8

Responsible Use of Large Language Models for Customer-centric Banking in India[1]

Deepankar Roy | Saurabh Pathak

8.1. Introduction

Banks across the globe have been undergoing digital transformation for quite sometime. As the technology advances, the focus shifts merely from implementation of technology to adoption for better experiences. The first half of this decade was defined by cloud led transformation. The later part of this decade will be defined by AI led transformations. The AI technologies have been known for the innovative and creative ways to automate, create the necessary insights and augment the necessary human like intelligence among others. These technologies have led to several innovations that not only improved the operational work but also impacted customer experience as whole. These have been possible due to improved compute, storage and algorithmic capabilities.

The latest advancement in AI field is creation of Large Language Models (LLMs). LLMs are very sophisticated AI systems which have been created and trained on large amount of data. These models have been created assuming that they will mimic the human-like capabilities when it comes to understanding the problem and generating the responses for same. The available literature points to the fact that the experimentations around development of such systems have been ongoing for more than a decade now (Nawazish, 2023). While there are many organization who are creating these LLMs models, the pioneers in this field are tech-giants such as Microsoft, Google, OpenAI, and Meta.

Several organizations including banks across the globe have carried out pilots to understand the capabilities of these LLMs. These organizations are re-defining the ways of working for adoption of this technology. Adoption requires the necessary technology platforms, collaboration of cross functional teams and the governance framework. With the right ways of working, the enterprise adoption and quantification of benefits realised by these technologies becomes much easier. In the banking context, LLMs are being proposed for the fraud detection, financial risk analysis, and documentation automation (Crisanto et al., 2024; McKinsey, 2024a, 2024b; Ranković et al., 2023; Sindhu & Namratha, 2019).

Globally there has been more excitement around adoption of LLMs for various purposes and across industries. The tech-giants have now understood the potential India offers in terms of adoption of LLM models. India a huge consumer base and its digital footprint across sectors is only growing to support the aspirations of several initiatives such as Digital India, IndiaAI Mission and Atal Innovation Mission (AIM) among others. One of the objectives of these missions is Viksit Bharat. While there are several examples that can be quoted on India's digital footprint and governance, one of the greatest examples is usage of UPI & Aadhaar enablement.

1. The authors are grateful to Atta Omar Basheer and Paritosh Basu for their valuable comments and suggestions. The usual disclaimer applies.

There are more than 485 million Aadhaar-linked accounts and more than 12 billion UPI transactions (NPCI, 2024) happens monthly. The nation's extensive digital footprint across such services offers a ripe environment for scalable AI applications across banking value chain.

The Section 8.4 explains the abilities of LLMs to transform banking from transactional exchanges to highly individualised relationships. This can be achieved by providing inclusive multilingual support and contextual advice. Legacy systems, disjointed data, and the moral dangers of model bias and opacity are some of the difficulties that this integration presents. However, Indian regulators have taken action in response to these worries. The Ministry of Electronics and Information Technology (MeitY) has committed ₹10,000 crore to create LLMs under IndiaAI Mission. The Reserve Bank of India (RBI) now recommends governance frameworks for AI-based applications for e.g., credit risk algorithms (RBI, 2024a, 2024b).

The actions taken by India to be digitally native have been encouraging so far. However, the implementation and risk management approaches applied for earlier initiatives would be insufficient for LLMs adoption. These models are not yet matured and pose several challenges related to accuracy, reliability and privacy among others. The usage of generic global models available at disposal may serve certain use cases needed by banks, but from the customer experience perspective it may offer limited benefits to Indian banking customers. Hence, this chapter makes the case that India should prioritise the creation of independent regional LLMs. These models should be suited to India's heterogeneous demographic diversity (focus should also be on cultural linguistic diversity). This will turn national diversity into a strategic AI advantage by using the country's distinctive digital public infrastructure (WEF, 2019). In Section 8.3, a thorough ethical framework specific to the Indian banking environment is also suggested (OECD, 2021; UNESCO, 2021). This will lead to the models that are tailored to Indian banking customers protecting their privacy, removing the biases and improving the fairness of the outcomes.

8.2. Literature Review

The available literature suggests that LLMs are revolutionizing the banking. These models are personalizing the services based on the huge training data leading to improved decision making. Several researchers and practitioners suggest that adoption of these models in the banking context have very positive effects. However, many of them including authors believe that a governance framework should be in place. This framework should focus on accountability, openness, and justice without diminishing the benefits of these models.

The Emergence of LLMs and Gen-AI in Financial Services

According to Shahzad et al. (2025), LLMs like GPT-4 and LLaMA are distinguished by their ability to provide contextual and language-based outputs on a huge scale. Billions of parameters are utilised to allow for task flexibility and personalisation. International banks have started using this technology for various services & offering such as loan processing, and customised financial advice among others (Sudjianto et al., 2024). Indian banks have also started adopting this technology (Sinha & Sinha, 2023; Xu, 2024) for automation of business processes. Narang et al. (2024) highlighted the improved institutional efficiency in addition to consumer value when these models were used. The other examples include mimicking sympathetic human conversation, and report summarisation among others.

Important Uses & Acceptances in Banking

Several research have noted the value delivered by LLMs across operational and customer-facing roles in the banking industry. A few applications have been noted below:

- *Conversational Support and Service Automation*: Chatbots and voice assistants driven by LLM offer 24/7 assistance. These chatbots enhance customer satisfaction and service effectiveness (McKinsey, 2024a) by removing wait times. Other examples include tasks automation with transformer models like BERT. For e.g., automatically classifying the support tickets based on the products (Bonechi et al., 2024).

- *Personalised Engagement*: LLMs can examine consumer behaviour and transaction history. This analysis can be used to hyper-personalise the financial advice and product recommendations (Bain & Company, 2024; Standford HAI, 2023; Wu et al., 2025).
- *Risk Management and Compliance*: LLMs help in various aspects of regulatory duties. Few examples include documentation and audit trail generation among others (Narang et al., 2024).
- *Intelligent Document Processing*: LLMs are excellent at processing unstructured data/inputs such as chat logs, and legal documents. They are able to convert complex legal or financial documents into English or any other supported language for better comprehension (FAccT Conference Proceedings, 2023; Sleiman, 2023).

Trends in Adoption in the Indian Banking Industry

Whenever there are advances in the technology, the regulators across the globe have demanded the need for sector-specific governance and transparency. This also remains a constant theme in research and applies to usage of LLMs. The recent actions from the major Indian banks also suggests the seriousness and diligence with which they are approaching the adoption of these models.

- In August 2024, Punjab National Bank (PNB) held a public tender to implement BFSI-specific LLMs for risk compliance and underwriting. It emphasised on domain accuracy and vernacular support (Sood & Shaw, 2025).
- In February 2025, Union Bank of India released a request for proposal (RFP) for the usage of GenAI. This RFP aimed at automating loan document summarisation and grievance resolution in several Indian languages (Sood & Shaw, 2025).
- In order to select AI and GenAI partners for front-end and back-end automation pilots, Bank of Baroda issued a tender in July 2024 (Sood & Shaw, 2025).
- In order to facilitate advanced LLM implementations, State Bank of India (SBI) released tenders for API integration layers in October 2024.

The broad agreement across the usage of LLMs is evident from the above, however the implementation would depend on a methodical, values-based approach to governance that protects the interest of stakeholders. To contribute to body of knowledge, authors have created a framework that could be adopted by banks (and other industries) for LLMs implementation.

8.3. Ethical Hazards and Countermeasures for LLMs in Banking

The scholars across globe including authors emphasis the need for fairness, accountability, and transparency whenever LLM models are used. Several issues with usage of LLMs have been noted across the available literature. These issues are related to inaccurate results or 'hallucinate', reliability, biases and fairness among others. Authors firmly believe that a strong governance framework backed by right technology interventions can solve majority of these issues.

Hazards of Hallucinations, Bias, and Data Sensitivity

Large amounts of training data expose LLMs to biases. Injustices in society may arise from this, for instance, through producing unjust results in loan approvals or customer service. This inclination to 'hallucinate,' or make up information, further undermines the validity of these models. Federated learning, fine-tuning on representative datasets, and other technological methods are a few important risk reduction techniques. According to existing research, improved models reduce bias and increase accuracy (Lajčinová et al., 2024; Sleiman, 2023).

Institutional and Regulatory Structures

The Indian regulators have taken already the first steps towards AI governance. The RBI (RBI, 2024a) has set up regulatory sandboxes. These sandboxes assess the safe implementation of emerging technologies. MeitY has started creating local LLMs in India under IndiaAI mission. Scholars (Narang et al., 2024; Ray, 2023; Yoon et al., 2025) across the globe call for algorithmic openness and ongoing human control. They also caution that the absence of a unified regulatory framework could result in inconsistent adoption resulting in erosion of public trust.

A Multifaceted View of Ethical Principles

The advantages and drawbacks of LLMs usages have been already established in the previous sections. Indian Banks must take the rights steps to address the following major obstacles to ethically and successfully utilize these models (MeitY, 2023).

i. technology implementation, and

ii. adhering to rules and regulations such as Digital Personal Data Protection (DPDP) Act.

Indian banks can look at several solutions from technology perspective. Banks can implement robust encryptions, role based access, and proactive monitoring to protect the data (Proceedings of the FAccT Conference, 2023; NIST, 2023). AI-based risk management has been implemented by the banks. However, in the context of cyberthreats an evaluation would be needed to understand the LLM applicability and usability (Akinnagbe et al., 2025). Banks can look at following NIST 800-53 guidelines for building domain specific LLMs that addresses the Threat Modeling which includes discovery and mitigation of security threats (Wu et al., 2025).

Another approach that Banks can follow is Layered risk containment while implementing LLMs. The layered risk containment must include several components which are listed below.

i. User override options and backup decision mechanisms for LLM generated responses

ii. Explicit labelling of LLM generated responses and human-approved judgements

Numerous studies highlight the necessity of comprehensive validations for delicate decision-making tasks, such as fraud detection or credit underwriting. Authors recommend implementation of AI risk frameworks that incorporate bias discovery, model drifts, and audit trails.

Banks have the legal responsibility to comply with the rules and regulations, and ensure that public confidence in banking systems improves with time. Authors have created a framework (as shown in Table 1) that can act as a guide for implementation for Banks and safeguard the interest of its stakeholders. The framework provide brief details on the various LLM risks and how those risks could be mitigated ethically. Furthermore, it helps address the issues that may be broadly categorised into three categories – Business, Technological and Legal.

- *Business*: Reputational risks arising out of inaccurate results or 'hallucination', transparency, reliability, biases and fairness among others.
- *Technological*: Operational risks arising out of technical debt produced by old infrastructure, model drifts, Shadow AI and explainability of LLM generated results (Standford HAI, 2023).
- *Legal*: Compliance risk arising out of failure to comply with the DPDP Act and other guidelines issued by regulators.

Banking is essentially a relationship and trust-based industry. LLMs must be used responsibly and ethically in India in order to build credibility. This can successfully strike a balance between responsibility and innovation. A sector-specific ethical framework that is founded on both general AI principles and LLM-specific considerations is therefore essential.

TABLE 8.1

Ethical Guidelines for the Use of AI and LLM in Banking

Ethical Principle	*DPDP Characteristic*	*LLM/AI Perspective*	*LLM-Specific Risks*	*Implementation Challenges*	*Control Measures*	*References*
Fairness	Lawful and consent-based data processing	AI systems must not exhibit bias in decision-making	Training on biased or unrepresentative datasets	• Business: Reputational risks due to perceived discrimination • Technical: Model bias • Legal: Discrimination non-compliance	• Fairness audits • Diverse datasets • Bias mitigation during training	(Bain & Company, 2024; FAccT Conference Proceedings, 2023; IEEE, 2019; McKinsey, 2024a; NIST, 2023; Standford HAI, 2023)
Transparency	Right to information & notice	Users should know when and how AI is used	Opaque nature of LLM decisions	• Business: Customer mistrust • Technical: Lack of explainability tools • Legal: Disclosure gaps	• Disclosure norms • Explainable AI (XAI) tools • Human-readable justifications	(Izard, 2023; NIST, 2023; OECD, 2021; UNESCO, 2021; WEF, 2019)
Accountability	Purpose limitation & fiduciary duty	Assign AI risk management roles	Harmful LLM decisions with unclear accountability	• Business: Responsibility dilution • Technical: Missing audit trails • Legal: Legal ambiguity in AI-driven decisions	• Human-in-the-loop • Governance boards • Model risk frameworks	(IEEE, 2019; OECD, 2021; RBI, 2024b)
Privacy	Consent, minimization, retention	Avoid storing or leaking personal data	LLM memorization of sensitive data	• Business: Loss of trust • Technical: Data leakage • Legal: DPDP violations	• Data masking & anonymization • Access controls and Personally Identifiable Information (PII) filtering	(FAccT Conference Proceedings, 2023; Standford HAI, 2023)
Non-maleficence	Protection from harm	LLMs must avoid harmful content	Hallucinations, toxicity, misinformation	• Business: Brand damage • Technical: Output risks • Legal: Harmful advice liability	• Prompt moderation • Red teaming • Model output filters	(FAccT Conference Proceedings, 2023; NIST, 2023; OECD, 2021; WEF, 2019)
Autonomy & Choice	Right to withdraw consent	Users must control AI interaction	No opt-out for AI-based decisions	• Business: Alienation • Technical: Lack of fallback • Legal: Consent management gaps	• Opt-out options • Human fallback channels • Logged consent preferences	(Bain & Company, 2024; UNESCO, 2021)

contd…

...contd...

Inclusivity	Accessible, non-discriminatory use	LLMs must serve diverse populations	Weak vernacular or multilingual support	• Business: Market exclusion • Technical: Language gaps • Legal: Equal service mandates	• Train on regional data • Support dialects and scripts • Public sector use cases	(Izard, 2023; McKinsey, 2024a; Standford HAI, 2023)
Explainability	Transparency in decisions	Explainable AI in high-stakes cases	No rationale for decisions like credit/fraud	• Business: Customer complaints • Technical: LLM interpretability • Legal: Loan rejection explanations	• SHAP/LIME tools • Post-hoc explanations • Model documentation standards	(NIST, 2023; OECD, 2021)
Security	Breach notification, data integrity	Secure model infrastructure	Prompt injection, adversarial attacks	• Business: Loss of data • Technical: Prompt vulnerabilities • Legal: Breach penalties	• Prompt filtering • Secure access layers • Incident response plans	(FAccT Conference Proceedings, 2023; NIST, 2023)
Sustainability & Governance	Fiduciary oversight & grievance redressal	Lifecycle monitoring, drift detection	Model decay, versioning issues	• Business: Declining performance • Technical: Retraining gaps • Legal: Model explainability lags	• AI oversight committees • Scheduled model reviews • Continuous evaluation metrics • Preservation of all Data and all output-related records for a minimum of the prescribed statutory period.	(Standford HAI, 2023; WEF, 2019)
Oversight & Control	Fiduciary Duty & Breach accountability	All AI/LLM usage must be sanctioned, documented, and auditable.	Use of unsanctioned public LLMs (Shadow AI) leading to data leakage, compliance breaches, and use of inaccurate information	• Business: Widespread, hidden risk from employees seeking efficiency • Technical: Difficulty in blocking all external AI services • Legal: Massive liability exposure from data breaches	• Clear usage policies & training, network-level blocking of public AI tools, providing sanctioned internal alternatives.	(MeitY, 2023; RBI, 2024b; WEF, 2019)

Source: created by authors.

The Explainability Conundrum: A Methodical Approach to Model Choice

Despite the clear need for explainability, banks are caught in a strategic conflict. Regulators demand simple, transparent models, but the most powerful models are inherently complex and opaque (Bank for International Settlements, 2024; Surkov et al., 2022). This is a strategic business decision about where to prioritise performance versus where to prioritise trust and compliance. It is not just a technological problem that can be resolved with tools. Banks should choose and implement models using a tiered strategic framework in order to manage this (Finance Watch, 2025; Fritz-Morgenthal et al., 2022).

Tier 1: High-Stakes Decisions (Prioritising Trust over Performance): Processes like credit scoring and loan approval have a direct, substantial financial impact on customers. In critical areas such as these, banks may not really find any value from any improvements gained from using these models that are not transparent. Hence, the focus must be on mitigating the far greater cost of regulatory violations and loss of customer trust. The strategic decision, in this case, is to use simpler and fully transparent models, even if they are marginally less accurate than the complex and generic ones. Accountability has to be established for every decision taken when these models are used. This is achieved via the Human-in-the-Loop (HITL) system and advanced explainability methods such as Shapley Additive Explanations (SHAP) or Local Interpretable Model-Agnostic Explanations (LIME). These tools ensure that transparent, clear explanations are provided for each customer outcome (Lakshmanan, 2024).

Tier 2: Customer-Facing Advisory (Balancing Performance with Transparency): Banks can employ more better models for applications such as chatbots that provide financial advise or personalised product suggestions. Operational transparency must become the primary priority when these models are used for any purposes. Here, striking a balance between user autonomy and performance is the strategic objective. In order to provide customers control, banks must make it obvious that they are engaging with an AI and offer explicit explanations and opt-out channels (Hepplewhite, 2024).

Tier 3: Internal Operations (Unleashing Maximum Performance): For low-risk, internal-facing tasks, banks can evaluate the usage & deployment of the most powerful LLMs. Examples include summarizing the documents/ reports or classifying internal support tickets. Since explainability is not a primary concern here, the organization can focus on optimizing for cost reduction and efficiency where the potential for customer harm is minimal (McKinsey, 2021).

Explainability is viewed as a strategic business decision in this tiered approach. It is one of the ways to help build trust and confidence with the stakeholders.

8.4. Indian Banks' Strategic Policy Priorities and International Practices

LLMs have already been successfully applied in regulated settings by major international financial institutions like Morgan Stanley, HSBC, and JPMorgan Chase. These models have been used for various services such as real-time advising and regulatory automation. Indian banks can gain more insights of these implementations along with the learnings to equip them better before any implementations. Indian government and regulators have taken several steps in creating regulatory and governance framework for AI usage. The implementation of these models can be further expedited with the enablement of digital infrastructure like Aadhaar and UPI (RBI, 2024a).

A Critical View on Indian Banks' Preparedness

While Indian banks are undergoing digital transformation, there still are certain challenges that may prevent the widespread use of LLMs. The banks are still modernising their outdated infrastructure. The consolidation of fragmented data systems is another deterrent. Banks will have to spend lot of efforts to integrate LLMs into the technology landscape before widespread adoption can happen (Deloitte, n.d.; World Bank, n.d.). Another hurdle is availability of people with the right skills to implement these models. Also, driving the change management initiative to upskill people in risk-averse banking culture is also challenging (Chowdhary, 2025; Mani, 2025).

Most public sector banks serve clients in rural or underbanked areas. These clients risk receiving poor digital services. This may not be the case with the customers in cities or private banks with more resources. This creates an uneven experience between different groups of customers. This problem will only magnify with the growth of LLMs which can be termed as "AI divide." This will have an adverse impact on the economy if not controlled early on (Jha, 2025; RBI, 2024c). It is important to recognise these barriers for developing a feasible strategy that addresses the difficulties of LLM integration.

Priorities for Strategic Policy

Adoption of LLMs at scale will only yield the benefits when the right regulatory frameworks are in place. These frameworks should encourage innovation at scale. The usage of LLMs should adhere to Digital Personal Data Protection (DPDP) Act when LLMs are being trained and deployed (MeitY, 2023). This should be inclusive of consent-based processing of data. Key recommendations include:

- *Establish Transparency Norms*: Customers should be notified in advance if LLMs are used in customer service contacts. Additional checks should be in place to identify information produced by AI (UNESCO, 2021).
- *Required Explainability Standards*: NIST (2023) recommends establishing the bare minimum of explainability criteria for all use scenarios.
- *Create Mechanisms for Humans in the Loop (HITL)*: Human oversight with the option to manually override should be incorporated in LLMs based systems. This will help in responsible use of technology and establish accountability as necessary (2019, IEEE).
- *Expand AI Regulatory Sandboxes*: Banks can use regulatory sandboxes to test solutions tailored to LLMs (WEF, 2019).
- *Provide Model Risk Management (MRM) Guidelines specific to LLMs*: Develop MRM frameworks tailored to banking that are appropriate for LLMs. Model evaluation, drift monitoring, and auditability must all be covered by these frameworks (RBI, 2024c).
- *Bridge the AI Divide*: The government should support public sector banks in implementing LLMs for financial literacy and rural outreach. This will foster inclusive growth and reduce digital inequality (McKinsey, 2024a). This collaboration should lead to creation of standardized LLM governance throughout the financial services sector (Floridi et al., 2018; Gandharv, 2021; IITB, n.d.).
- *Invest in Supervisory Capacity Building*: Provide regulators and auditors with specialised training programs to enable them to evaluate the opportunities and dangers associated with LLMs in banking (Bain & Company, 2024).

India may create a regulatory climate that permits the safe and significant deployment of LLMs in banking by implementing specific policy measures. It should focus on creating a strategy that is ethically sound, locally relevant, and globally competitive by focusing on innovation with accountability, and transparency.

Indian Banks' Implementation Roadmap. Putting Responsible LLM Adoption into Practice

Banks should follow a clear strategy outlining the step-by-step plan to use LLMs responsibly.

- *Strategic Pilots and Use Case Selection*: Banks can start the pilots in low-risk domains such as document summarisation or multilingual chatbots (Bain & Company, 2024; PwC, 2023). This will help measure the returns on investment and facilitate iterative learnings for future implementations.

- *Operationalising Data Governance*: The banks must adhere to provisions laid out in DPDP Act before training or using the LLMs. The usage should adequately address the data privacy and security concerns (MeitY, 2023).
- *Secure Model Development*: Banks should work with trusted partners to improve LLM's safety. Use specific and anonymous data as required and if needed generate the synthetic data. Relevant safety measures such as measuring the accuracies, checking for biases etc., should be put in place (FAccT Conference Proceedings, 2023; WEF, 2019).
- *Creating AI Governance Structures*: Create specialised LLM oversight groups and implement a Digital AI Policy that has been authorised by the board. To examine model behaviour in customer-facing scenarios, do "red teaming" exercises and algorithmic effect assessments (IEEE, 2019; OECD, 2021; RBI, 2024c; SEBI, 2025).
- *Modernising Infrastructure*: Banks should upgrade legacy systems to work better with AI models. The systems should use flexible designs to handle fast processing (McKinsey, 2024a; Standford HAI, 2023).
- *Developing Talent and Culture*: Banks should build a culture that puts AI first. They should train the employees in key skills such as explaining the AI decisions, creating good prompts, and using LLMs responsibly. Alongside training, they should use a clear plan to manage the changes involved (Bain & Company, 2024; Bersin, 2025; McKinsey, 2025; PwC, 2023).
- *Lifecycle Management and Auditing*: Banks should have the right governance in place to manage the model drift resulting in inaccurate results. The LLMs usage should be logged and audited as needed (Abhishek et al., 2025; NIST, 2023; RBI, 2024c; Standford HAI, 2023).

These recommendations can help banks set the vision for LLM usages with focus around building the systems around responsible and ethical use.

The Imperative of Inclusion: From Theory to Application

Indian banks have a great opportunity to build strong and emphatic relationship with customers by using LLMs. This relationship has to be based on inclusion, transparency and responsible use of AI. This will make banking easier and more accessible for many Indians and break down the language barriers.

Inclusive Design Fundamentals

Banks have the responsibility to build long-term trust with its stakeholders and only then widespread adoption of LLMs would become easier. LLMs should be used for localization for breaking down the language barriers. This will help banks in reaching out to more people in rural and semi-urban areas. The banks should focus on following aspects to maximise the adoption of LLMs:

- *Multilingual Support*: AI-powered banking services should be designed to support India's 22+ official languages and regional dialects (UNESCO, 2021).
- *Cultural Sensitivity*: AI-powered banking services should take into account the cultural sensitivity. AI powered services that are mindful for the local customs and communication methods will improve the consumer comfort and trust (Floridi et al., 2018).
- *Adaptive Interfaces*: For older or visually challenged users, adaptive interfaces greatly increase accessibility. This is accomplished through the development of tools like visual aids, localised voice assistants, and audio-first platforms. A broad spectrum of user literacy levels should be accommodated by these technologies (WEF, 2019).
- *Enhanced Financial Literacy*: By utilising regional languages and well-known cultural examples, LLMs can be utilised to explain difficult financial topics. This may result in knowledgeable client choices(PwC, 2024).

Evidence in Practice: Practical Implications

The applications of these ideas and the observable advantages they yield demonstrate their usefulness. Among the examples are:

- *Multilingual Assistance in Rural Banks*: An LLM chatbot was implemented by a rural Maharashtra bank to connect with underprivileged farmers. Marathi, Hindi, and English were the three languages in which the tool helped with loan applications. It was successful in increasing credit availability and reducing the average loan processing time by 25% (Ujjivan Small Finance Bank, 2024).
- *Voice-Enabled Banking for Users with Low Literacy*: An Odisha pilot study demonstrated the effectiveness of voice assistants for basic banking duties. Senior citizen's financial knowledge increased and in-branch visits decreased as a result of this pilot. Additionally, by customising the bots for regional languages, user comprehension increased by 23% and on-time rural loan payments increased by 27% (Saxena, 2025).

The Bigger Picture: A Plan for Equity and Trust

The successful pilot projects show that a big change in LLM usage strategy is needed. Indian banks will have to rethink how the usage of LLMs can lead to an AI future. Their focus should be on building a financial system that includes everyone and cares about social impact. To do this, three important steps must be taken:

i. fostering digital equity,

ii. embedding empathy into design, and

iii. create governance framework that helps build the trust

8.5. Existing Research Gaps and Future Prospects

There is a wealth of ethical principles discussed in current literature and industry reports. The empirical evidence of their practical application is still limited. Future studies should focus on the following areas in order to close this gap:

- *Performance Benchmarking and Quantitative ROI*: First, long-term research is needed to determine the actual return on investment (ROI) of LLMs in both public and commercial institutions. These studies ought to look at scaled implementations rather than just sandbox outcomes. Second, in order to compare the cost-effectiveness, bias, and performance of different models (private, open-source, and sovereign Indian LLMs), we require independent research. Several Indian languages should be used for domain-specific benchmarking activities. This will make it easier to comprehend these models' behaviours and correctness. (PwC, 2022; Accenture, 2024).
- *Customer Trust and Adoption Studies*: Trust is crucial for customer-focused banking. However, the perceptions of Indian consumers regarding AI-driven financial services remain largely unknown and remains to be explored. Large-scale surveys and qualitative studies involving a range of demographics are necessary for empirical research. This is required to identify the main factors influencing trust and the obstacles to the uptake of LLM-powered technologies (Zhang et al., 2023).
- *Impact and Transformation of the Workforce*: Although upskilling is clearly necessary, there is a dearth of empirical information regarding how the adoption of LLM is actively changing work roles, affecting productivity, and affecting the net employment situation in the Indian banking industry. Monitoring these changes and assessing the effectiveness of various change management and reskilling programs should be the main goals of research (Jain, 2024).
- *Systemic Risk Analysis*: A new line of inquiry into emergent systemic hazards is required as institutions depend more and more on comparable core models for vital operations like credit underwriting. To monitor and reduce these new, AI-induced

hazards, future research should investigate the creation of macro-prudential oversight tools and model the possibility of algorithmic herding (Daníelsson et al., 2022).

To make sure LLMs work well in Indian banking context, the gaps in current research must be fixed. The solutions must be accepted by society, affordable for banks, built on strong governance framework and backed by robust technology foundation.

8.6. Conclusions

It is very evident that one-size-fits-all approach can not work in Indian context for LLMs adoption. The adoption has to be based on diversity, and cultural sensitivity which may lead to creation of regional multilingual AI models. The nation's excellent digital public infrastructure and dedication to financial inclusion can further accelerate creation of customer-focused banking systems.

While technology and strong governance framework play an important role for adoption of LLMs, it is important to note that the citizens should benefit from a more equal and accessible systems. These AI systems must be ethical, consistent with the law, and focused on the needs of people (OECD, 2021; UNESCO, 2021). It will result in upl public confidence by firmly establishing a strong ethical foundation for their innovations.

The choices that banks make today will shape how well financial firms compete and affect the financial security and trust of millions of people. The goal should be to make these firms not just service providers but trusted partners in strengthening the nation's economy. This will show the big impact of today's decisions on the future (Stanford HAI, 2023).

References

Abhishek, A., Erickson, L., & Bandopadhyay, T. (2025). "Data and AI governance: Promoting equity, ethics, and fairness in large language models." MIT Science Policy Review, 6, 139–146. https://doi.org/10.38105/spr.1sn574k4lp

Accenture. (2024, February 28). "Banking in the Age of Generative AI." https://www.accenture.com/us-en/insights/banking/generative-ai-banking

Akinnagbe, O. B., Akintayo, T. A., & Adanma, A. B. (2025). "The Impact of Artificial Intelligence on Risk Management in Banking and Finance." Mikailalsys Journal of Advanced Engineering International, 2(2), Article 2. https://doi.org/10.58578/mjaei.v2i2.5195

Bain & Company. (2024, January 2). "Adapting Your Organization for Responsible AI." https://www.bain.com/insights/adapting-your-organization-for-responsible-ai/

Bank for International Settlements. (2024). "Regulating AI in the financial sector: Recent developments and main challenges." FSI Insights No. 63. https://www.bis.org/fsi/publ/insights63.pdf

Bersin, J. (2025, March 16). "Job Redesign Around AI: Work Intelligence Tools Arrive." https://joshbersin.com/2025/03/job-redesign-around-ai-work-intelligence-tools-arrive/

Bonechi, S., Palma, G., Caronna, M., Ugolini, M., Massaro, A., & Rizzo, A. (2024). "Enhancing Customer Support in Banking: Leveraging AI for Efficient Ticket Classification." Procedia Computer Science, 246, 128–137. https://doi.org/10.1016/j.procs.2024.09.235

Chowdhary, S. (2025, July 31). "Is the IT workforce AI-ready?" FE Tech Bytes. https://www.financialexpress.com/life/technology-is-the-it-workforce-ai-ready-tcs-layoffs-spark-fresh-concerns-over-developer-skills-3932033/

Crisanto, J. C., Leuterio, C. B., Prenio, J., & Yong, J. (2024). "Regulating AI in the financial sector: Recent developments and main challenges." https://www.bis.org/fsi/publ/insights63.htm

Daníelsson, J., Macrae, R., & Uthemann, A. (2022). "Artificial intelligence and systemic risk." Journal of Banking & Finance, 140, 106290. https://doi.org/10.1016/j.jbankfin.2021.106290

Deloitte. (n.d.). "Modernizing Legacy Systems in Banking." https://www.deloitte.com/us/en/Industries/financial-services/articles/modernizing-legacy-systems-in-banking.html

FAccT Conference Proceedings. (2023). Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency. https://dl.acm.org/doi/proceedings/10.1145/3593013

Finance Watch. (2025). "Artificial intelligence in finance: How to trust a black box?" https://www.finance-watch.org/wp-content/uploads/2025/03/Artificial_intelligence_in_finance_report_final.pdf

Floridi, L., Cowls, J., Beltrametti, M., … & Vayena, E. (2018). "AI4People—An Ethical Framework for a Good AI Society." Minds and Machines, 28(4), 689–707. https://doi.org/10.1007/s11023-018-9482-5

Fritz-Morgenthal, S., Hein, B., & Papenbrock, J. (2022). "Financial Risk Management and Explainable, Trustworthy, Responsible AI." Frontiers in Artificial Intelligence. https://doi.org/10.3389/frai.2022.779799

Gandharv, K. (2021, December 6). "Top Five AI Initiatives from Indian Academia in 2021." IndiaAI. https://indiaai.gov.in/article/top-five-ai-initiatives-from-indian-academia-in-2021

Hepplewhite, T. (2024, October 3). "AI in Financial Services: Regulatory Opportunities." https://www.twobirds.com/en/insights/2024/uk/ai-in-financial-services-regulatory-opportunities

IEEE. (2019). Ethically Aligned Design—A Vision for Prioritizing Human Well-being with Autonomous and Intelligent Systems (Version 2). https://standards.ieee.org/wp-content/uploads/import/documents/other/ead_v2.pdf

IITB. (n.d.). "Transforming the Banking Sector: SBI and IIT Bombay's Data Hub Initiative." https://acr.iitbombay.org/transforming-the-banking-sector-sbi-and-iit-bombays-data-hub-initiative/

Izard, S. (2023, December 18). "How can generative AI shape the banking industry?" https://sitsi.pacanalyst.com/whitepaper/white-paper-how-can-generative-ai-shape-the-banking-industry/

Jain, P. (2024). "Research Paper on Impact of Artificial Intelligence on Banking Sector." *Social Science Research Network (SSRN Scholarly Paper No. 4907776)*. papers.ssrn.com/abstract=4907776

Jha, A. (2025, 14 August). "RBI Panel Flags AI Gap in Co-op Banks, Moots Shared 'Landing Zones'." *Indian Cooperative*. indiancooperative.com/banks/rbi-panel-flags-ai-gap-in-co-op-banks-moots-shared-landing-zones/

Lajčinová, B., P. Valábek, and M. Spišiak. (2024). "Intent Classification for Bank Chatbots Through LLM Fine-Tuning (arXiv:2410.04925)." *arXiv*. doi.org/10.48550/arXiv.2410.04925

Lakshmanan, A. (2024, 13 December). "Exploring Explainable AI: Financial Services." *Aspire Systems Blog*. blog.aspiresys.com/artificial-intelligence/exploring-explainable-ai-xai-in-financial-services-why-it-matters/

Mani, V. (2025, 23 July). "AI Talent Gap: Savvy Freshers Bag 4x More Pay." *The Times of India*. timesofindia.indiatimes.com/business/india-business/ai-talent-gap-savvy-freshers-bag-4x-more-pay/articleshow/122847650.cms

McKinsey. (2021). *Building the AI Bank of the Future*. mckinsey.com/~/media/mckinsey/industries/financial%20services/our%20insights/building%20the%20ai%20bank%20of%20the%20future/building-the-ai-bank-of-the-future.pdf

McKinsey. (2024a). *The State of AI in Early 2024*. mckinsey.de/capabilities/quantumblack/our-insights/the-state-of-ai-2024

McKinsey. (2024b, 9 December). *Extracting Value from AI in Banking: Rewiring the Enterprise*. mckinsey.com/industries/financial-services/our-insights/extracting-value-from-ai-in-banking-rewiring-the-enterprise

McKinsey. (2025, 28 January). *AI in the Workplace: A Report for 2025*. mckinsey.com/capabilities/mckinsey-digital/our-insights/superagency-in-the-workplace-empowering-people-to-unlock-ais-full-potential-at-work

MeitY. (2023). *Digital Personal Data Protection Act 2023*. meity.gov.in/static/uploads/2024/06/2bf1f0e9f04e6fb4f8fef35e82c42aa5.pdf

Narang, A., P. Vashisht, and S.B. Bajaj. (2024). "Artificial Intelligence in Banking and Finance." *International Journal of Innovative Research in Computer Science and Technology*, 12(2), Article 2. doi.org/10.55524/ijircst.2024.12.2.23

NIST. (2023). *AI Risk Management Framework*. nist.gov/itl/ai-risk-management-framework

NPCI. (2024). *UPI Product Statistics*. npci.org.in/what-we-do/upi/product-statistics

OECD. (2021, 17 June). "State of Implementation of the OECD AI Principles." *OECD*. oecd.org/en/publications/state-of-implementation-of-the-oecd-ai-principles_1cd40c44-en.html

PwC. (2022). *AI Adoption in Indian Financial Services and Related Challenges*. pwc.in/assets/pdfs/research-insights/2022/ai-adoption-in-indian-financial-services-and-related-challenges.pdf

PwC. (2023). *Responsible AI Toolkit*. pwc.com/sg/en/services/reimagine-digital/data-optimisation/what-is-responsible-ai.html

PwC. (2024). *Graph LLMs: AI's Next Frontier in Banking and Insurance*. pwc.com/m1/en/publications/documents/2024/graph-llms-the-next-ai-frontier-in-banking-and-insurance-transformation.pdf

Chapter 8C — References

Ranković, M., Gurgu, E., Martins, O. M. D., & Vukasović, M. (2023). "Artificial Intelligence and the Evolution of Finance: Opportunities, Challenges and Ethical Considerations." *EdTech Journal*, 3(1), 20–23. https://doi.org/doi.org/10.18485/edtech.2023.3.1.2

Ray, P. P. (2023). "ChatGPT: A comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope." *Internet of Things and Cyber-Physical Systems*, 3, 121–154. https://doi.org/10.1016/j.iotcps.2023.04.003

RBI. (2024a, February 28). "Enabling Framework for Regulatory Sandbox." https://www.rbi.org.in/Scripts/PublicationReportDetails.aspx?UrlPage=&ID=1262

RBI. (2024b, August 5). "Draft Circular—Regulatory Principles for Management of Model Risks in Credit." https://www.rbi.org.in/scripts/bs_viewcontent.aspx?Id=4479

RBI. (2024c, December 26). "Framework for Responsible and Ethical Enablement (FREE) of Artificial Intelligence (AI) in the Financial Sector – Setting up of a committee." https://www.rbi.org.in/Scripts/BS_PressReleaseDisplay.aspx?prid=59377

Saxena, S. (2025, May 6). "How Voice Bots Are Transforming Rural Lending." *Gnani.Ai*. https://www.gnani.ai/resources/blogs/voice-bots-are-revolutionizing-rural-lending-breaking-language-barriers/

SEBI. (2025, June 20). "Consultation Paper on Guidelines for Responsible Usage of AI/ML in Indian Securities Markets." *SEBI*. https://www.sebi.gov.in/reports-and-statistics/reports/jun-2025/consultation-paper-on-guidelines-for-responsible-usage-of-ai-ml-in-indian-securities-markets_94687.html

Shahzad, T., Mazhar, T., Tariq, M. U., Ahmad, W., Ouahada, K., & Hamam, H. (2025). "A comprehensive review of large language models: Issues and solutions in learning environments." *Discover Sustainability*, 6(1). https://doi.org/10.1007/s43621-025-00815-8

Sindhu, J., & Namratha, R. (2019). "Impact of Artificial Intelligence in Chosen Indian Commercial Bank – A Cost Benefit Analysis." *Asian Journal of Management*, 10(4), 377–384. https://doi.org/10.5958/2321-5763.2019.00057.X

Sinha, A. B., & Sinha, A. (2023). "Blending of AI in Financial Sector with Special Reference to the Banking Sector." *Globsyn Management Journal*, XVII(1 & 2), 53–61.

Sleiman, J.-P. (2023). "Generative artificial intelligence and large language models for digital banking: First outlook and perspectives." *Journal of Digital Banking*, 8(2), 102–117.

Sood, N., & Shaw, R. (2025, August 6). "Indian banks spark AI gold rush as tech firms race to tailor language models, build agents." *Moneycontrol*. https://www.moneycontrol.com/artificial-intelligence/indian-banks-spark-ai-gold-rush-as-tech-firms-race-to-tailor-language-models-build-agents-article-13403238.html

Stanford HAI. (2023). *The 2023 AI Index Report*. https://hai.stanford.edu/ai-index/2023-ai-index-report

Sudjianto, A., Fahs, R., Pan, Y., & Swamy, K. (2024). "Banking on AI: How Large Language Models Can Succeed in a High-Stakes World." *SSRN Scholarly Paper No. 5039309*. https://doi.org/10.2139/ssrn.5039309

Surkov, A., Gregorie, J., & Srinivas, V. (2022, May 17). "Unleashing the power of machine learning models in banking through explainable artificial intelligence (XAI)." *Deloitte Insights*. https://www.deloitte.com/us/en/insights/industry/financial-services/explainable-ai-in-banking.html

Ujjivan Small Finance Bank. (2024). *Transformative Ideas. Sustainable Growth. Annual Report 2023–24*.

UNESCO. (2021). *Recommendation on the Ethics of Artificial Intelligence*. https://unesdoc.unesco.org/ark:/48223/pf0000381137

WEF. (2019). *AI Governance: A Holistic Approach to Implement Ethics into AI*. https://www.weforum.org/publications/ai-governance-a-holistic-approach-to-implement-ethics-into-ai/

World Bank. (n.d.). *Artificial Intelligence in the Public Sector: Summary Note*. https://documents1.worldbank.org/curated/en/746721616045333426/pdf/Artificial-Intelligence-in-the-Public-Sector-Summary-Note.pdf

Wu, T., Yang, S., Liu, S., Nguyen, D., Jang, S., & Abuadbba, A. (2025). "ThreatModeling-LLM: Automating Threat Modeling Using Large Language Models for Banking Systems (arXiv:2411.17058)." *arXiv*. https://doi.org/10.48550/arXiv.2411.17058

Xu, J. (2024). "GenAI and LLM for Financial Institutions: A Corporate Strategic Survey." *SSRN Scholarly Paper No. 4988118*. https://doi.org/10.2139/ssrn.4988118

Yoon, S.-H., Yang, S.-B., & Lee, S.-H. (2025). "Comprehensive examination of the bright and dark sides of generative AI services: A mixed-methods approach." *Electronic Commerce Research and Applications*, 70, 101491. https://doi.org/10.1016/j.elerap.2025.101491

Zhang, W., Siyal, S., Riaz, S., Ahmad, R., Hilmi, M. F., & Li, Z. (2023). "Data Security, Customer Trust and Intention for Adoption of Fintech Services: An Empirical Analysis from Commercial Bank Users in Pakistan." *SAGE Open*, 13(3), 21582440231181388. https://doi.org/10.1177/21582440231181388