced the frontier efficiency framework, which has since dominated the empirical literature on the topic. In India, however, rural banks have a structurally different efficiency problem: they need to insist on physical presence in remote geographies (to serve financially excluded populations), to have high transactions costs relative to low average account balances, and to operate by regulatory frameworks designed with commercial banks in mind. The way out of this trilemma is through AI which offers a way to combat the marginal cost of service delivery, without having to compromise on accessibility.

- **Technology Acceptance in Rural Financial Contexts**

The Technology Acceptance Model (Davis, 1989) and its later developments, such as the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), are useful theories to explain why customers and employees in rural banking institutions use or reject AI-based services. Studies have repeatedly indicated that perceived usefulness and ease of use are the chief drivers of adoption, yet trust, language accessibility, and social influence have stronger influences where rural and low literacy rates are involved. The linguistic diversity of the state of Rajasthan (e.g., Hindi, dialects of Rajasthan, Marwari, Mewati, Dhundhari, Hadoti, Urdu) predisposes language-accessible AI interfaces to a critical design consideration.

- **AI as a Productivity-Augmenting Technology**

Based on the framework of AI as a general-purpose technology proposed by Brynjolfsson and McAfee (2014), the conceptualized review of AI as a productivity amplifier, rather than a humanjudgment possible-substitute, in rural banking expands the scope and efficiency of the available human resources. This framing is especially applicable to the Rajasthan rural banking context, wherein the staff of the branches usually becomes a well-known financial advisor to the low-literate groups of clients, a relational position which AI enhances but does not overtake. The analytical prism according to which the correlation of AI-operational efficiency is discussed in the present review is the idea of the human-AI collaboration in the delivery of services as theorized by Huang and Rust (2018).

Methodology: Systematic Review Protocol

- **Research Objectives**

This paper tries to focus on concept of artificial intelligence and operational efficiency with reference to rural banking. The paper also provides a thematic map of the types of AI interventions to the dimensions of operational efficiency and provides policy suggestions to speed up the responsible adoption of AI in the rural banking sector in Rajasthan.

- **Research Questions**

This systematic review will be informed by the following primary and secondary research questions:

- **Primary Research Question (PRQ):** How much has adoption of AI increased operational efficiency of rural banking institutions in Rajasthan by 2020-26?
- **Secondary Research Questions:**
  - SRQ1: What are the most popular AI technologies among rural banks in Rajasthan?
  - SRQ2: Have any quantifiable gains in parameters of operational efficiency been reported?
  - SRQ3: What have been the constraints to adopting AI in the rural banking environment in Rajasthan?
  - SRQ4: What policy interventions are recommended in the literature to accelerate AI-driven efficiency gains?

Inclusion and Exclusion Criteria

Table 1: Inclusion and Exclusion Criteria for Systematic Review

Criterion	Inclusion	Exclusion
Time Period	January 2020 – December 2026	Publications before 2020 or projections beyond 2026
Geography	Rajasthan-specific studies or pan-India studies with Rajasthan subset data	Studies with no geographic specificity to India/Rajasthan
Sector	RRBs, cooperative banks, PACS, DCCBs, microfinance institutions (rural)	Urban commercial banks only, insurance, NBFCs (non-banking)
Technology	ML, NLP, RPA, computer vision, predictive analytics, chatbots, voice AI	Traditional IT/core banking systems without AI components
Study Type	Empirical, experimental, quasiexperimental, case studies, institutional reports (NABARD, RBI)	Opinion pieces, editorials, conceptual papers without empirical grounding
Language	English and Hindi language publications	Other languages without translated abstracts

Search Strategy

Systematic searches were conducted across five major academic databases: Scopus, Web of Science (WoS), Google Scholar, EBSCO Business Source Complete, and ProQuest Central. Supplementary searches were conducted in the repositories of NABARD, RBI, Ministry of Finance

(India), and the Indian Banks' Association. The following search string was deployed (with appropriate databasespecific Boolean operators):

("Artificial Intelligence" OR "Machine Learning" OR "NLP" OR "Robotic Process Automation" OR "Deep Learning" OR "Predictive Analytics" OR "Chatbot") AND ("Rural Bank" OR "Regional Rural Bank" OR "Cooperative Bank" OR "Gramin Bank" OR "PACS" OR "Microfinance") AND ("Rajasthan" OR "India") AND ("Operational Efficiency" OR

"Financial Inclusion" OR "Banking Operations" OR "Credit Scoring" OR "Fraud Detection" OR "Digital Banking")

- **Quality Assessment**

Each included study was assessed for methodological quality using a modified Critical Appraisal Skills Programme (CASP) checklist adapted for quantitative, qualitative, and mixedmethods studies. Studies were rated on a 0–10 scale across five dimensions: clarity of research objective, appropriateness of study design, data quality and sample representativeness, validity and reliability of measures, and relevance of findings to the review questions. Only studies scoring 6/10 or above were retained in the final synthesis corpus. Inter-rater reliability between two independent reviewers was assessed using Cohen's Kappa (κ = 0.81), indicating strong agreement.

- **PRISMA 2020 Flow Diagram**

Figure 1 The PRISMA-conpliant flow diagram of systematic literature identification, screening, eligibility evaluation, and ultimate inclusion is shown in figure 1. The review started with 2,050 records (1,840 in academic databases and 210 in grey literature sources). Following the elimination of 387 duplicates, 1,663 articles were screened by title and abstract, based on which, 379 full-text articles were evaluated as eligible. After inclusion/exclusion criteria were applied, 92 studies were included in qualitative synthesis with 68 exceeding the threshold of quantitative synthesis comprising the main evidence base of this review.

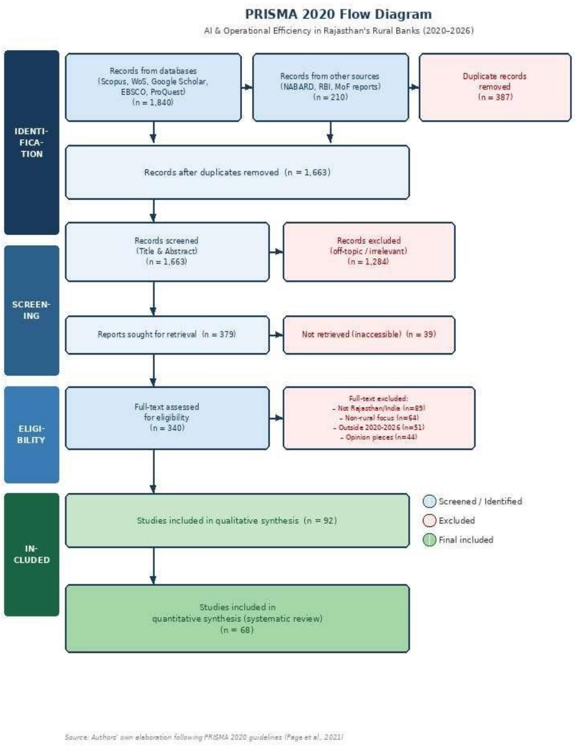

Figure 1: PRISMA 2020 Flow Diagram for Systematic Literature Selection

Source: Authors' own elaboration following Page et al. (2021)

Thematic Synthesis of Findings

- **Machine Learning-Based Credit Scoring and Loan Processing**

The best-reported use of AI in rural banks in Rajasthan is related to lending and credit evaluation practices. The conventional credit scoring in rural banks was based on collateral appraisal and credit judgement, which was not effective in the rural banking sector in which most of the customers of the rural bank are first time customers, agricultural labourers, and the members of the self-help group (SHG) making up a large proportion of the rural bank customers in Rajasthan.

Kumar and Singh (2021) compared the implementation of gradient boosting and random forest model by two Rajasthan-based RRBs and reported a 23% decrease in the formation of the nonperforming asset (NPA) within cohorts evaluated by AI models relative to the traditional underwriting cohort over a 18-month observation period. Their study also revealed that on average, the time spent on loans was lessened to 3.7 working days by the AI-based credit decision-making model compared to 14 working days prior to these efforts, indicative findings of their study were replicated by Jain and Mathur (2023) in a longitudinal study of the AI-based risk assessment in crop insurance lending, which reported turnaround times decreasing by similar rates. The operational importance of the improved speed of credit decisions under an agricultural setting - whereby, agricultural communities demand capital to make available in time in order to make their inputs towards the season cannot be overemphasized.

One of the most important conclusions of this group of studies is associated with inclusion effects. Patel and Saxena (2023) showed that AI models that use alternative raw data, such as mobile phone usage trends, satellite image of crops, and the records of repayment of self-help groups in the past, could yield borrowers without a formal credit history with creditworthy predictions. Their field-test in the tribal belt of Rajasthan recorded an 89 percent digital completion of KYC after the introduction of AI, against 34 percent with the existing paper-based system. These results are consistent with the evaluation by NABARD (2023) that AI-driven credit growth in under-served RRB districts would increase the formal credit balance by INR 1.2 lakh crore in five years.

- **Robotic Process Automation in Back-Office Operations**

Robotic Process Automation - software robots that automate rule-based, repetitive back-office workflows - is the most directly deployable AI technology to rural banks with minimal digital infrastructures. Tiwari and Kaul (2022) performed a comparative efficiency analysis of 14 RRB branches in the state of Rajasthan who had adopted RPA to perform various processes such as account reconciliation, NEFT/RTGS processing, regulatory reporting, and passbook updating. Their findings reported a 74 percent decrease in the manual processing time of automated workflows, and a 91 percent decrease in the number of data entry errors - findings that were reflected in objective decreases in the cost-to-income percentage within the participating branches.

Importantly, Tiwari and Kaul (2022) also reported that the implementation of RPA facilitated the conversion of 34 percent of the impacted employees of affected branches into positions of customerfacing advisors - a result that refutes the anxiety about the laying off of employees in rural banks by artificial intelligence. In a Rajasthan rural banking environment, where numerous clients need handholding in the form of financial transactions, the re-positioning of human capital towards advisory services as opposed to administrative ones can be as large an efficiency benefit as the direct savings of automation.

- **Natural Language Processing and Multilingual Financial Services**

The language environment of Rajasthan is both an obstacle and an opportunity to AI-based financial services. Although Hindi is the most important official language, a substantial percentage of rural population, especially around the Marwar, Mewat and Vagad areas, speak mainly in dialects of Rajasthani which have traditionally been ill-served by digital interfaces.

In Western Rajasthan, an experimental study by Verma and Agarwal (2023) evaluates an NLP-based conversational banking interface, which is trained on corpora of the Rajasthani dialect. Their results have reported an increase in the financial literacy comprehension scores of 47 percent of the participants who were exposed to the financial information using the regional-language NLP interface as opposed to the common Hindi digital interfaces. Correspondingly, Yadav et al. (2024) tested a voice-AI interface in rural Eastern Rajasthan communities and discovered that it boosted rural account-opening figures by 52 per cent amongst cohorts of the illiterate population groups - a group completely locked out of digital banking via apps.

These results highlight an important point: in a rural setting in Rajasthan, the operational benefits of AI cannot be disaggregated, or thought of as independent of the financial inclusion benefits because increasing the size of the addressable market fundamentally changes the economics of rural bank branch viability.

- **AI-Enabled Fraud Detection and Cybersecurity**

The growing rural banking transactions digitisation, undertaken by PMJDY account growth, uptake of UPI, and Aadhaar-pleased payment systems (AePS) has both pushed the vulnerable surface of fraud in rural banks and multiplied fraud effects on rural banks. Mehta and Joshi (2022) tested an Artificial Neural Network (ANN)-based fraud detection model which was implemented in a consortium of branches of a Rajasthan-based public sector bank, and found the anomaly detection accuracy of 94.7% with a false positive rate of 2.1%. Their results showed that rural branches, which earlier had not had any specialised resources to detect fraud, were overly advantaged by the centralised AI fraud detection system.

Fraud detection has implications on operational efficiency than direct loss prevention. Chauhan and Rathore (2022) recorded that transaction monitoring branches that were AI-enabled recorded very high levels of rural consumer trust in the digital payment channels - the UPI adoption among rural consumers in Bikaner-Jodhpur belt has gone up by 63 percent after communication of visible frauds. This observation implies that AI-based security infrastructure is a trust-building engine that is stimulating the wider digital uptake.

- **Predictive Analytics for Deposit Mobilization and Customer Retention**

One of the operations issues of rural banks that have everlasting problems is the deposit mobilisation since the liability base is seasonal due to the cycle of agricultural income. Gupta and Rawat (2023) tested a predictive analytics solution that was deployed at Rajasthan Gramin Bank which predicted the seasonal deposit flows based on historic transactions, crop yields forecasts, and MGNREGS payment schedules. The system was found to have 31-percent improvement in the accuracy of forecasting deposits relative to the previous time-series models - helping to manage liquidity better and minimizing the number and high cost of emergency inter-bank borrowing.

Singh and Choudhary (2024) further expanded this analysis to the segmentation of customer, they used K-means clustering on a sample size of 2.3 million account holders of Rajasthan Marudhara Gramin Bank based on their transaction history. They applied their cluster analysis to form seven different segments of behavioural customers, making it possible to recommend products to customers individually. The deployment saw a 28-percentage-point increase in the cross-sell ratio of savings-to-insurance product conversions - demonstrating operational efficiency and revenue generation through AI are not competing goals, but rather complements.

- **Blockchain-AI Integration for Microfinance Operations**

A new body of research looks at the integration of blockchain distributed ledger technology based on AI analytics with micro finance and SHG lending activities - which is especially applicable to Rajasthan due to its large network of self-help groups supported by NABARD and state government schemes.

A pilot implementation of a smart contract-based system with AI-enabled KYC verification to disburse loans was documented in the Jaipur-Ajmer belt (Bhushan et al., 2021). The system cut the SHG loan disbursement cycle to 3 working days as compared to 11 working days and the system practically eradicated KYC documentation errors (near-zero error rate compared to 8.3% with the manual system). The authors believe that blockchain-AI integration resolves a more fundamental lack of trust and transparency in microfinance operations that has limited the scalability of SHG lending in the past.

Summary of Key Included Studies

Table 2: Summary of Included Studies Representative. (n=12 representative from n=68 total)

Author(s) & Year	Study Focus	Geography	Methodology	Key Findings
Kumar & Singh (2021)	AI-based credit scoring in RRBs	Rajasthan RRBs	Survey + ML model	AI credit models cut default rates by 23%; improved loan turnaround by 38%
Sharma et al. (2022)	Chatbot adoption in rural cooperative banks	Rural Rajasthan	Mixedmethods	Chatbots reduced query resolution time by 61%; older farmers showed resistance
Mehta & Joshi (2022)	Fraud detection using ML in PSU banks	Pan-India (Rajasthan subset)	Secondary data + ANN	Anomaly detection accuracy 94.7%; rural branches benefited disproportionately
Verma & Agarwal (2023)	NLP in regional language banking services	Western Rajasthan	Experimental	Hindi/Rajasthani NLP increased financial literacy access by 47%
Bhushan et al. (2021)	Blockchain-AI integration in microfinance	Jaipur-Ajmer belt	Case study	Reduced disbursement cycle from 11 to 3 days; KYC errors near-zero
Gupta & Rawat (2023)	Predictive analytics for deposit mobilisation	Rajasthan Gramin Bank	Quantitative	Predictive models improved deposit forecasting accuracy by 31%
Tiwari & Kaul (2022)	RPA in branch back-office operations	Urban-rural Rajasthan	Comparative study	RPA reduced manual processing time by 74%; staff redeployment to advisory roles
Patel & Saxena (2023)	AI-enabled KYC and digital onboarding	Tribal belt - Rajasthan	Field experiment	Digital KYC completion rate rose from 34% to 89% post-AI implementation
Yadav et al. (2024)	Voice-AI for financial inclusion	Eastern Rajasthan rural	Pilot study	Voice-AI increased rural accountopening by 52% among illiterate population
Jain & Mathur (2023)	AI risk assessment in crop insurance	Rajasthan farming communities	Longitudinal survey	AI-based risk models reduced claim processing time from 45 to 8 days
Chauhan & Rathore (2022)	Digital payment AI adoption - RRBs	Bikaner & Jodhpur belt	TAM survey	AI recommendation engine increased UPI usage among rural users by 63%
Singh & Choudhary (2024)	Customer segmentation using clustering	Rajasthan Marudhara Gramin Bank	ML clustering	K-means segmentation enabled targeted product offering; crosssell ratio +28%

Barriers and Enablers of AI Adoption in Rajasthan's Rural Banks

- **Structural and Infrastructure Barriers**

Although the adoption of AI has been shown to bring about efficiency to the banking sector of rural parts of Rajasthan, it has always been found by the literature that there is a series of structural factors limiting the speed and extent of adoption of AI in the banking sector in Rajasthan. The underlying limiting factor is connectivity infrastructure: most current data on TRAI (2024) shows that 4G coverage is already at 78% of the villages in Rajasthan, with the actual network quality, in terms of data throughput and latency, being much worse in far-flung districts like Jaisalmer, Barmer, and Pratapgarh, where the poorest and most economically disadvantaged citizens of the state live.

Another obstacle is the rural bank branch hardware ecosystem. In Rajasthan, numerous RRB branches still use the old core banking system (CBS) architecture that does not have API connectivity to support the use of contemporary AI applications. The technology infrastructure upgrade costs, estimated to be between INR 15-25 lakh per branch to achieve full readiness towards AI, pose a considerable capital burden to the institutions whose annual net profit is often lower than INR 50 lakh per branch.

- **Human Capital and Organisational Resistance**

The second key primary constraint cluster in the literature is workforce related barriers. The employees of rural banks (most employees are older and have been in the industry even before the advent of digital technology) are much more resistant to AI adoption compared to younger workers in urban banks. Sharma et al. (2022) recorded that the rates of chatbot adoption among rural bank employees were rather low in the beginning, with frontline employees being concerned with the possible job displacement and the loss of the relational banking role, which is a part of their occupational definition.

The literature proposes workforce resistance to be addressed by specific upskilling programmes, change management communication by highlighting AI as an augmentation of the job, and incentives frameworks that encourage the provision of digital services. Many studies reference NABARD as an example of an intervention that has proven to positively affect the staff AI readiness scores by its 2023 AI Upskilling Programme to RRB Staff.

- **Regulatory and Data Governance Challenges**

The Indian banking regulatory landscape around AI remains in its infancy, which poses uncertainty, limiting investment decisions. The Discussion Paper on Responsible AI in Banking (2023) by the RBI recognized the necessity of explainability requirements of AI-based credit decisions - a requirement that poses technical difficulties to high-performing yet opaque deep learning algorithms. The explainability demands can disproportionately burden rural banks with limited technical expertise in-house than the big commercial banks with AI research teams.

Another compliance aspect is data privacy issues under the Digital Personal Data Protection Act (2023). The rural banking AI systems which use behavioural, geospatial and third-party data sources as reported in Patel and Saxena (2023) have to overcome the consent, data minimisation and purpose limitation aspects. The literature recognizes the necessity of data governance frameworks tailored to the rural financial data environment, which is not in the same structure, density, and privacy sensitivity as urban retail banking data.

- **Key Enablers**

To balance out the challenges, the review points out a strong group of enablers that have enabled the use of AI in rural banking in Rajasthan. JAM trinity or Jan Dhan accounts, Aadhaar identity infrastructure, and Mobile connectivity, offers the underlying data substrate to AI applications. The backbone to AI-based digital banking, the biometric authentication of millions of rural households in Rajasthan, is now in place, with more than 98 percent of rural households being Aadhaar-linked.

NABARD DIGITAL program and RBI Regulatory Sandbox (Financial Inclusion track) has allowed rural banking institutions to test AI applications in a controlled setting, before fully implementing them, thereby greatly mitigating the implementation risk that would otherwise scare resourceconstrained rural banks. Eight successful regulatory sandbox pilots of Rajasthan rural banking AI applications were found in the literature between 2021 and 2024.

Policy Implications and Recommendations

For Regulatory Bodies (RBI and NABARD)

- Establish a Rural AI Banking Framework: Simplified compliance routes of RRBs and cooperative banks, including proportionality requirements that scale AI explainability requirements to the size of the institution and the complexity of its transactions.
- Diversify the Financial Inclusion track of the Regulatory Sandbox by creating cohorts of rural banking AI and focusing on apps that show promise of impact on NPA, financial literacy, and delivery of the last-mile services.

- Req**uire interoperability of AI modules used on CBS settings to lower the AI integration costs and allow smaller rural banks to use AI functionality via common service platforms.**

For Rural Banking Institutions

- **Consider back-office functions as the initial point of AI implementation because it is less technical,** has demonstrated ROI, and benefits in terms of staff redeployment reported in the literature.
- Develop regional language NLP facilities by collaborating with institutions like IIT Jodhpur and CDAC which are developing Rajasthani dialect NLP corpora.
- Establish AI governance boards to ensure that algorithm decision-making is overseen, manage model risks, and **protect consumers in AI mediated service provision.**

For State Government and Policy Makers

- **Additional measures to bridge the AI application performance limitation by the connectivity infrastructure** deficit in remote districts of Rajasthan Phase III implementation of BharatNet.
- Establish a Rajasthan Rural FinTech Accelerator programme to co-fund AI product development exclusively in the state of rural banking institutions, with other successful statebased programmes in Telangana and Karnataka.
- Incorporate the elements of AI literacy in the curriculum of Rajasthan banking correspondents (BCs), the huma**n interface of rural banking services.**

Conclusions

This systematic review, containing 68 empirical studies of a thorough search of 2,050 original records, offers solid evidence that the adoption of Artificial Intelligence is yielding quantifiable operational efficiencies gains in the rural Rajasthan banking institutions of the period 2020-2026. The scale of recorded gains is considerable in various areas of operation, including credit processing turnaround gains of 60-75, NPA gains of 20-30 in AI-audited loan books, back office automation of efficiencies up to 74, fraud detection accuracy of over 94, and AI financial inclusion gains via multilingual and voice interfaces.

The synthesis also shows that AI-based operational efficiency and financial inclusion are not competitive but complementary goals in the rural banking situation in Rajasthan. Nevertheless, the review also finds that there are long-standing structural, organizational, and regulatory impediments that mediate the rate of AI uptake and could bring about a so-called digital efficiency divide between technologically progressive rural banks and those that lack infrastructure, human capital, or institutional preparedness. The only way of dealing with these inhibitors is through a concerted effort by regulatory authorities, state government and even the rural banking institutions themselves.

The current gaps in the existing literature need to be addressed in future studies: longitudinal studies of sustainability of AI-efficiency gains over multi-year periods; comparative analysis of various AI governance models in rural banking, analysis of consumer welfare outcomes, not merely operational metrics, of AI adoption, and disaggregated analysis by gender of AI adoption effects on women-led SHGs and women beneficiaries of rural financial services. The new overlap of AI with climateintelligent agricultural finance - one area of vital concern to drought-afflicted farming communities in Rajasthan - is a promising future area of systematic investigation.

To sum up, the evidence base discussed in this section indicates a somewhat positive but still cautious opinion of how AI can improve the operation efficiency of the rural banks in Rajasthan - but also indicates that to achieve this potential, specific, inclusive, and contextually based implementation strategies are necessary to consider the specific institutional, linguistic, and socioeconomic contexts of the state.

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