Students' ECONOMIC FORUM

A monthly publication from South Indian Bank

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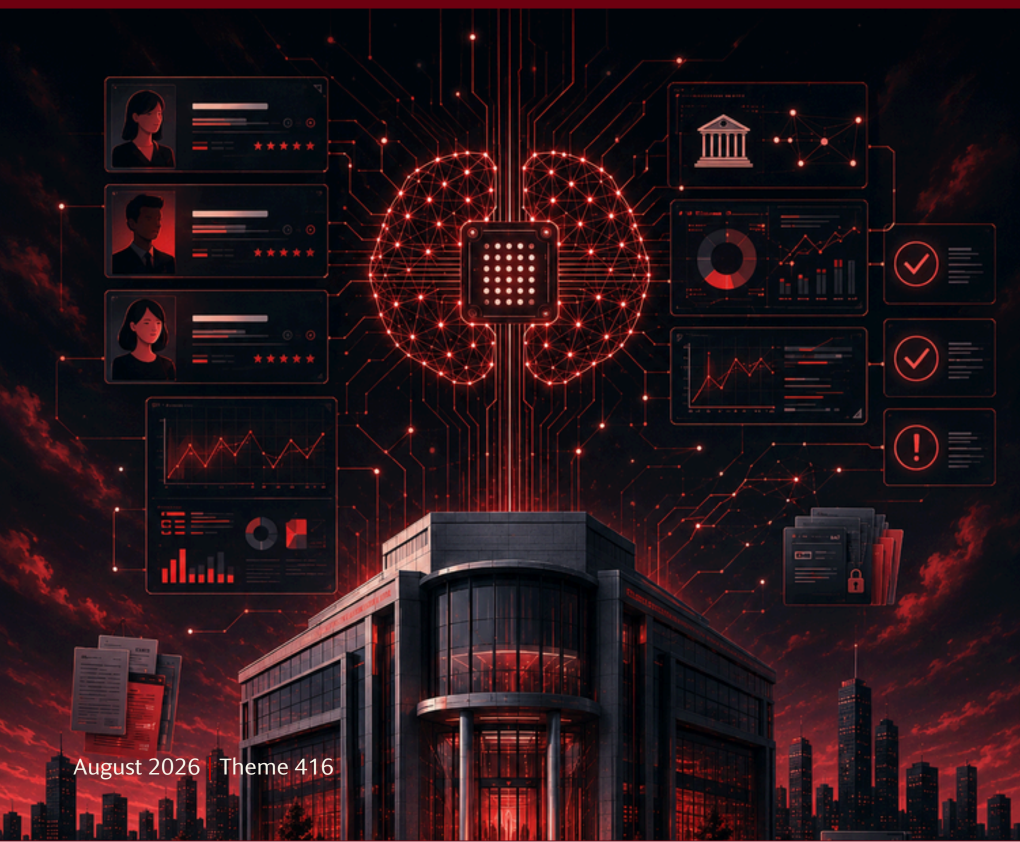
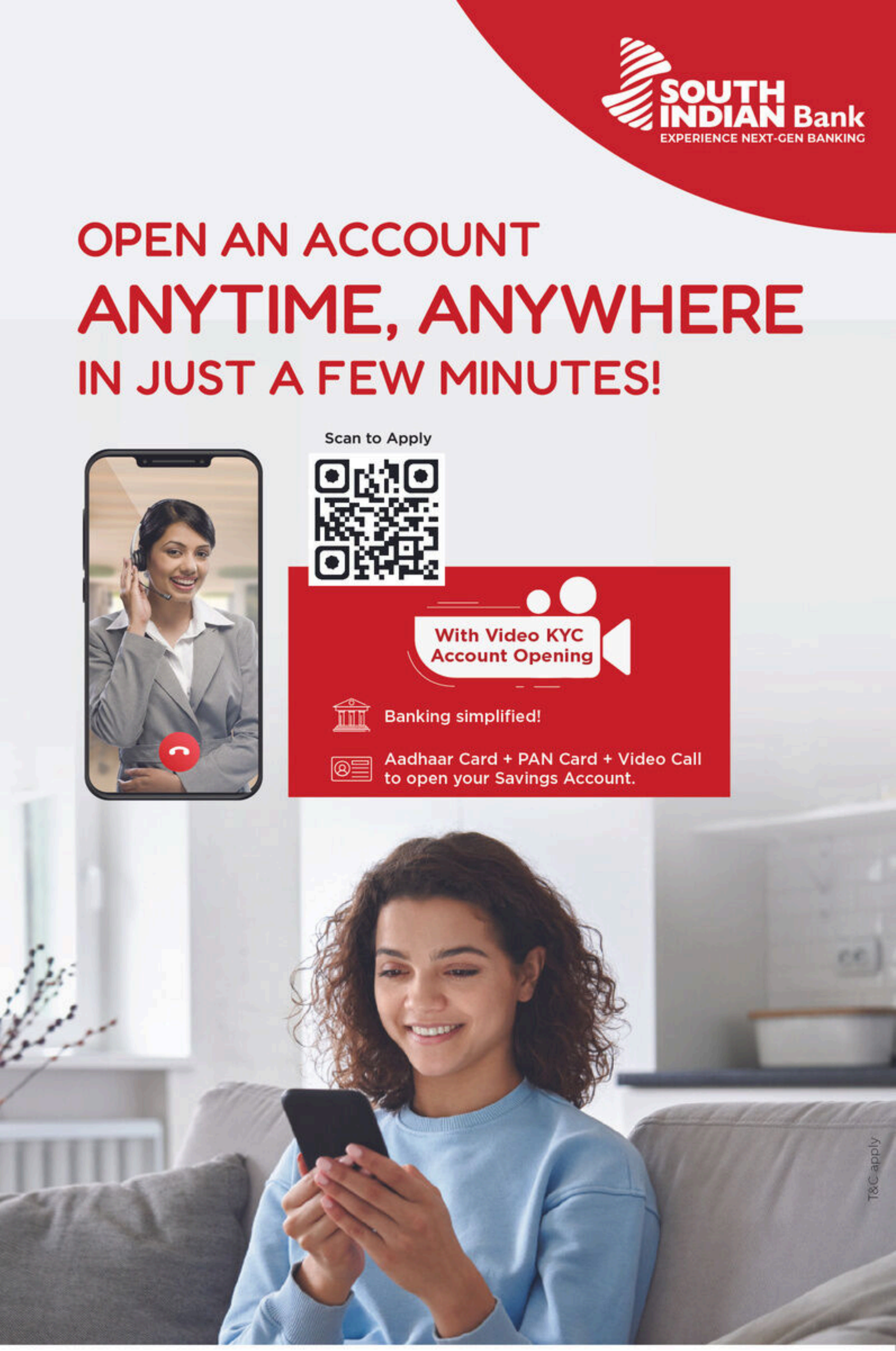
AI-based Credit Screening

Promise, Risk & Regulation



August 2026 | Theme 416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AI-based Credit Screening

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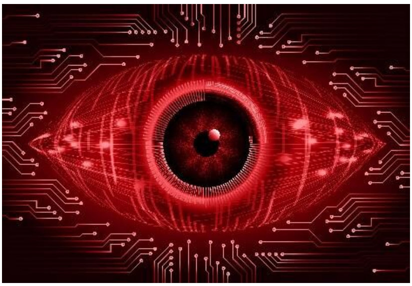
"AI models on alternative data, which we have a lot now - cash flows, GST filings, utility payment bills, digital platforms - they can all extend the frontier of bankable India considerably."

Sanjay Malhotra, Governor, RBI

The 'SIB Students' Economic Forum' is designed to kindle interest in the minds of the younger generation. We highlight one theme in every monthly publication. Topic of discussion for this month is **AI-based Credit Screening.**



AI-based credit screening is rapidly moving from experimental pilots to mainstream practice in India's banking and lending ecosystem.

For banks, non-banking financial companies (NBFCs), and fintechs, AI models promise faster decisions, sharper risk discrimination, and greater financial inclusion. Yet they also introduce new forms of model risk, governance challenges, and ethical questions that Indian institutions and regulators are only beginning to fully confront.

This edition of the SEF offers a practitioner's overview of how AI-driven credit screening works in India, the data and models involved, the benefits and risks, and the evolving regulatory expectations. The perspective is based on publicly available research, industry reports, and regulatory pronouncements as of mid-2026, and is intended as a professional analysis rather than legal advice.

From Scorecards to Learning Models

For decades, Indian banks have relied on a combination of traditional tools for credit screening: bureau scores (such as CIBIL scores), financial ratios, cash-flow analysis, collateral coverage and manual underwriting based on documents like audited financial statements and bank statements.

This approach works reasonably well for established borrowers with long credit histories but struggles with new-to-credit customers, thin-file borrowers and small businesses operating with informal or variable incomes.

AI-based credit screening represents a shift from static, rules-based scorecards to models that learn patterns from data. Instead of relying solely on a handful of ratios and thresholds, machine learning algorithms analyse thousands of borrower attributes to estimate the probability of default. These models can be retrained periodically, allowing them to adapt as economic conditions and borrower behaviour change.

In practice, this means that a loan application is no longer evaluated only on a bureau score and a few financial indicators. An AI model combines multiple signals - *traditional and alternative* - to form a more holistic picture of repayment capacity and intent. Banks can then use the resulting risk score to drive automated or semi-automated decisions, subject to their credit policy and risk appetite.

The Indian Data Advantage

AI systems are only as good as the data they consume. Here, India's rapidly digitising financial ecosystem creates a fertile environment for AI-based credit screening.

Beyond conventional credit bureau data, Indian lenders increasingly tap into a rich mix of digital information:

1. **Banking and cash-flow data**
   Current account and savings account statements reveal salary credits, business inflows, EMI debits, cheque returns, and cash deposit patterns. For MSMEs, these flows offer a more dynamic view of business health than static balance sheets.

2. **Tax and formal business data**
   Goods and Services Tax (GST) returns and filing history provide insight into turnover trends, seasonality, and tax discipline. For many smaller enterprises, GST data is the most reliable indicator of actual business volumes.

3. **Digital payment behaviour**
   Unified Payments Interface (UPI) transactions, card swipes, and QR-based merchant payments show both the volume and nature of financial activity. Frequent, regular digital payments can signal stability and engagement with the formal economy.

4. **Utility and recurring payments**
   Electricity, water, telecom and internet bills, rental payments, and subscription debits create a history of recurring obligations. Consistent on-time payments suggest financial discipline even where formal credit history is thin.

5. **Behavioural and device-level indicators**
   Some lenders use stability of mobile numbers, patterns of app usage, frequency of logins, and other behavioural data as supplementary signals of reliability and continuity.

In many cases, these data streams are accessed via consents-based mechanisms such as account aggregators or through digital lending platforms, subject to prevailing privacy and consent norms.

The central idea is that the combination of traditional credit data and alternative digital footprints allows lenders to assess borrowers who would otherwise remain invisible or ambiguous using legacy methods.

How AI Credit Models Work

While implementations vary widely, most AI-based credit screening systems in India follow a broadly similar lifecycle.

1. Data Ingestion and Feature Engineering

The process begins with aggregating data from multiple sources: credit bureaus, bank statements, GST returns, payment systems, and internal banking systems. This data is standardised and cleaned and then converted into "features" that capture relevant patterns.

Examples include average monthly inflows, month-to-month variability, the ratio of bounced to successful debits, length of credit history, number of past delinquencies, GST filing regularity, and digital payment frequency. Feature engineering is a critical step; it encodes domain knowledge and often determines whether the model will capture the true risk drivers or be misled by noise.

2. Model Training

Supervised machine learning algorithms are then trained on historical loan performance data. Past loans are labelled as "good" (repaid) or "bad" (default, write-off, or significant restructuring), and the model learns which combinations of features are associated with each outcome.

Commonly used techniques include gradient boosting machines, random forests, and other ensemble methods. Deep learning is occasionally used, especially where unstructured data (such as transaction narratives or semi-structured documents) is involved, though many banks prefer more interpretable models.

3. Risk Scoring and Decisioning

Once trained and validated, the model can score new applications. For each borrower, it outputs a probability of default or an internal risk grade. These scores are then mapped to credit policy: certain bands might be approved automatically, others declined, and borderline cases routed to manual underwriters.

In retail and small-ticket lending, this can enable near-instant decisions for low-risk segments and reduce the load on credit officers. In higher value or more complex cases, the AI output serves as a decision-support tool rather than a replacement for human judgement.

4. Monitoring and Recalibration

Performance does not end at deployment. Banks track the model's accuracy, stability and bias over time. If default patterns shift or the borrower mix changes, the model may need to be recalibrated or retrained. This ongoing monitoring is central to emerging model risk management expectations, especially when AI models materially influence lending decisions.

Use Cases Across Segments

In India, AI-based credit screening has found its way into multiple lending products and customer segments.

1. Digital personal loans and consumer credit

Many banks and fintechs use AI to power fully digital journeys for small-ticket personal loans, credit cards, and "buy now, pay later" products. For existing customers, transactional and repayment data enable pre-approved offers with instant disbursal. For new customers, AI augments bureau data with alternative signals to support quick decisions.

2. MSME and small business lending

AI models designed around GST, bank statements and invoice flows are particularly well-suited to MSMEs. Instead of relying solely on collateral and static statements, lenders can build cash-flow based risk profiles. This is especially relevant for working capital, invoice discounting and supply chain finance, where speed and recurring credit limits matter.

3. Rural and agri-focused lending

In rural contexts, where formal documentation can be sparse, AI-driven tools may combine limited financial records with digital transaction patterns and, in some pilots, external data such as satellite imagery or weather patterns. While this area is less mature, it aligns with broader financial inclusion objectives.

4. **P2P and digital lending platforms**

Peer-to-peer and other fintech lending platforms were early adopters of AI-driven underwriting, often operating with richer behavioural datasets and more aggressive experimentation than traditional banks. Their practices have, in turn, influenced mainstream players and provided case studies for both success and caution. Across these use cases, AI is rarely deployed as a standalone “black box”. It sits within a broader credit framework that includes policy rules, human oversight, and product-specific constraints.

Benefits for Banks and Borrowers

When implemented prudently, AI-based credit screening can deliver several important benefits.

1. **Enhanced Risk Differentiation**
   AI models can capture non-linear interactions between variables and exploit a far larger feature set than traditional scorecards. Empirical studies on Indian lending portfolios have reported improvements in default prediction accuracy when AI models incorporate alternative data alongside bureau scores and financial ratios. In practice, this translates into sharper separation between low-risk and high-risk borrowers, which can reduce credit losses over time.

2. **Faster Turnaround Times**
   
   Automated scoring and decisioning significantly reduce turnaround times for simple, standardised products. For pre-approved existing customers, decisions that once took days can be delivered in minutes or even seconds. Faster decisions improve customer experience and competitiveness, especially in segments where fintech lenders set high expectations for speed.

3. **Broader Financial Inclusion**
   Perhaps the most compelling promise of AI-based screening in India is its potential to extend credit to underserved segments. By using digital payment histories, utility payment patterns, and other non-traditional signals, lenders can form a view of creditworthiness for borrowers with little or no formal credit history. This can bring new-to-credit individuals and micro-enterprises into the formal credit system, aligning commercial goals with public policy objectives.

4. **Operational Efficiency**
   Automating repetitive aspects of underwriting - such as document parsing, basic ratio calculations and initial scoring - frees up credit officers to focus on complex cases, policy exceptions and portfolio management. Over time, this can reduce unit costs per loan, particularly in high-volume retail and SME portfolios.

Emerging Risks and Limitations

The upside of AI-based credit screening comes with meaningful risks that must be managed.

a. Model Risk and Robustness

Complex AI models can fail in subtle ways. They may overfit historical patterns that no longer hold, misinterpret new borrower segments, or react poorly to macro shocks. If unchecked, such failures can lead to mispriced risk, unexpected default clusters, or undue credit tightening.

This is why regulators and risk managers emphasise model validation, back-testing, stress testing and challenger models. AI-based credit tools are treated as high-impact models that require disciplined oversight, not experimental gadgets.

b. Fairness and Bias

AI models trained on historical data can inadvertently learn and amplify existing biases. If past lending patterns systematically disadvantaged certain groups, the model may encode that behaviour unless specifically checked and corrected. Even innocuous-seeming variables - like geography, device type, or certain behavioural proxies - can correlate with protected characteristics.

In a diverse country like India, fairness in AI-driven lending is both an ethical imperative and a regulatory concern. Lenders need frameworks to detect and mitigate disparate impact, as well as to ensure that alternative data sources do not become backdoor proxies for discrimination.

c. Transparency and Explainability

A recurring challenge with AI/ML models is explaining their decisions. Borrowers, regulators, internal auditors and senior management all need to understand, at least at a high level, why a loan was approved, declined, or priced in a particular way.

Explainable AI techniques, model documentation, and clear communication of key factors can help bridge this gap. In many jurisdictions, and increasingly in India, transparency around credit decisions is not just good practice but embedded in fair lending and customer rights frameworks.

d. Data Privacy and Consent

AI-based credit screening relies on extensive data collection, including sensitive personal and financial information. This raises questions about consent, purpose limitation, data minimisation, and security.

Regulatory frameworks for digital lending, IT governance and data protection increasingly stress explicit, informed consent and strict limits on what data can be collected and how it may be used.

Implementation Roadmap for Banks

For banks exploring or expanding AI-based credit screening, a phased, risk-aware approach may be advisable.

a. **Starting with Clear Use Cases**
Identify specific products and segments where AI can deliver clear value - such as digital personal loans, co-lending arrangements, or MSME working capital - and define success metrics in terms of NPA control, turnaround time, and inclusion.

b. **Investing in Data Infrastructure**
Robust data pipelines, standardisation, quality controls and secure storage are prerequisites. Integrating bureau, banking, GST and payment data in a scalable way often requires upgrades to existing data architecture.

c. **Building Cross-Functional Teams**
AI initiatives should not be left solely to data scientists or IT. Credit risk, compliance, legal, operations and business teams must jointly design and govern models, ensuring that they align with both risk appetite and regulatory expectations.

d. **Piloting with Human-in-the-Loop**
Early deployments can use AI outputs as decision-support tools, with human underwriters retaining final authority. This allows institutions to learn from model performance while containing risk and building internal confidence.

e. **Formalising Governance**
Document model design, assumptions, limitations and use cases. Implement periodic validation, monitoring and governance committee reviews. Connect AI model decisions to existing policy frameworks rather than treating them as separate, experimental systems.

f. **Embedding Ethics and Fairness**
Establish processes to test models for bias and disparate impact. Consider how alternative data sources are selected, and ensure they are defensible, relevant, and minimally intrusive. Clear policies on what is off-limits are as important as what is allowed.

AI-based credit screening in India is no longer a fringe experiment. It is becoming a strategic capability that can reshape how banks and NBFCs assess risk, compete in digital lending, and serve new segments of borrowers. The opportunity is significant: better risk differentiation, faster and more convenient credit, and expanded inclusion.

Yet the risks are equally real. Complex models, opaque decisions, and extensive data use can undermine trust, fairness and resilience if not handled carefully. Indian institutions that succeed with AI-based credit screening will be those that

Banks and their partners must ensure that AI initiatives comply not only with prudential norms but also with consumer protection and privacy requirements.

Regulatory Direction in India

India's central bank and related policymakers have not issued a single, monolithic "AI in credit" regulation. Instead, AI-based credit screening is addressed through a combination of guidelines and principles that evolve over time.

Key themes in current and emerging guidance include:

1. **Model Governance and Risk Management**
AI/ML models used in underwriting are expected to fall within the bank's model risk management framework. This typically involves board-approved policies, model inventories, independent validation, and ongoing monitoring. Draft and consultative documents in recent years have moved towards more explicit coverage of AI and machine-learning models.

2. **Digital Lending and Fair Practices**
RBI's digital lending guidelines and fair practices codes emphasise transparent communication of credit terms, clear disclosure of partners, and communication of reasons for loan rejection. These principles apply equally when decisions are AI-assisted or AI-driven.

3. **Human Oversight and Accountability**
Even when credit decisions are automated, regulated entities remain responsible for outcomes. Guidance increasingly stresses human-in-the-loop or human-on-the-loop mechanisms for high-impact models, as well as the ability to override or suspend models if risks become unacceptable.

4. **Customer Rights and Recourse**
Borrowers should have channels to understand adverse decisions, seek clarification, and escalate grievances. As AI becomes more prominent, these mechanisms will need to accommodate explanations of model-driven factors without overwhelming customers with technical jargon.

Because the regulatory landscape continues to evolve, banks must treat AI-based credit screening as a living area of compliance. Periodic reviews, legal consultation and alignment with updated circulars and directions are essential.

combine technological sophistication with strong risk culture, robust governance, and a clear commitment to responsible, customer-centric lending.

For professionals in risk management, compliance and learning and development, this is an ideal moment to build internal understanding of AI-based credit screening - its mechanics, its promise, and its constraints - and to equip teams with the knowledge needed to use these powerful tools wisely.

Sources:

a) **Reserve Bank of India.** *Reserve Bank of India (Digital Lending) Directions, 2025.* Mumbai: RBI, 2025. *Covers regulated-entity accountability, borrower disclosures, customer protection and digital-lending controls.*

b) **Reserve Bank of India.** *Master Direction – Non-Banking Financial Company – Account Aggregator (Reserve Bank) Directions, 2016*, as amended. *Covers explicit customer consent, purpose-specific sharing, auditability, secure data flows and consent revocation*.

c) **Committee for Framework for Responsible and Ethical Enablement of Artificial Intelligence (FREE-AI).** *Framework for Responsible and Ethical Enablement of Artificial Intelligence in the Financial Sector.* Reserve Bank of India, August 2025. *Addresses AI adoption, risks, governance, evaluation, mitigation and monitoring across banks, NBFCs and fintechs.*

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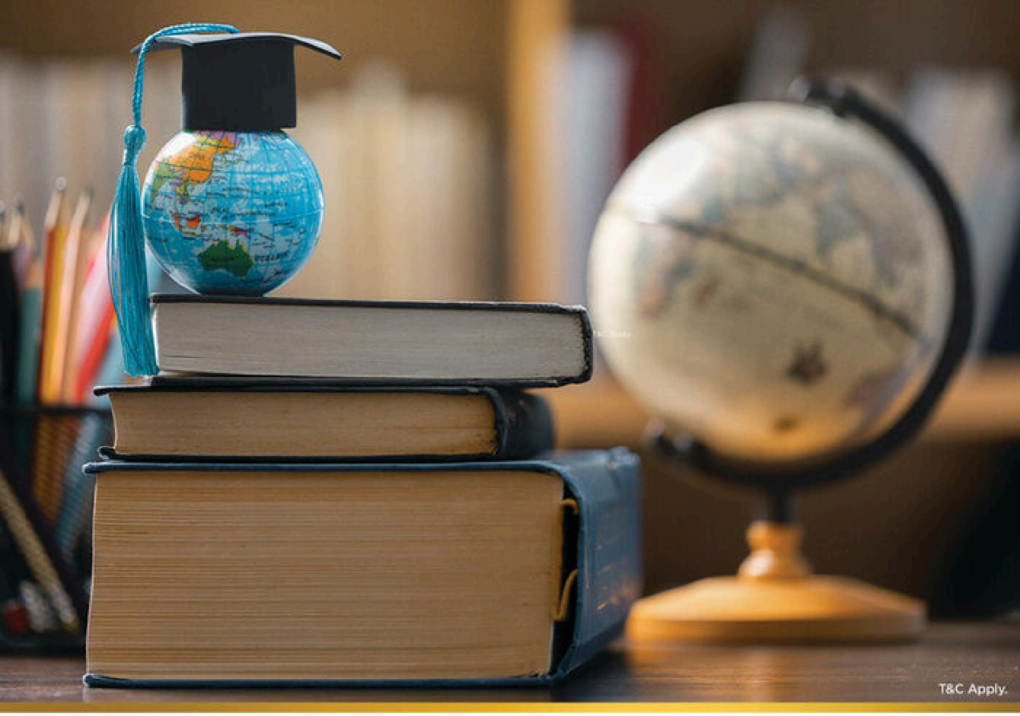

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