

Responsible AI Adoption in Nepalese Banking: A Structured Review

Rishi Dhital

Academia International College,

Nepal

rishi.dhital@gmail.com

ORCID: 0009-0007-8525-3670

Abstract—Artificial intelligence (AI) is becoming more common in Nepalese banking, where it supports customer service, fraud monitoring, credit assessment, personalized services, investment analysis, and internal decisions. Yet the evidence is scattered across journal articles, theses, policy documents, institutional reports, and review papers. This structured review synthesizes 20 unique sources from an initial register of 31 records. After three duplicate, parallel-language, or incomplete records were removed or consolidated, 28 records were screened and eight were excluded for limited relevance or insufficient evidence. The final set included Nepal-specific studies, government and regulatory documents, comparative research, and contextual sources. The evidence indicates that AI can improve decision speed, credit scoring, service automation, personalization, and investment analysis, although the reported benefits vary by application and study quality. It also identifies persistent weaknesses in model transparency, validation, vendor oversight, data privacy, and responsibility for harmful decisions. Employees are often comfortable with ordinary digital tools but less able to explain AI systems or challenge their outputs. Customer satisfaction and financial inclusion depend not only on convenience but also on security, understandable explanations, digital skills, accessible design, and continued human support. Overall, AI adoption is advancing faster than the arrangements needed to govern its risks. The article therefore proposes a practical framework based on risk classification, data and model checks, clear human authority, staff training, customer protection, and continuous monitoring. AI can strengthen Nepalese banking only when technical development and responsible governance progress together.

Keywords—artificial intelligence; AI adoption; responsible governance; Nepalese banking sector; customer trust; workforce readiness; financial inclusion

I. INTRODUCTION

Artificial intelligence is becoming part of routine financial work. Banks use it to automate repetitive tasks, flag unusual transactions, support lending and investment decisions, tailor products, and communicate through digital channels. These applications may shorten processing times, improve consistency, and extend service availability. They also shift part of the decision process from employees to computer models and, in some cases, to external technology providers. AI adoption is therefore not only a technical choice. It raises questions about responsibility, fairness, staff capability, and public trust.

Nepalese banking provides a useful setting for examining these questions. Digital payments and online banking are expanding, but access and confidence remain uneven across locations and customer groups. Internet quality, income, language, digital skills, and familiarity with automated services continue to shape how people use banking technology. Recent Nepalese research discusses chatbots, fraud detection, automated credit scoring, personalized

recommendations, investment analysis, and AI-supported human-resource practices. It also raises concerns about privacy, cybersecurity, bias, vendor dependence, job insecurity, unclear automated decisions, and the loss of human judgment [1]–[6].

The literature does not yet form a consistent body of evidence. Employee studies and customer studies often address different outcomes, while other publications focus on digital payments, cybersecurity, microfinance, or human-resource management. Research quality also varies. Some studies use relatively large samples; others are small and exploratory. Most are cross-sectional and rely on self-reported perceptions. In several cases, claims in the discussion do not fully match the statistics shown in the tables. Policy documents set expectations for institutions, but they do not demonstrate that those expectations have been implemented across the sector. A balanced review must therefore report the positive findings while also examining the limits of the evidence.

This article responds to that need through a structured review of a deduplicated evidence set, with Nepalese banking as the principal financial-sector setting. Direct evidence from Nepalese banks is considered separately from policy, contextual, and comparative sources. Broader studies on cybersecurity, workforce capability, digital payments, and inclusion help interpret banking-related risks and adoption conditions; they are not treated as direct evidence of AI use or outcomes in Nepalese banks. Greater weight is given to studies that describe their methods clearly and report internally consistent results.

Four questions guide the review. How is AI being used in Nepalese financial services, and what operational value is associated with those uses? What ethical, regulatory, and management problems accompany adoption? How do workforce readiness, customer trust, and digital inclusion influence outcomes? Finally, what practical controls are needed for responsible and sustainable use?

The article contributes in three ways. It first brings together a scattered literature while keeping distinct studies separate, including Lal Mani Pokhrel's 2025 banking study [3] and his 2026 cross-sector study of AI in human-resource practices [4]. It then identifies a recurring gap between rapid technical adoption and the slower development of governance, staff capability, and customer safeguards. On that basis, it presents a practical framework for banks and regulators working in a resource-constrained setting.

II. METHODS

A. Review Design and Scope

This study used a structured integrative review. This method was suitable because the evidence set included many

types of sources: quantitative studies, mixed-method studies, two theses, review papers, a national policy, an AI guideline, a supervision report, a strategic plan, and an editorial. A statistical meta-analysis was not suitable because the studies examined different groups, technologies, variables, and outcomes and did not report results in a form that could be combined reliably.

The review focused on AI adoption, responsible governance, operational performance, staff readiness, customer experience, trust, and inclusion in Nepalese banking and related financial services. Banking studies formed the main empirical focus. Broader workforce, cybersecurity, and digital-inclusion sources were used for their relevance to financial-service delivery and responsible adoption. International studies were included only when they offered a useful theory, method, microfinance example, or inclusion perspective that could reasonably inform Nepalese banking. Foreign studies with little relevance to this focus were excluded.

B. Search and Source Identification

Sources were identified through NepJOL, Google Scholar, Nepal Rastra Bank publications, Government of Nepal websites, and institutional repositories. The search covered four linked areas: technology, sector, country, and outcome. The main reconstructed search string was: ("artificial intelligence" OR AI OR "machine learning" OR algorithm*) AND (bank* OR "financial institution*" OR fintech OR "digital payment*") AND (Nepal OR Nepalese) AND (adoption OR governance OR ethics OR regulation OR trust OR workforce OR customer OR risk). Reference lists and related-source searches were also used to locate policy documents and connected Nepalese studies.

The source set was assembled iteratively and updated before the final synthesis. Screening decisions were documented in a record-level register, and the search strategy was reconstructed from the terms used across the selected platforms. Database-specific hit counts were not used to estimate effects or determine eligibility; every retained record was assessed against the same inclusion criteria.

C. Eligibility, Duplicate Handling, and Screening

Sources were eligible when they examined AI or AI-supported digital systems in banking, finance, financial inclusion, digital payments, workforce management, cybersecurity, or governance. They also had to be directly relevant to Nepal or provide a clear comparison that could help explain the Nepalese setting. Empirical studies, theses, policy and regulatory documents, institutional reports, and substantial review articles were included. Short news items, administrative publication manuals, unrelated journal articles, reference-only extracts, and foreign studies with little comparative value were excluded.

The corrected register contained 31 records. One exact duplicate of the Shrestha and Mahat article [7] was removed. The Nepali-language version of the national AI policy was treated as another language version of the same policy, not as a separate source. One incomplete Shrestha record was combined with its complete source. This left 28 records for screening. Eight records were excluded after the relevance and evidence review. The final synthesis included 20 unique sources. These figures describe the assembled review register, not the total hits returned by the search platforms. Figure 1

presents the complete selection, data-abstraction, and synthesis process; Table I summarizes the composition of the included evidence.

TABLE I. COMPOSITION OF THE INCLUDED EVIDENCE

Evidence category	Number
Nepal-specific empirical or analytical studies	11
Government, regulatory, and institutional documents	4
Global or comparative sources	4
Editorial or broad contextual source	1
Total unique sources	20

D. Data Abstraction and Quality-Sensitive Synthesis

Data abstraction involved extracting the relevant information from each source: publication type, setting, sample, research method, AI application, operational result, governance issue, staff or customer effect, theory, and stated limitation. Sources were grouped as core, supporting, contextual, comparative, policy, or institutional evidence. More weight was given to Nepalese studies that clearly described their methods and reported internally consistent findings. Less weight was given to small studies, secondary discussions, weak statistical designs, and sources with conflicting claims.

The findings were organized into four themes: operational and business innovation; governance and regulation; workforce readiness and organizational outcomes; and customer trust, service experience, and financial inclusion. Conflicting findings were kept in the review instead of being forced into a single conclusion. When the text of a study did not match its tables, the reported table values and the study limitations were given more attention. The synthesis informed the six areas of the practical framework in Section IV-E, as shown in Fig. 1.

III. RESULTS

A. Characteristics and Quality of the Evidence

Most of the 20 included sources were published between 2024 and 2026, indicating that research on AI in Nepalese finance is still at an early stage. The empirical studies covered bank employees, customers, investment managers, technology officers, and workers from several sectors. The largest reported banking survey included 400 professionals, whereas the smallest employee study included 41 respondents. Customer samples ranged from 50 to 386 participants. Four official or institutional documents contributed policy, supervision, and strategic context.

The studies varied substantially in purpose and quality. Shrestha and Mahat [7] examined relationships between AI, employee satisfaction, customer behavior, and profitability among employees of four commercial banks. Pokhrel [3] studied operational performance and governance among 400 banking professionals. Shahi [5] assessed the effects of five AI-supported banking services on customer satisfaction in Karnali Province. Rahman et al. [8] combined questionnaires and interviews to examine AI-supported investment work in five commercial banks. Khadka et al. [9] considered AI-based customization and social innovation. The theses by Shrestha [10] and Dhakal and Acharya [11] add useful evidence on customers and digital transformation, but their findings require caution because of limited samples and statistical inconsistencies.

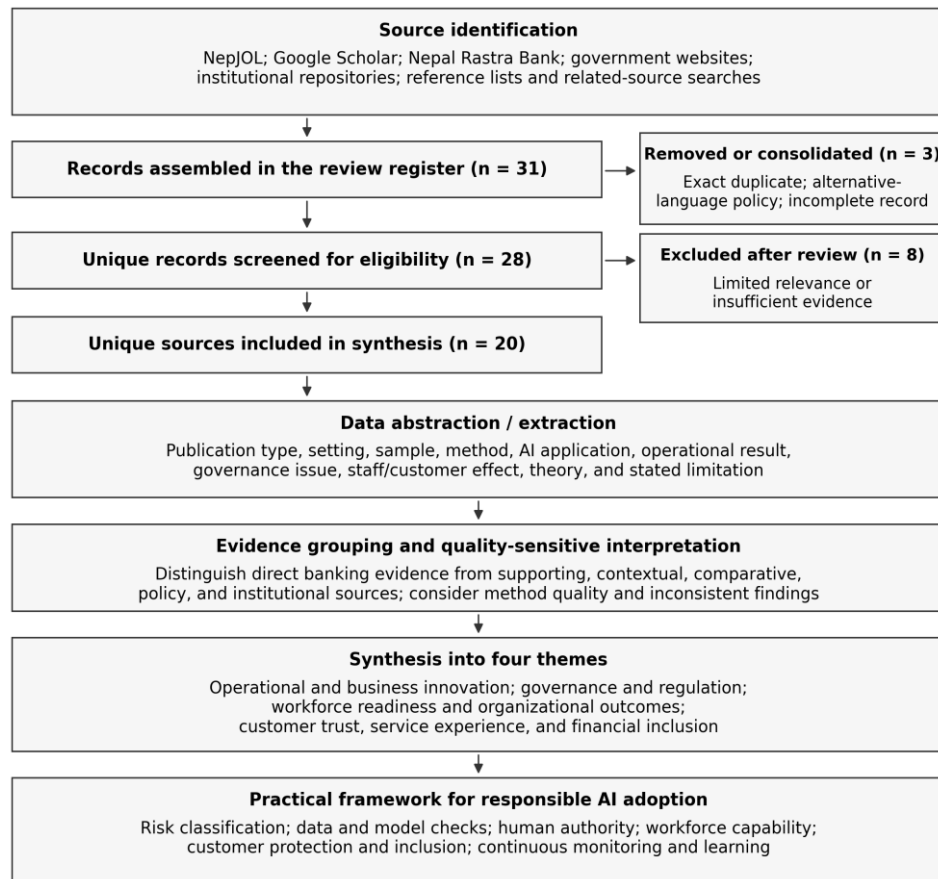


Fig. 1. Source selection, data abstraction, and evidence synthesis. Counts refer to the assembled review register; database-level search totals were not recorded.

Other publications were used mainly for interpretation and comparison rather than for precise numerical estimates. Goswami et al. [12] reviewed barriers faced by older adults, Cherian and Kumar [13] discussed microfinance and inclusion, and Malepati et al. [14] focused on AI and machine-learning competencies. Khanal [1] offered a broad overview of AI in finance. Rahman [15] examined financial literacy through mobile and branch channels, although the reported ANOVA results do not fully align with the group means.

B. Operational and Business Innovation

Across the evidence, banks most often used AI for fraud detection, credit assessment, customer-service automation, personalized services, investment analysis, and internal decision support. These uses address common banking problems such as high transaction volumes, the need to identify unusual activity quickly, inconsistent manual work, and growing demand for faster and more personalized service.

Shrestha and Mahat [7] reported positive links between AI use and employee satisfaction, customer behavior, and bank profitability. Khadka et al. [9] also linked AI-based customization and social innovation with better decision-making. In five commercial banks, Rahman et al. [8] reported that perceived usefulness ($\beta = .31, p < .001$) and relative advantage ($\beta = .26, p < .001$) were the strongest predictors of AI adoption in investment work. The model reported an adjusted R-squared of .64. Regulatory support strengthened the link between usefulness and adoption, while technical expertise strengthened the link between ease of use and adoption. Interviews described faster portfolio adjustment and risk detection, but also reported skill shortages, old systems, and unclear regulations. These estimates should be read carefully because the article did not report the number of

interview participants, construct reliability results, or the promised factor-analysis outputs.

The strongest customer-level evidence for specific applications came from Shahi [5]. In a sample of 150 users in Karnali Province, AI-supported credit scoring had the largest significant link with satisfaction ($\beta = .419, p < .001$). Personalized recommendations followed ($\beta = .281, p = .011$), and automated customer service also had a smaller significant effect ($\beta = .151, p = .040$). Chatbots and AI-based fraud detection did not have significant direct effects on satisfaction. The model explained 77% of the reported variance, but the fit was weak: the standardized root mean square residual was .087 and the normed fit index was .574. These results suggest that customers do not value every AI application in the same way. Services that directly save time or support a decision may be more visible to customers than background security tools. However, the results should not be generalized beyond the study's young, highly educated, and purposively selected sample.

Pokhrel [3] described operational performance through four areas: AI infrastructure, model governance, service integration, and ethics capacity. The article reported that AI-supported services and ethics training improved performance, while poor infrastructure and unclear model governance reduced it. However, the direction of one model-governance coefficient differs between the equation and the written discussion. The article also reports a precise 2.7-year break-even period and an ideal 50 hours of annual ethics training. These values are unusually exact for cross-sectional data. The broader conclusion is more reliable: technical investment may not produce benefits unless the bank also has suitable systems, trained staff, and clear controls.

TABLE II. SELECTED CORE STUDIES AND IMPORTANT CAUTIONS

Source	Design and sample	Main contribution	Important caution
Shrestha and Mahat [7]	Cross-sectional survey; 195 employees from four commercial banks	AI use was linked with employee satisfaction, customer behavior, and profitability.	Convenience sampling and limited bank coverage.
Pokhrel [3]	Explanatory survey; 400 banking professionals	Connected AI services and ethics capacity with operational performance and highlighted model-governance problems.	Reported bank count and some highly precise claims require checking; one coefficient direction is inconsistent.
Shahi [5]	PLS-SEM; 150 customers in Karnali	Credit scoring, automated service, and personalization predicted satisfaction.	Purposive regional sample and weak overall model fit.
Pokhrel [4]	Cross-sector survey; 41 employees, including 13 from banking	AI use and employee performance predicted organizational outcomes; trust was moderate.	Low statistical power, male and education bias, and not limited to banking.
Shrestha [10]	Thesis; 386 customers in Kathmandu Valley	Identified optimism, usefulness, discomfort, and insecurity as adoption factors.	Some regression and correlation results do not support the written conclusions.
Dhakal and Acharya [11]	Mixed methods; 50 customers and five professionals	Highlighted usability, connectivity, security, and support barriers.	Small urban sample and several statistical inconsistencies.
Rahman et al. [8]	Mixed methods; questionnaire N=50 plus manager and technology-officer interviews in five banks	Usefulness, advantage, ease of use, readiness, and compatibility predicted adoption in investment work.	Purposive top-bank sample; interview count, reliability tests, and factor-analysis details were not reported.
Khadka et al. [9]	Employee survey; 230 commercial-bank employees	Linked AI customization and social innovation with bank decision-making.	Self-reported cross-sectional evidence.

Taken as a whole, the evidence does not support the claim that AI automatically improves banking performance. Benefits are more likely when a bank begins with a clear use case, has dependable data and suitable infrastructure, prepares its staff, redesigns the relevant work, and maintains effective oversight.

C. Governance and Regulatory Readiness

Across the reviewed sources, governance has developed more slowly than AI use. The recurring risks include privacy breaches, unfair outcomes, decisions that are difficult to explain, unclear responsibility, dependence on external vendors, weak model testing, cyber threats, and limited complaint or appeal mechanisms [1]–[3], [12]. These concerns become especially serious when AI influences credit, recruitment, employee assessment, fraud action, or another decision with a direct effect on individuals.

Pokhrel [3] reported that formal ethical systems and explainable-AI tools were uncommon among the banks represented in the study. The exact percentages should be treated as indicative rather than as confirmed national estimates because the article's reported number of commercial banks requires independent checking. The wider pattern is nevertheless consistent with the other evidence: employees express only moderate confidence in fairness and transparency, customers remain concerned about security, and policy documents call for stronger model controls and meaningful human review.

Nepal Rastra Bank's Artificial Intelligence Guidelines provide the clearest banking-specific direction in the reviewed material. They address privacy, bias monitoring, model testing, understandable decisions, security, accountability, and human oversight for higher-risk systems [16]. The National Artificial Intelligence Policy sets a broader national direction [17], while the NRB Strategic Plan 2022-2026 places digital modernization within wider institutional priorities [18]. The Financial Institutions Supervision Report 2024/25 describes the supervision of development banks and finance companies, but it does not establish that AI-specific controls are being assessed consistently across all licensed institutions [19]. Nepal therefore has an emerging policy base, but evidence of implementation remains limited.

Vendor oversight deserves particular attention because smaller institutions may purchase models developed outside Nepal. Those systems may not reflect local languages, occupations, rural income patterns, customer behavior, or credit histories. A general cybersecurity review is not enough. Banks need model documentation, information about training data, performance results for relevant customer groups, change records, incident-reporting duties, audit rights, and workable exit terms. Responsibility remains with the bank even when an outside provider built the system.

Broad principles such as fairness and transparency become useful only when they are translated into day-to-day controls. Banks need named roles, documented testing, monitoring thresholds, escalation rules, and practical remedies for customers or employees affected by an incorrect decision.

D. Workforce Readiness, Trust, and Organizational Outcomes

AI changes both the tools employees use and the work they must do. Staff may need to interpret model outputs, identify warning signs, explain automated decisions, protect customer data, and decide when a recommendation should be rejected or sent for further review. The evidence shows that being comfortable with normal digital tools does not always mean that an employee understands AI.

Pokhrel [4] studied 41 employees from service, banking, information technology, and telecommunications, including 13 banking employees. Respondents reported moderate AI use and integration ($M = 3.69$) and moderate trust, fairness, and transparency ($M = 3.51$). AI use and integration significantly predicted organizational performance ($\beta = .34$, $p = .014$). Employee job performance was the strongest predictor ($\beta = .42$, $p < .001$), and the model reported $R^2 = .61$. The study also found that employees were more confident using digital tools than explaining how AI worked. Because the sample was small, statistical power was only .52, 80.5% of respondents were male, and the participants were highly educated, the findings should be treated as exploratory.

The same study points to a trust problem. Employees were more confident that their organizations wanted to use AI responsibly than they were that AI decisions were always transparent or fair. Concerns included reduced human decision-making, job loss, privacy, and less human treatment

at work. Trust, fairness, and transparency had a strong simple relationship with organizational performance, but their effect became only marginal in the full model. This may mean that trust affects results indirectly by influencing how employees use AI and how well they perform their jobs.

Malepati et al. [14] likewise emphasize continuous skill development, staff participation, and clear communication. The evidence supports a layered approach to training. All employees need basic AI and digital literacy. Staff who use AI in their roles need instruction in data quality, model interpretation, and customer communication, while risk, audit, compliance, and technology teams require deeper technical skills. Managers also need a clear understanding of accountability and strategic risk. Training should cover both the use of a tool and the conditions under which its output should be questioned or referred for human review.

E. Customer Trust, Service Experience, and Financial Inclusion

Customer evidence shows that convenience alone is not enough for long-term use. Satisfaction also depends on usefulness, ease of use, reliability, security, personalization, and access to help. Shahi's results [5] show that different AI services have different effects. Credit scoring, automated service, and personalization were linked with satisfaction, while chatbots and fraud detection did not show a significant direct effect. One possible explanation is that customers notice services that save time or help them reach a financial decision, while background security systems create value mainly when they prevent harm.

Shrestha's Kathmandu Valley thesis [10] examined optimism, innovativeness, discomfort, insecurity, perceived usefulness, and intention to use AI. It is useful for identifying customer concerns and possible drivers of use. However, some correlations and regression results do not fully support the written claim that usefulness and optimism are the main drivers. The study is therefore more useful for identifying topics than for making precise causal claims.

Dhakal and Acharya [11] identify usability, internet reliability, digital skills, cybersecurity, and customer support as common barriers to digital banking. Their sample of 50 customers and five professionals is too small for broad conclusions, and several statistics do not match the displayed tables. Even so, the interviews and descriptive evidence support a pattern found elsewhere in the review: poor connectivity, difficult interfaces, limited local-language support, weak customer assistance, and fear of fraud can discourage confident use.

Comparative sources provide further context. Goswami et al. [12] show that older customers may benefit from voice support, adjustable displays, biometric options, simple steps, clear explanations, and quick access to a person. Cherian and Kumar [13] identify similar needs in microfinance, where digital capability and responsible design can widen or restrict access. Shrestha [20] presents AI-supported digital payments as an opportunity for greater security and inclusion, while also emphasizing infrastructure, regulation, and customer protection. Rahman [15] raises the possibility that preferred service channels differ by age: younger users may favor mobile tools, whereas older users may benefit from branch or mixed support. Because the reported ANOVA values do not fully match the means, that relationship should be treated as a question for future study rather than a confirmed effect.

Financial inclusion should therefore mean more than opening an account or registering an application. An inclusive AI service allows customers to understand what they are doing, complete transactions safely, question an automated decision, receive help, and use a human alternative when needed.

IV. DISCUSSION

A. Technology Is Moving Faster Than Governance

The review points to an implementation gap in Nepalese banking. AI is attractive because it can speed up service, process large transaction volumes, support consistent analysis, and tailor customer interactions. Conversely, these features can make decisions harder to understand and can weaken human control. When governance and staff capability lag behind deployment, efficiency gains may coexist with model errors, unfair outcomes, privacy failures, and declining trust.

This finding is not an argument against innovation. It shows that technical capacity and institutional capacity need to grow together. Installing a chatbot, risk model, or analytics platform does not automatically enable a bank to test it, recognize its limits, compare outcomes across groups, manage the vendor, explain a decision, or correct harm. A bank's AI maturity should therefore be judged by the quality of its management and oversight, not by the number of tools.

The mixed customer findings also show why each application needs its own performance measures. A service that gives a faster decision or more relevant advice may directly improve satisfaction. A security system can be valuable even when customers do not notice it. Fraud tools should be evaluated through detection accuracy, false alerts, losses prevented, customer disruption, and fairness. Chatbots require different measures, including problem resolution, effective transfer to staff, language access, and customer effort.

B. Governance Should Be Part of Normal Operations

Responsible governance belongs within normal banking operations rather than at the edge of compliance. Documentation, bias testing, human review, privacy protection, and incident reporting can prevent repeated errors and reduce complaints, regulatory exposure, and reputational damage. Despite the statistical concerns in Pokhrel [3], the reported link between ethics capacity and operational performance is consistent with this broader logic.

A practical starting point is to classify each system by the harm it could cause. Low-risk productivity tools may be managed through established information-security and quality controls. Stronger safeguards are needed when AI influences lending, employee assessment, fraud action, customer profiling, or eligibility. For these uses, the bank should define the purpose and limits of the system, check data quality, test outcomes across relevant groups, obtain independent validation, preserve human approval, document decisions, and provide a route for appeal. The level of control should follow the risk of harm rather than the novelty of the technology.

Regulatory support can develop in stages. Minimum controls and reporting duties should be stated first. Controlled testing environments can then help institutions examine useful applications without weakening customer-protection obligations. Supervision must finally examine evidence of practice, not only written policies. Relevant evidence includes model inventories, validation reports, recorded overrides, incidents, complaints, and vendor controls.

TABLE III. MAIN FINDINGS AND PRACTICAL PRIORITIES

Theme	Main finding	Main risk	Priority action
Operational innovation	AI can support data-heavy decisions, automation, and personalization when work processes are also improved.	Automation with poor data or unclear decision authority.	Select clear use cases, redesign processes, test systems, and monitor results.
Governance	Policies are developing, but practical controls often lag behind use.	Bias, unclear decisions, privacy harm, weak responsibility, and vendor dependence.	Classify risk, require audit rights and explanations, keep human review, and create incident and appeal systems.
Workforce readiness	Employees may be confident with digital tools but still have limited understanding of AI.	Overreliance, weak escalation, resistance, and reduced human judgment.	Provide role-based AI literacy, involve staff in implementation, and protect human authority.
Customer trust and inclusion	Convenience leads to use only when security, accessibility, understanding, and support are also present.	Fraud fear, inaccessible design, exclusion, and no way to challenge decisions.	Use inclusive design, local-language support, mixed digital and human channels, clear disclosure, and accessible remedies.

C. Human Judgment, Trust, and Changes in Work

Employee caution should not be interpreted automatically as resistance to change. Concerns are reasonable when an unexplained system affects hiring, appraisal, credit, or fraud decisions and offers no meaningful way to challenge the result. Trust is more likely when employees understand the purpose of the system, take part in implementation, receive practical training, observe reliable performance, and retain authority in high-impact cases.

Human oversight must have practical force. A reviewer cannot challenge a system without enough time, information, authority, and confidence. Banks should distinguish between decisions that AI may recommend, decisions it may complete, cases that require two approvals, and decisions that must remain fully human. Recorded overrides should be reviewed for patterns because they can reveal either repeated model weaknesses or inconsistent staff practice.

AI may remove repetitive tasks, but it can also create new work in monitoring, exception handling, customer explanation, and error management. Performance assessment should therefore consider the quality of work, staff stress, skill development, and the allocation of responsibility alongside speed and cost.

D. Inclusion Needs Both Digital and Human Services

Evidence from customer research, digital-transformation studies, microfinance, and older-adult inclusion supports a mixed service model. Digital-only delivery may reduce cost but can exclude customers with poor connectivity, limited digital skills, older devices, language barriers, or low confidence. Branch-only service, however, cannot match the availability and speed expected in modern banking. A more inclusive approach combines digital self-service with accessible human help and clear transfer procedures.

Testing should include rural users, older adults, people with disabilities, customers with limited literacy, and speakers of Nepali and other regional languages. Banks need to observe whether customers can follow instructions, recognize fraud warnings, correct errors, recover accounts, and challenge automated outcomes. Financial education is most effective when it appears at the point of need rather than only through general awareness campaigns.

E. Practical Framework for Responsible AI Adoption

The reviewed evidence supports six connected areas of responsible AI adoption in Nepalese banking:

1) Use-case and risk classification. Define the business problem, the affected groups, the expected benefit, the

importance of the decision, and the maximum acceptable harm before a system is bought or built.

2) Data and model checks. Document data sources, consent or legal basis, known quality limits, representation of customer groups, performance results, validation procedures, and controls over model changes.

3) Human authority and responsibility. Specify who may approve, reject, or escalate a recommendation, how overrides will be recorded, and who is accountable when harm occurs.

4) Workforce capability. Train staff in practical use, model limits, bias, privacy, explanation, escalation, and incident response.

5) Customer protection and inclusion. Use understandable language, accessible design, local-language support, a choice of service channels, security guidance, and simple appeal procedures.

6) Continuous monitoring and learning. Track accuracy, model drift, false alerts, outcomes across customer groups, complaints, overrides, incidents, vendor changes, and actual business value. Correct or discontinue a system when the evidence shows unacceptable problems.

These areas are interdependent. Governance, training, and customer protection should influence the selection, design, testing, and launch of a system from the beginning rather than being added after deployment.

V. IMPLICATIONS

A. Implications for Banks and Financial Institutions

Banks should first create a complete list of all AI and algorithm-based systems. This list should include outside tools built into digital banking, fraud monitoring, credit scoring, human resources, customer analysis, and investment work. Every system should have a named owner, a clear purpose, a risk level, a validation status, known data sources, vendor details, and a plan for replacement or closure.

Investment decisions should include the full cost of responsible adoption, not only the purchase price of software. Budgets should cover data preparation, security, testing, staff training, customer communication, monitoring, audit, and correction of problems. Performance reports should combine financial results with model-risk, customer-protection, and inclusion measures.

Banks should also establish a cross-functional governance group that includes business units, risk, compliance, legal, internal audit, technology, data, human resources, and customer-service staff. High-impact systems should not be

approved only by the technology team or the business unit that wants to use them.

B. Implications for Nepal Rastra Bank and Policymakers

Nepal Rastra Bank can make its AI guidance more practical through risk-based supervisory expectations, standard model inventories, minimum validation rules, incident reporting, and evidence-based reviews of higher-impact systems. A financial-sector testing environment may help banks examine local-language service, rural credit, and fraud intelligence, but it should include clear customer-protection rules.

National policy should support local technical skills, secure infrastructure, privacy enforcement, digital education, and access to independent expertise. Shared resources such as testing procedures, model-risk templates, anonymous fraud information, and training for smaller institutions could reduce repeated effort and improve minimum standards across the sector.

C. Implications for Research

Future studies should move beyond intention and perception surveys. Nepal needs longer-term research across several institutions using real operational data. Important measures include error rates, false alerts, differences in approval outcomes, complaint resolution, employee overrides, customer loss, staff workload, actual cost savings, and incidents over time.

Research should include rural branches, development banks, finance companies, cooperatives, microfinance institutions, older adults, people with disabilities, and customers from different language groups. Researchers should use validated measures, report complete statistical tables, separate correlation from causation, and test whether systems perform differently across demographic and geographic groups.

The most useful research question is not whether AI is generally good or bad. It is which applications create real value, for which groups, under which controls, and with what risks.

VI. LIMITATIONS

This review has several limitations. First, the search was conducted iteratively, and database-specific dates, complete platform histories, and initial hit counts were not recorded in a form that permits exact PRISMA-style replication. The screening flow is documented at the record level, but the platform-level search cannot be reproduced precisely.

Second, the evidence is heterogeneous, and many studies are cross-sectional and based on self-reported perceptions. Several samples are limited to one location, younger users, urban customers, highly educated respondents, or a small number of institutions. The review therefore cannot estimate a national AI-adoption rate or calculate a combined effect on profitability, satisfaction, or performance.

Third, some studies contain internal inconsistencies. These include the direction of a governance coefficient in Pokhrel [3], the interpretation of statistical results in Shrestha [10], several reported relationships in Dhakal and Acharya [11], and the ANOVA calculations in Rahman [15]. The review treats these sources cautiously and does not use them to support strong numerical conclusions.

Fourth, policy and institutional documents describe expected practice but provide limited evidence about how consistently AI controls are implemented across financial institutions. The technical and regulatory environment is also changing quickly, so the policy context and bibliographic details should be checked again immediately before publication.

VII. CONCLUSION

AI is being used in Nepalese banking for credit assessment, fraud monitoring, customer service, personalization, investment analysis, and internal management. The evidence points to possible gains in efficiency, decision support, and customer value, but these gains vary by application and depend on the quality of data, infrastructure, staff preparation, work design, and oversight. The literature also identifies continuing weaknesses in model transparency, data governance, vendor management, staff understanding, and customer protection.

Technology investment alone will not produce sustainable adoption. Nepalese banks need the capacity to select suitable uses, test data and models, preserve meaningful human authority, prepare employees, protect customers, and monitor results. Responsible governance is not a barrier to innovation; it is what makes innovation more reliable, fair, and useful over time.

Banks and regulators now need to convert broad principles into controls that can be observed and tested. Researchers need longer-term, multi-institution studies based on real outcomes rather than scattered perceptions. AI can strengthen Nepalese banking without weakening responsibility, fairness, or trust when technical development, governance, workforce capability, and customer protection advance together.

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