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Financing India's Next Growth Cycle: AI Credit Scoring and the CA's Role

Artificial Intelligence (AI) is reshaping credit scoring in India by moving beyond traditional CIBIL-based assessments toward data-driven, algorithmic decision-making. While these systems improve speed, coverage, and risk sensitivity in lending decisions, they also introduce new challenges related to governance, internal controls, audit assurance, and regulatory compliance. For CAs, the adoption of AI-driven credit scoring has direct implications for audit

planning, evaluation of internal controls, regulatory compliance, and the exercise of Professional Skepticism. This shift creates new responsibilities in auditing AI systems and assuring transparency, interpretability, and ethical use of algorithms. CAs equipped with AI governance expertise will play a critical role in enabling responsible and inclusive credit practices.

As India moves towards its objective to become a developed country by 2047, access to formal credit remains a critical enabler of entrepreneurship, which is essential for job creation, productivity, and sustainable growth. India's development roadmap under the Viksit Bharat @2047 vision, supported by initiatives like Digital India, the Jan Dhan–Aadhaar–Mobile (JAM trinity), and MSME formalisation programmes, emphasises widening access to institutional finance. Despite this progress, structural gaps persist, with over 400¹ million individuals remaining outside the formal credit system due to limited conventional credit histories. As per the sample survey, 78% of first-generation entrepreneurs access formal credit for the first time, and nearly 75%² of MSMEs still depend on informal lenders. India's aspiration to become a developed nation by 2047 rests not only on infrastructure and technology, but also on the capacity of its financial system to extend timely and affordable

credit to productive economic participants.

Artificial Intelligence is changing this equation. By interpreting digital transactions, alternative data, and behavioural patterns, AI can integrate excluded borrowers into the formal credit ecosystem.

Historical Evolution of Credit Scoring Systems

Credit scoring traces its roots to the 1950s, when lenders in the United States began using statistical analysis of repayment behaviour to assign numerical scores and standardize risk assessment. The FICO score, introduced in 1989 by Fair Isaac Corporation, dominates credit assessment worldwide, particularly in the United States.

India's formal credit scoring system developed much later compared to its Western counterparts. CIBIL (Credit Information Bureau India Limited), established in 2000 and regulated

under the Credit Information Companies Regulations Act, 2005, pioneered organized credit assessment in India. The CIBIL score operates on a 300-900 range, with scores above 750 considered excellent. India's credit infrastructure includes four major credit bureaus:

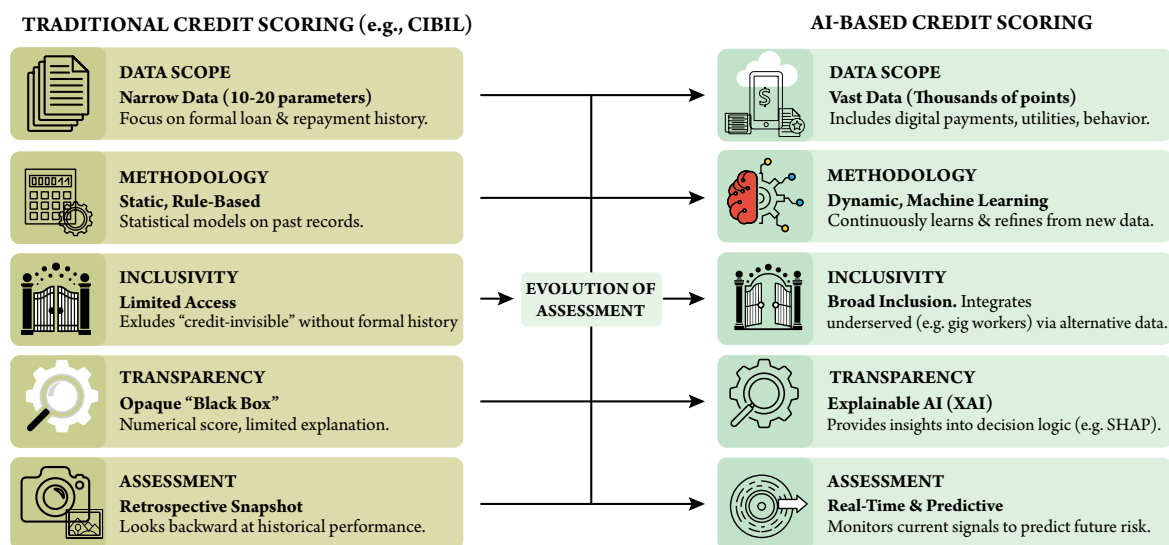
- TransUnion CIBIL
- Experian
- Equifax India
- CRIF High Mark Credit Information Services

Limitations of the Traditional Credit Scoring System

Traditional credit scoring relies on historical financial data from banks. Credit bureaus collect repayment and loan records, apply statistical models to assess default risk, generate a numerical credit score, and lenders use it to decide loan approvals and interest rates. Over the decades,

¹ <https://newsroom.transunioncibil.com/41-of-first-time-borrowers-are-gen-z-according-to-transunion-cibils-latest-cmi-report/>

² <https://economictimes.indiatimes.com/small-biz/sme-sector/78-of-our-borrowers-are-first-generation-entrepreneurs-accessing-formal-credit-ugro-capital/articleshow/122896417.cms>

Figure 1: Traditional vs. AI-Based Credit Scoring: A Comparative Paradigm

this methodology evolved into sophisticated proprietary algorithms, but its fundamental premise, which relies primarily on past borrowing and repayment records, remains unchanged. The Traditional system has several inherent flaws, which raise the need to adopt AI in credit scoring, as depicted in Figure 1.

1. Historical Bias and Structural Discrimination:

- Traditional credit models tend to favour borrowers with stable, salaried employment and established banking relationships, while this approach inadvertently disadvantages large sections of the workforce—particularly farmers, start-up entrepreneurs, daily wage earners, and individuals whose income flows are inherently non-linear yet often reliable over time.
- Further, credit bureaus rely on past formal borrowings; the poor remain trapped in a cycle where the absence of credit history prevents access to credit, and lack of access prevents creation of history.

2. Narrow and Static Assessment Framework:

- Current systems primarily analyse 10–20 parameters focused on loan repayment behaviour, outstanding debt, and credit utilization, and exclude a wide range of financially meaningful indicators such as rental payments, utility bills, insurance premiums, digital wallet transactions, tax payment consistency, etc.
- The absence of these real-time indicators limits innovation in credit products and prevents lenders from identifying genuinely creditworthy individuals.

3. Inability to Capture Informal Economic Activity:

- The Current credit scoring system is built for formal economies, while India's more than 80%³ workforce is employed in unorganised sectors, and around 45% of GDP came from the unorganised sector.
- Informal entities like chit funds, self-help groups, and state-regulated local money

lenders have detailed but non-digitised records of lending and repayment, which reflect borrowers' financial discipline, but it remains invisible under the current system.

- As a result, many small business owners who have relevant repayment potential are prevented from accessing affordable credit and rely on higher-interest-rate informal credit.

4. Counterintuitive and Arbitrary Outcomes:

- Existing models often penalise prudent behaviour. Borrowers who manage finances through cash or repay loans early may see reduced scores, while multiple loan inquiries for better terms can further harm ratings. Such inconsistencies discourage sound financial management and create confusion regarding what constitutes good credit behaviour.

5. Opacity and Lack of Explainability:

- Borrowers are only shown a numerical score without clear insight into how specific factors

³ https://mospi.gov.in/sites/default/files/publication_reports/Annual%20Report%2C%20PLFS%202017-18_31052019.pdf

affect the credit score, such as repayment timing, credit utilisation, or loan closure. This opacity prevents individuals from understanding or improving their credit behaviour and limits their ability to correct errors. Moreover, it reduces accountability and may conceal biases against those lacking a formal borrowing history, such as self-employed or informal workers.

Key AI Technologies in Credit Risk Assessment

Artificial Intelligence is fundamentally reshaping credit scoring in India, breaking away from the rigid, history-bound models of the past to create systems that are dynamic, data-rich, and inclusive by design. AI-driven models draw strength from continuous learning, analysing diverse, real-time signals from across the digital economy. Below are the key AI technologies and their applications reshaping the credit assessment landscape:

1. Machine Learning-Based Risk Modelling:

- Machine Learning (ML) enables systems to learn from historical data and predict credit outcomes by recognising complex patterns. It automatically refines its accuracy as new borrower data is introduced.
- Supervised ML models such as Logistic Regression, Decision Trees, and Gradient Boosting algorithms evaluate thousands of borrower variables, including income, repayment history, and transaction frequency, to estimate default probability. These models allow lenders to approve credit for first-time borrowers and small entrepreneurs who may lack a formal bureau record.
- A private sector bank, Kotak Mahindra Bank, deployed a Perfios credit-assessment and fraud-analytics pipeline to

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automate statement analysis and fraud checks; it materially reduced manual effort in the initial stage.

2. Natural Language Processing (NLP) and Conversational AI

- NLP algorithms are increasingly used to extract meaningful insights from unstructured text data such as customer feedback and financial reports. AI-powered OCR can read and process information from forms (even handwritten ones), detect tampering or forgery in documents, and automatically extract key borrower data. This reduces manual effort and speeds up underwriting.
- Beyond chatbots, NLP can analyse an applicant’s written or spoken responses for additional credit signals (though this is emerging). Sentiment analysis on customer reviews or even social-media activity is being explored by some fintechs.
- Conversational AI is improving financial literacy and helping borrowers understand credit products better. Virtual agents can provide pre- and post-loan

support, enhance customer experience while reducing support costs.

3. AutoML and No-Code AI Platforms

- AutoML (Automated Machine Learning) makes AI in credit scoring easy to use. Instead of experts writing complex code, the system itself prepares the data, selects important borrower factors, builds the model, and checks whether it works properly.
- This allows credit and finance teams to use AI without technical skills. They focus on understanding borrower behaviour and risk, while AutoML takes care of the technical modelling in the background.
- Indian banks such as Axis Bank are using cloud AutoML tools like Google Vertex AI to test credit-risk models faster, making strong controls and CA oversight more important than ever.

4. Explainable AI (XAI) and Model Governance Tools

- RBI’s FREE-AI framework emphasises that AI-based credit decisions should be understandable by design, supported by proper documentation explaining how models arrive at loan approvals or rejections, rather than operating as opaque black boxes.
- To meet this requirement, lenders use explainability tools such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations), which allow human reviewers, including auditors, to understand the reasons behind automated credit decisions
- SHAP shows how each factor, such as income stability, repayment behaviour, or

cash-flow patterns, affects the final score, while LIME explains one specific credit decision by approximating the model's behaviour around that borrower.

5. Behavioural and Anomaly Detection Systems

- Unsupervised ML and anomaly detection algorithms identify patterns that differ from historical norms, such as sudden cash withdrawals, inconsistent income deposits, or missed payments.
- These systems continuously track borrower behaviour to detect unusual financial activity or spending deviations. Behavioural models allow lenders to adjust risk scores dynamically, preventing defaults through timely interventions.
- The private Bank named Citibank employs behavioural segmentation models that combine credit bureau data with lifestyle and transaction analytics. Its AI-driven "Customer 360" system tracks how borrowers use their credit

lines, pay bills, and respond to reminders. The behavioural data feeds into Citi's Decision Management System, which dynamically reassigns risk bands and pricing tiers.

RBI's FREE-AI: Framework for Responsible and Ethical Enablement of AI

The RBI's FREE-AI represents India's first principle-based governance framework for AI adoption in financial services. As AI becomes integral to financial services, from credit underwriting to fraud detection, the FREE-AI Framework provides guiding principles to govern responsible and trustworthy use of such technologies.

The RBI articulates the framework through seven guiding "Sutras," which together form the ethical foundation of AI use in finance:

1. **Trust is the Foundation** – building public confidence in AI systems.
2. **People First** – ensuring human oversight and accountability.
3. **Innovation over Restraint** – encouraging responsible experimentation.

4. **Fairness and Equity** – avoiding bias and discrimination.

5. **Accountability** – assigning clear responsibility for AI decisions.

6. **Understandable by Design** – making AI transparent and explainable.

7. **Safety, Resilience, and Sustainability** – ensuring long-term reliability and adaptability.

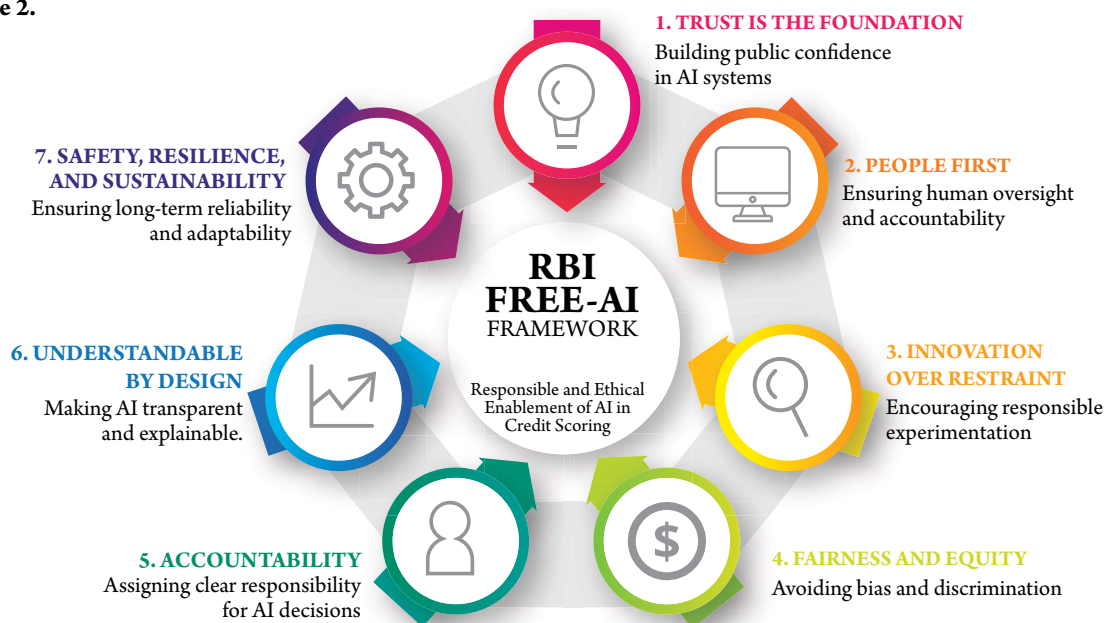
Auditing the Algorithm: Internal Controls, Governance, and Professional Skepticism

AI-driven credit models now shape credit decisions, portfolio risk, and Expected Credit Loss (ECL) outcomes at scale. This shifts the Auditor's role from reviewing individual loan files to applying Professional Skepticism over data governance, model governance, explainability, and management reliance on automated outputs. By assuring the following elements, CAs help to preserve transparency, accountability, and reliability in AI-influenced financial reporting:

1. Audit Considerations for Data Usage and Consent:

- AI-based credit scoring systems use vast amounts of sensitive

Figure 2.



personal and behavioural data, including financial transactions, tax records, and digital footprints. Therefore, compliance with the Digital Personal Data Protection (DPDP) Act, 2023, becomes integral to audit. The auditor should evaluate controls, ensuring purpose limitation, consent validity, and lawful use of data within the AI-based credit scoring system.

- Accordingly, auditors must evaluate data-protection controls as a part of assessing the overall internal control environment supporting AI-enabled credit processes and may consider the following audit checks:

1. Verify that each category of personal and alternative data used is supported by a clearly documented and lawful credit-risk purpose, and that such purpose is consistent with internal credit policies and disclosures made to borrowers.
2. Examine borrower consent records to confirm that consent is informed, specific, and explicitly permits use of personal data for AI-based credit assessment.
3. Evaluate system and governance controls that ensure personal

data collected for assessment purposes is not reused for other analysis and cross-selling without appropriate consent.

4. Review whether automated controls exist to ensure personal data is retained only for the approved credit purpose and is deleted or anonymised once the purpose is fulfilled or consent is withdrawn.
5. Review data breach detection and response processes to ensure timely identification, escalation, and regulatory or stakeholder notification where AI credit systems are compromised.

2. Audit Considerations for Model Drift and Overfitting in AI Credit Systems

- AI-based credit models are built using historical borrower behaviour and economic data, and their effectiveness can deteriorate when underlying conditions change. For example, models trained during periods of low interest rates may underestimate risk when rates rise, inflation increases, or borrower cash flows weaken, particularly in MSME or unsecured retail portfolios.
- Changes in lending products, regulatory relief measures, or

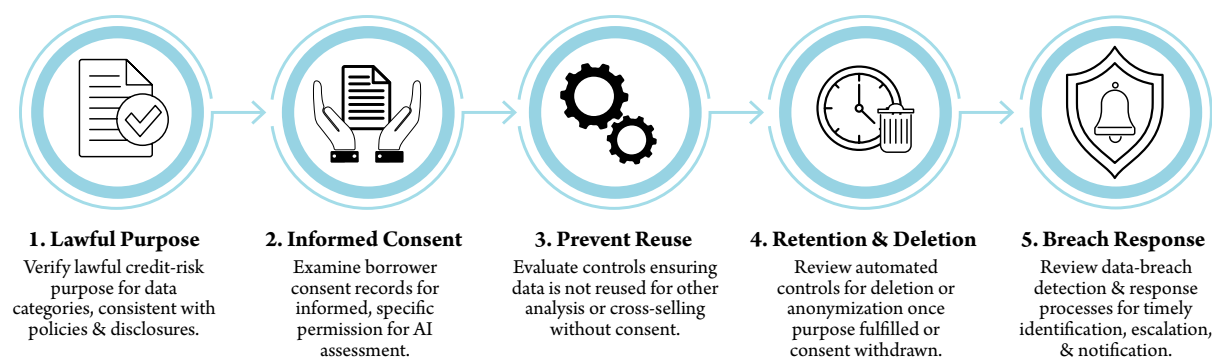


portfolio mix can further reduce model relevance. This creates audit risk where outdated models delay recognition of credit deterioration and understating provisions.

- Auditors should review independent model validation to confirm that credit models are logically designed, perform as expected in practice, and remain reliable under stressed conditions. This includes comparing model predictions with actual default experience, evaluating results under adverse economic scenarios, and checking that defined thresholds trigger timely human intervention.
- Auditors should also review challenger models to benchmark performance and identify early signs of model deterioration or drift.

Figure 3: Auditor Checks for AI-Enabled Credit Processes

Auditors evaluate data-protection controls for AI-enabled credit systems.



3. Audit Considerations for Explainability and Transparency of AI's Decision:

- AI-driven credit decisions must be explainable to regulators, customers, and auditors. Where models operate as black boxes, management may be unable to justify loan rejections, approvals, or risk classifications, creating litigation and compliance risk.
- Lack of explainability also limits audit assurance, as auditors may be unable to obtain sufficient appropriate evidence to support management assertions or provisioning judgments. This risk is heightened where automated decisions disproportionately affect specific borrower segments, leading to customer grievances and regulatory scrutiny.
- Auditors should ensure weather the explainability tools and standardised reason codes are embedded in the credit process.
- Auditor should review system-generated explanations for selected decisions, test consistency with credit policy thresholds, and perform decision replay, where historical applications are re-processed using archived model versions to verify traceability, consistency, and audit trail.

4. AI-Driven ECL Measurement and Financial Statement Impact:

- For banks, the RBI has mandated the ECL approach, and AI-based credit models influence default risk assessment, early warning signals, and forward-looking assumptions. Weak governance over these models may delay migration of stressed accounts,

resulting in understated provisions and misleading financial statements.

- Auditors address this by linking AI model results to ECL assumptions and testing their reasonableness. Auditors perform sensitivity analysis on key inputs such as default rates, recovery assumptions, and macroeconomic variables; compare AI-driven outcomes with historical stress periods; and assess management overlays to ensure they appropriately compensate for known model limitations and emerging economic risks.

5. Audit consideration for Governance, Accountability, and Vendor Dependence:

- Banks increasingly rely on third-party vendors for AI-based credit models, which can weaken governance if internal ownership and understanding are inadequate. When decision logic, model changes, or data practices remain vendor-controlled, accountability for credit outcomes may become unclear, creating a "responsibility gap" and increasing compliance and audit risk.
- Auditors address this by performing vendor governance and accountability assessment, reviewing board-approved AI policies, and outsourcing contracts to confirm that responsibility for model outcomes remains with the bank.
- In practice, auditors verify whether the bank has contractual rights to obtain and review vendor-provided model documentation, validation summaries, change notifications, and incident disclosures, and assess whether management evaluates these

inputs and records critical vendor models in the model inventory and risk register. This ensures auditors can evaluate model integrity rather than being limited by opaque vendor practices.

Case Study: Strategic Integration of AI in Credit Risk Management

1. Transforming Traditional Credit Assessment Challenges

- A leading global financial services firm, JP Morgan Chase, adopted artificial intelligence (AI) in credit risk assessment, replacing slow manual processes and static scoring with dynamic machine learning (ML) models for superior accuracy. These systems analyse vast datasets, from financial histories to alternative sources like online behaviour and transaction patterns, delivering comprehensive borrower profiles that reduce defaults and accelerate approvals. This evolution enhances efficiency and extends credit access to underserved segments, balancing inclusion with risk control.

2. Key AI-Driven Operational Enhancements

- AI excels in comprehensive data analysis, uncovering patterns that traditional methods overlook, such as economic signals in spending habits. Predictive risk modelling forecasts defaults using diverse variables, including market trends and behaviours; real-time processing speeds applications without compromising standards; continuous learning refines accuracy amid market shifts. COiN (Contract Intelligence) reviews 12,000 credit agreements in seconds,

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saving 360,000+ annual hours⁴ while flagging default clauses and risks.

3. Primary Risks Introduced by AI Systems

- The company's use of AI in contract analysis, fraud detection, and credit assessment introduces several risks. AI models trained on historical data may unintentionally reflect past patterns, leading to biased outcomes, such as repeatedly flagging certain transaction types as high-risk without adequate context.
- Advanced AI tools may also operate as complex systems where decision logic is difficult to fully interpret, limiting management's ability to explain outcomes to regulators or customers. In highly automated environments, excessive reliance on AI may amplify errors during volatile market conditions if models misread new signals. Additionally, increased dependence on large volumes of sensitive data increases data privacy risks.

4. Effective Risk Mitigation and Governance Strategies

- The company mitigates these risks through strong governance and oversight. Regular model validation and retraining help reduce bias and ensure models remain relevant across changing conditions. Explainability tools and documented decision logic support transparency and regulatory review. Critical AI-driven decisions are supported by human oversight, especially during abnormal market movements. Robust data-governance controls, access restrictions, and monitoring mechanisms further safeguard data integrity.

Conclusion

The adoption of AI in India's credit ecosystem is not a question of *if*, but *how responsibly* it can be scaled. In the long term, progress will not depend only on cutting-edge sophisticated algorithms but more on data infrastructure, robustness of internal controls, model validation, and ethical oversight.

In this evolving landscape, Chartered Accountants emerge as critical custodians of trust. The CA's role extends beyond traditional financial audits into auditing algorithms, validating model governance, challenging automated judgments through Professional Skepticism, and ensuring that AI-driven credit decisions translate into reliable financial reporting and prudent ECL recognition.

AI should be seen as an enhancement to risk judgment, not a replacement for it. Those who build expertise in AI governance, audit of automated systems, and ethical assurance will not only safeguard the integrity of India's financial system but also define the future relevance of the profession itself.

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⁴ https://reports.jpmorganchase.com/investor-relations/2016/ar-ceo-letter-matt-zames.htm?utm_source