MADAD

The Missing Middle

Why SME Credit Is Fintech's Biggest Unfinished Business

Rewiring SME Credit Across the GCC and ASEAN Through Trusted Data, Alternative Credit Assessment and Responsible AI

White Paper

Prepared for the Singapore FinTech Festival 2026 and the Qatar FinTech Hub delegation

November 2026 | Doha, Qatar

Executive summary

The central argument, evidence and implications for action

Small and medium-sized enterprises are central to employment, trade and diversification, yet formal credit systems still struggle to serve them at scale. The gap is especially visible in the Gulf Cooperation Council, where SME lending represents about 4% of commercial bank loans, compared with 33.5% in the IMF's selected emerging-market comparison group. Qatar's 2023 data show an SME credit balance of QAR 17.8 billion, around 3% of private-sector credit, alongside an SME non-performing loan ratio of 10.5%, versus 3.9% for the private sector overall. These figures point to two truths at once: SMEs remain underfinanced, and lenders face legitimate risk and information constraints. [1][2]

This paper argues for treating the SME financing gap as an information and infrastructure problem alongside a capital problem. Fragmented records, expensive underwriting and weak trade verification obstruct financing. Madad's team also identifies payment timing as a major source of SME liquidity pressure in Qatar. A financially strong buyer can still create a cash-flow shortfall through late settlement. Buyer credit quality, payment behaviour and SME repayment capacity require separate assessment.

The proposed framework combines three assessment layers: SME creditworthiness, paymaster risk and transaction risk. Verified identity, permissioned financial data, buyer confirmation and duplicate-financing controls support the decision. Rules, statistical models and accountable human review then translate evidence into financing terms. Singapore's Trade Finance Registry, Hong Kong's CargoX programme and India's TReDS and central receivables registry illustrate complementary infrastructure functions. [11][13][14][15]

Alternative data and AI support this framework rather than replace credit policy. IFC's review of 448 firms identifies transaction data and hybrid approaches as prominent features of alternative credit assessment. Research on specific Chinese and US lending datasets finds improved risk differentiation from richer data and modelling methods. These results support further testing, not an assumption of equivalent performance in Qatar. [8][10][22]

Madad provides a Qatar implementation case. Its AI-enabled credit intelligence engine, Pulse, combines configurable rules, financial statement extraction, buyer behaviour and payment forecasting. Pulse also converts plain-language credit criteria into scoring rules and standardises financial statements into a common structure. Madad's platform data covers 426 invoice records across 21 SMEs and 42 buyers, describing an underwriting workflow rather than a book of financed receivables. Validation of forecasting across new SMEs is the focus of the next phase.

The practical agenda is to connect trusted ledgers, verified receivables and responsible models to decisions on eligibility, limits, advance rates, tenor, repayment structure, pricing and monitoring. Additional statements of account and later settlement outcomes will support the next validation phase. Credit officers retain responsibility for policy, exceptions and financing decisions.

Five conclusions

1. Assess SME, paymaster and transaction risks together. 2. Distinguish settlement timing from default risk. 3. Use reconciled ledgers alongside financial statements. 4. Keep credit policy under human accountability. 5. Match every performance claim to validated outcomes.

Method and evidence hierarchy

The paper separates official market evidence, study-specific research, Madad's operational records and product documentation. Madad figures are reported with their reporting date. Descriptive invoice data, implemented functionality and validated predictive performance are treated as distinct evidence categories.

Contents

- 1. The missing middle in SME finance
- 2. GCC and ASEAN: one problem, different market outcomes
- 3. Why conventional underwriting struggles to scale
- 4. The trust layer for receivables finance
- 5. From alternative data to credit intelligence
- 6. Responsible AI and model validation
- 7. Shariah-compliant SME finance and digital infrastructure
- 8. Madad: a Qatar implementation case
- 9. From invoice records to underwriting evidence
- 10. Validating payment behaviour as underwriting evidence
- 11. An action agenda for GCC and ASEAN stakeholders
- 12. Conclusion
- Appendices: evidence boundaries and references

1. The missing middle in SME finance

Why economic importance has not translated into proportionate credit access

MSMEs account for an average of 99.8% of enterprises, 67.6% of the workforce and 38.7% of economic output across the 26 Asia-Pacific economies covered by the Asian Development Bank's 2025 monitor. Their economic role is therefore not marginal. Yet lending systems often remain optimized for larger firms with audited histories, collateral, standardized reporting and dedicated finance teams. [3]

The mismatch is especially important in the GCC. The IMF reports that SME lending represents about 4% of commercial bank lending across the region, compared with 33.5% in its selected emerging-market comparison group. The IMF attributes the difference partly to perceived risk, limited credit information and limited collateral. This does not mean banks are irrationally withholding capital. It means the information and operating economics of SME underwriting remain weak. [1]

Qatar illustrates this tension. QDB's 2023 report records QAR 17.8 billion in SME credit, around 3% of private-sector credit, across 11,145 SMEs with an active facility. At the same time, the SME NPL ratio stood at 10.5%, well above the 3.9% ratio for private-sector credit overall. Small enterprises recorded the highest NPL ratio among the SME categories, at 14.8%. The right policy response is therefore neither indiscriminate credit expansion nor the preservation of slow, collateral-heavy processes. The objective is better risk identification at lower cost. [2]

> **The missing middle**
>
> Many firms are too established for microfinance, yet too small or poorly documented for conventional corporate underwriting. They trade, invoice and employ people, but remain difficult for lenders to assess efficiently. The missing middle is therefore both a capital gap and an information-processing gap.

Five sources of friction

- **Thin formal files.** Young or owner-managed firms often have short histories, limited bureau records and financial statements prepared primarily for compliance rather than lending.
- **High fixed underwriting cost.** Manual data collection, re-keying, verification and committee review can cost almost as much for a small facility as for a larger one.
- **Weak trade visibility.** A lender may see an invoice but lack a reliable view of whether the trade occurred, whether the buyer accepted it, whether a dispute exists or whether another financier already funded it.
- **Fragmented outcomes.** Payment behaviour, collections, fraud alerts and overrides often sit in separate systems, limiting the feedback loop needed to improve policy and models.
- **Payment timing risk.** Madad's team identifies delayed buyer settlement as a significant source of SME liquidity pressure in Qatar. Payment timing, buyer creditworthiness and the SME's capacity to absorb delays require separate analysis. Scoring the SME alone leaves this distinction unresolved.

These frictions explain why the central challenge is not simply to digitize an application form. A digital front end connected to the same fragmented evidence and manual workflow moves the queue online without changing the economics of credit.

2. GCC and ASEAN: one problem, different market outcomes

Cross-market variation shows the role of institutions, policy and data infrastructure

ASEAN is often presented as a single model for digital SME finance. The data show a more varied picture. Reported SME or MSME shares of business lending range from 3.6% in the Philippines in 2024 and 8.6% in Singapore, to 19.24% in Indonesia and 51.2% in Malaysia. Qatar's reported share was around 3% in 2023, while the GCC average was 4% in 2024. [1][2][4][5][6][7]

These figures should not be treated as a strict ranking. Countries use different SME definitions, reporting populations and denominators. Malaysia's 51.2% figure is the share of MSME financing within total business loans. The Philippines figure is the share of MSME financing in total banking-system loans.

Qatar's figure is the share of SME credit in private-sector credit. The comparison is directional: market outcomes differ substantially, and the institutional design around SMEs matters.

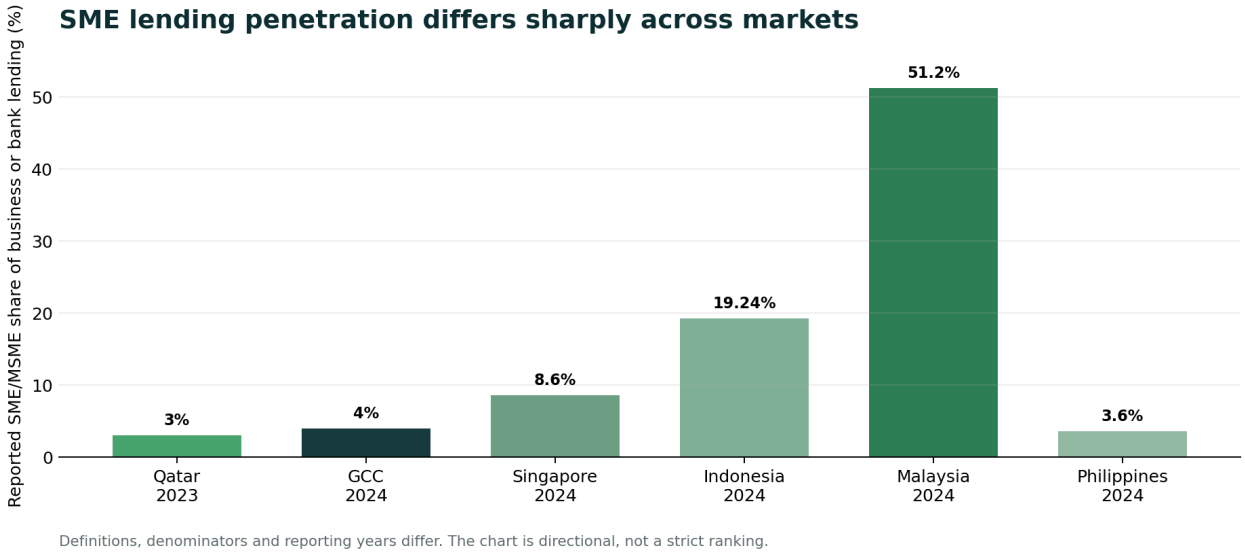


Figure 1. Reported SME/MSME lending shares. Sources and definitions differ; see Table 1 and references [1], [2], [4]-[7].

Market	Year	Reported share	Context	Source
Qatar	2023	~3.0% of private-sector credit	QAR 17.8bn SME credit; 11,145 SMEs with facilities	QDB
GCC	2024	4.0% of commercial bank loans	Regional average; significant variation across countries	IMF
Singapore	2024	8.6% of business loans	Declined to 8.0% in 2025	MAS/SingStat
Indonesia	2024	19.24% of business loans	IDR 1,506tn; declined to 17.49% in 2025	OJK/OECD
Malaysia	2024	51.2% of business loans	MYR 418.2bn outstanding MSME loans	BNM/OECD
Philippines	2024	3.6% of banking-system loans	PHP 545.2bn in December 2024	BSP

Table 1. Directional comparison. Definitions and denominators are not harmonized.

What the variation suggests

High SME lending penetration is not produced by technology alone. It reflects a combination of credit-guarantee systems, bank mandates, information infrastructure, market structure, public programmes, competition and data availability. Malaysia's experience shows how sustained policy and institutional support can move MSMEs above half of business lending. Indonesia's recent decline shows that large digital markets do not guarantee a rising SME share. Singapore combines advanced financial infrastructure with a relatively modest SME lending share. The Philippines remains close to Qatar's reported level despite a large and active MSME sector.

For GCC policymakers, the lesson is to avoid importing a product without its institutional context. The most transferable ASEAN assets are infrastructure patterns: permissioned data exchange, buyer confirmation, registry functions, standardized receivables records, digital identity, and governance frameworks for AI. These lower the cost and uncertainty of lending regardless of the final financing product.

3. Why conventional underwriting struggles to scale

The problem is economic, operational and informational

Traditional SME underwriting was built around periodic documents, relationship knowledge, collateral and human judgment. These inputs remain valuable, but the workflow becomes expensive when evidence is scattered, inconsistent or late. Credit officers spend time collecting documents, re-keying statements, reconciling names and dates, checking buyers, explaining exceptions and following up on missing information. The cost falls disproportionately on smaller facilities.

The unit economics problem

A lender earns less absolute income from a small facility, but many fixed tasks remain: KYC and KYB, financial spreading, credit bureau checks, collateral review, fraud screening, legal documentation, approval, monitoring and collections. Without reusable data and automated controls, the cost-to-serve can make the risk-adjusted return unattractive even when the SME is viable.

The information asymmetry problem

An SME knows whether an invoice is genuine, disputed, already financed or likely to be paid late. The lender may not. An invoice document alone is weak evidence. A financing decision becomes stronger when the lender can connect the invoice to the SME identity, buyer identity, purchase or service relationship, buyer confirmation, due date, dispute status, payment history and any prior financing claim.

The snapshot problem

Audited accounts provide an essential control point, but they are backward-looking and often annual. A fuller assessment may combine audited financials with bank transactions, platform activity, receivables, buyer payment behaviour, invoice integrity, sector context and ongoing repayment outcomes. This does not make audited statements obsolete. It places them inside a more current and auditable evidence set.

Statements of account and transaction-level ledgers supplement periodic financial statements with more current evidence of payment patterns and outstanding obligations. Where invoices and receipts are reconciled, an SME-buyer SOA shows how long the buyer takes to settle. A receivables ledger also reveals overdue ageing and buyer concentration. Supplier payment behaviour and upcoming cash requirements need corresponding payables records and cash-flow information. These records complement financial and qualitative assessment rather than replace either.

> **Design principle**
>
> The objective is not to approve more applications at any cost. The objective is to reach a better decision, faster, with a clear record of the evidence, policy, model output and human judgment used.

4. The trust layer for receivables finance

Verified trade data must precede credit intelligence

Receivables finance depends on more than the SME's credit profile. The lender must trust the asset. This requires controls over identity, authority, trade authenticity, buyer acceptance, disputes, due dates, assignment and prior financing. Where these controls are weak, model sophistication cannot remove the underlying uncertainty.

Transaction verification is one part of a wider assessment. The proposed Madad framework also considers the SME’s financial capacity and the buyer’s payment behaviour. A confirmed invoice supports evidence of an obligation, but does not establish timely settlement or remove the need to assess the parties and the financing terms.

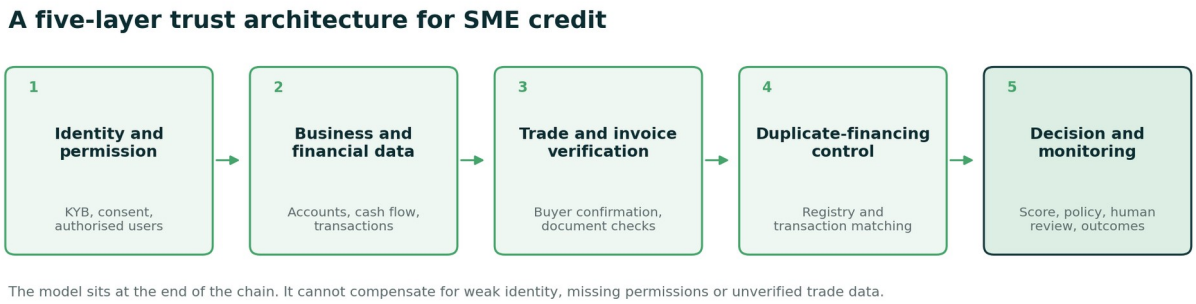


Figure 2. A proposed trust architecture for SME credit and receivables finance.

Singapore: shared duplicate-financing control

The Association of Banks in Singapore's Trade Finance Registry is a national industry utility designed to reduce information asymmetry, identify transactions financed simultaneously by several banks and validate the genuineness of trade. Nearly 40 banks have joined. Participating institutions register transactions, while duplicate matches trigger near-real-time notifications. The design also connects to SGTraDex for source information such as bills of lading. [11][12]

Hong Kong: consent-based trade and cash-flow data

HKMA's CargoX programme uses the Commercial Data Interchange to combine cargo, trade and cash-flow data. The 2026 pilot involves 21 banks and focuses on trusted connections to trade platforms, multi-dimensional SME credit assessment, digital corporate identity and regional trade corridors. SMEs provide explicit consent before data is shared. [13]

India: confirmed obligations and receivables registration

India's TReDS framework allows MSME sellers, buyers and financiers to create, accept, bid on and settle confirmed receivables. RBI regulations also require the assignment and satisfaction of TReDS-financed receivables to be registered with the Central Registry. This creates a legal and operational record around the financed asset and supports controls against double financing. [14][15]

Implications for Qatar

A Qatar trust layer does not need to replicate one foreign system. It needs the functions those systems perform: authoritative identities, buyer confirmation, a unique invoice or receivable reference, assignment and financing status, privacy-preserving matching, audit logs, dispute status, and interfaces for banks and regulated platforms. A registry should be treated as market infrastructure rather than a proprietary scoring feature.

Madad's proposed architecture places buyer confirmation and duplicate-financing checks before lender funding. This strengthens the receivable as evidence and supports both SME-led invoice finance and buyer-led reverse factoring. The final legal effect of assignment, payment undertakings and financing structures must be determined with partner banks, legal advisers, regulators and Shariah boards where relevant.

5. From alternative data to credit intelligence

More data is useful only when provenance, timing and purpose are controlled

Alternative data describes information used beyond, or in a new way alongside, conventional bureau and audited-financial inputs. Examples include bank transactions, digital payments, platform sales, invoice records, utility payments, buyer settlement behaviour, e-commerce activity and verified public signals. The category is context-dependent: a bank statement may be conventional in one market and a novel machine-readable input in another.

Statements of account and ledger evidence

An SOA is the invoice-by-invoice record of a customer relationship. Combined with allocated payments, due dates and dispute records, SOAs and accounting ledgers provide evidence of punctuality, overdue ageing, partial payments, credit notes, concentration and changes in settlement patterns. Reconciled histories across several SMEs also support analysis of a shared buyer.

For receivables financing, these are strong candidate inputs to assess payment behaviour and liquidity pressure, and their predictive value is tested against later outcomes. Customer-supplied records retain their original provenance, with validation and reconciliation controls forming part of the assessment.

IFC's 2026 landscape analysis mapped 448 firms. Transaction data was the most common input, and MSME/business credit represented 31.9% of mapped offerings. Fully autonomous models were rare. Many firms used rule-based or hybrid systems, with AI supporting transaction classification, feature generation, fraud detection or score production. [8]

Where AI adds practical value

- **Extraction.** Read and tag financial statements, bank statements and structured business documents, while preserving officer review.
- **Classification.** Categorize transactions, revenues, expenses and counterparties consistently.
- **Anomaly detection.** Identify duplicate records, unusual patterns, fraud indicators and integrity concerns for investigation.
- **Risk estimation.** Estimate relative risk or outcome probability from a controlled feature set.
- **Payment forecasting.** Estimate settlement dates, ranges and expected amounts when suitable historical outcomes exist.
- **Monitoring.** Detect changes in portfolio behaviour, data completeness, drift and early-warning indicators.

What the evidence does and does not show

BIS Working Paper 1041, using proprietary US small-business lending data, found internal fintech scores predicted later delinquency more accurately than FICO or VantageScore in the studied datasets. [10]

An IMF working paper analyses 1.8 million loans to small and micro firms at a Chinese digital bank. The paper reports AUC of 0.8414 for random forest using all available information, versus 0.7246 for a scorecard using traditional information. Gains were more pronounced for smaller firms. This comparison changes both the information set and the modelling method. AUC measures risk ranking, not the percentage of decisions proven correct, and the result is not evidence of Pulse’s performance. [22]

Separate BIS research on a Chinese fintech found machine learning and non-traditional data improved loss and default prediction during a negative credit-supply shock. [23] These findings are study-specific. Performance depends on the borrower population, outcome definition, prediction horizon, available information and validation design.

BIS also cautions that digital innovation alone is unlikely to resolve SME credit constraints without progress on deeper obstacles, including weak financial records, collateral systems, insolvency, market structure and lender incentives. Technology improves the information-production process. It does not remove the need for sound credit policy or functioning institutions. [9]

6. Responsible AI and model validation

Explainability, challenge and outcomes monitoring should be built into the product

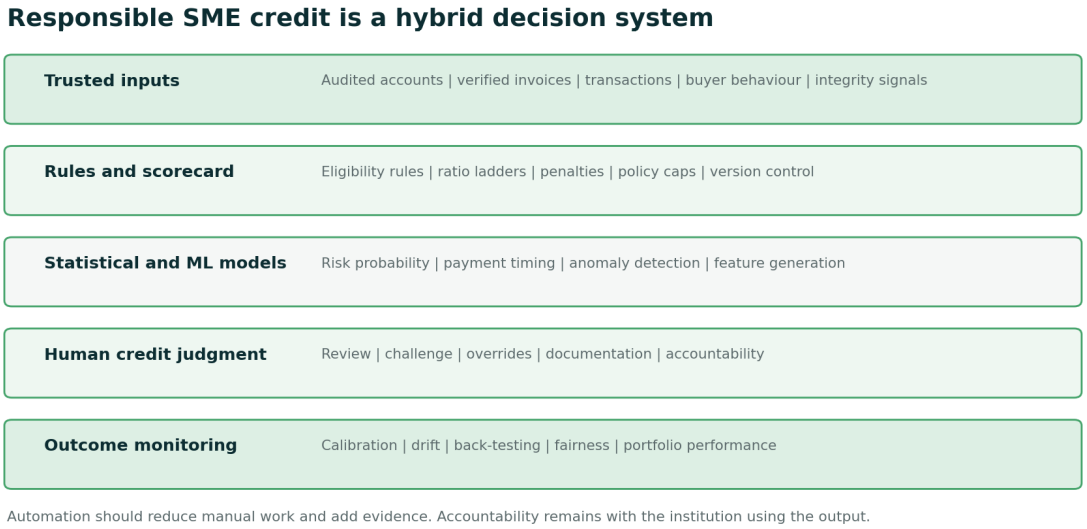


Figure 3. A hybrid decision architecture for responsible SME credit.

MAS issued final Guidelines on Artificial Intelligence Risk Management for Financial Institutions on 7 October 2026. The guidelines apply to all financial institutions and all forms of AI, with a risk-proportionate approach. They call for clear accountability, AI inventories, materiality assessment, data governance, testing, human oversight, cybersecurity, monitoring, change management and control of third-party AI risk. The guidelines take effect from 7 October 2027, with phased implementation for later sections. [16]

The revised 2026 US interagency guidance on model risk management similarly emphasizes risk-based controls, clear model purpose, out-of-sample and out-of-time testing, validation before use where practical, conceptual soundness, outcomes analysis, ongoing monitoring, documentation and effective challenge. It also states that users need to understand model limitations and supplement outputs with complementary information. [17]

The ECB's 2025 revised guide to internal models adds expectations for machine learning, focusing on governance, data maintenance, mathematical methods, explainability and whether performance justifies complexity. This principle is useful beyond regulatory capital models: a more complex system should earn its complexity through measurable performance or operational value. [18]

Credit policy governance

AI should support implementation of credit policy rather than independently determine risk appetite. Under the proposed control framework, Credit Risk reviews and approves a new criterion or parameter change before scoring use. Review covers the rule’s meaning, data inputs and expected portfolio impact. Version control and an audit record preserve the approved logic and its effective date. Exceptions and overrides remain accountable human decisions.

A minimum validation framework

Validation dimension	Question to answer
Purpose and population	What decision does the model support? Which SMEs, products, sectors and horizons are inside scope?
Conceptual soundness	Are variables, assumptions, data timing and transformations justified and documented?
Discrimination	Does the model rank higher-risk observations above lower-risk observations? AUC or Gini may be used when outcomes support it.

Validation dimension	Question to answer
Calibration	Do predicted probabilities or risk bands correspond to observed outcomes?
Out-of-time testing	Does performance hold on later periods not used for development or tuning?
Entity generalisation	Does the model work for SMEs and buyers not used in training?
Stability and drift	Are inputs, score distribution and performance changing over time?
Overrides and human review	How often are model outputs overridden, by whom, why, and with what subsequent outcomes?
Fairness and segmentation	Are errors concentrated by sector, SME size, geography or other protected or sensitive dimensions?
Operational resilience	Are data lineage, versioning, access, security, monitoring and fallback procedures adequate?

Table 2. Proposed minimum validation framework for an SME credit intelligence engine.

> **Evidence boundary**
>
> Operational capabilities, model development and independently validated predictive performance are different evidence categories. This paper describes implemented workflows and a validation programme. It does not claim established accuracy across new SMEs, reduced defaults or superiority over bureau scores.

7. Shariah-compliant SME finance and digital infrastructure

Better evidence supports product design, but does not determine Shariah compliance

Credit intelligence is financing-structure neutral. A score, fraud check or payment forecast can support a conventional facility or a Shariah-compliant transaction. Shariah compliance depends on the underlying contracts, asset or service flows, ownership and possession requirements, fees, promises, assignment of rights, treatment of late payment, and the institution's approved governance process.

AAOIFI's standards cover relevant areas including Murabahah, agency, online financial dealings, financial rights and their transfer, and sale of debt. The applicable structure and interpretation must be determined by the financing institution's Shariah board and the relevant legal and regulatory framework. This paper therefore does not treat a scoring model as making a transaction Shariah-compliant. [20]

The IFSB notes that Islamic crowdfunding and peer-to-peer platforms can provide important financing channels for SMEs, while requiring investor protection, transparency, disclosure and appropriate Shariah governance. It also highlights AI risks involving model integrity, data quality, bias and the limits of automated judgment for complex Shariah questions. [19]

Practical design implications

- **Separate credit evidence from contract execution.** The scoring layer evaluates risk; the financing module executes a bank-approved structure.
- **Preserve traceability.** The institution and Shariah reviewers need a clear record of the trade, approvals, sequence and contractual steps.
- **Do not automate jurisprudential judgment.** AI may support document review and monitoring, but product approval and Shariah interpretation remain governed human decisions.
- **Use partner-approved templates.** For reverse factoring or supply-chain finance, Madad should implement the partner bank's approved structure rather than infer a structure from software logic.

8. Madad: a Qatar implementation case

SME creditworthiness, paymaster behaviour and transaction verification in one assessment

Madad operates an invoice-financing marketplace inside the Qatar Central Bank Regulatory Sandbox. The workflow connects an SME, its buyer and financing partners around an authenticated receivable. The SME submits an application and invoice, the buyer confirms the trade and amount, Madad performs verification and credit assessment, and capital providers review or compete to finance the case. Madad originates, verifies and services the workflow rather than funding facilities from its own balance sheet.

Operating evidence

As of November 2026, Madad has 109 registered SMEs, 12 submitted financing cases and QAR 3.1 million in financing offers, with one facility fully repaid. Offer value is not disbursed financing: some offers lapse before funding, including where buyers settle early.

An integrated credit assessment framework

Madad's credit intelligence framework combines three interconnected assessment layers. Paymaster behaviour and alternative data complement traditional SME creditworthiness assessment. The financing decision remains subject to eligibility criteria, credit policy and the agreed allocation of recourse.

Assessment layer	Evidence examined	Credit question
SME creditworthiness	Financial performance, liquidity, cash flow, leverage, repayment capacity and qualitative factors.	Does the SME have sufficient capacity to meet its obligations?
Paymaster risk	Historical payment behaviour, settlement delays, disputes, concentration and payment reliability.	How reliable is the buyer, and when is settlement expected?
Transaction risk	Invoice authenticity, buyer confirmation, contractual terms, dilution, assignment and duplicate-financing exposure.	Is the receivable eligible, supported and controlled?

Table 3. Madad's integrated credit assessment framework.

Buyer creditworthiness and buyer payment behaviour answer different questions. A financially strong buyer can still create working-capital pressure through delayed settlement. The framework therefore distinguishes the likelihood of a credit loss, the timing of cash collection and the SME's ability to absorb the gap. Buyer evidence adds to the underwriting assessment. It does not erase SME or transaction risk.

The AI-enabled credit intelligence engine

Pulse is a live, dashboard-based credit intelligence and decision-support engine. Its outputs include a 0-100 Madad Score, ten rating bands, data-completeness information, explainable contributions, an adverse-outcome probability and payment forecasts across 30, 60 and 90-day windows.

Financial statement standardisation

Pulse maps extracted financial statements from supported document formats into a common structure defined by Credit Risk, including assets, liabilities and income-statement categories. This supports consistent derivation of financial ratios and cash-flow measures across SMEs, with extraction and tagging subject to analyst review.

Plain-language rule creation

Pulse converts a credit criterion written in plain English into a mathematical rule applied to extracted financial and business data. This removes the need for custom development for each new policy criterion.

Illustrative criterion: "Apply two penalty points when more than 50% of receivables are over 60 days past due."

The example illustrates the functionality, not an approved Madad credit policy. Each generated rule is subject to Credit Risk review, impact assessment and approval, with version control and an audit trail,

before it enters scoring. AI supports policy implementation; Credit Risk retains responsibility for risk appetite and the approved criteria.

Capability / evidence status	Scope
Live	Financial extraction and tagging, configurable scorecards, ratio ladders, qualitative criteria, penalties, manual signals, policy versioning, explainable contributions, paymaster scoring, screening and monitoring signals, manual parameter editing, portfolio rescoring and payment forecasts.
Live (new)	Plain-language rule creation and financial statement standardisation.
In progress	External-customer customisation, outcome labelling, bank-specific policy configuration and privacy controls.
Future or dependent on partners	ERP/accounting-system data feeds, bank-consumable integrations, credit-bureau and other partner feeds, larger outcome datasets, independent validation, automated recomputation and wider external deployment.

Table 4. Pulse capability status.

From assessment to financing decisions

The framework makes the score one input to a financing decision. Credit officers and financing partners use the underlying evidence to set terms within approved policies, across the decision areas below.

Decision area	How the assessment informs the decision
Eligibility	Assess the SME, buyer and receivable against the applicable product and credit-policy criteria.
Exposure limits and advance rates	Consider repayment capacity, buyer and sector concentration, invoice eligibility, dilution and collection uncertainty.
Tenor and repayment structure	Compare contractual terms with observed settlement behaviour and the SME's cash-flow requirements.
Pricing	Consider the approved risk assessment, financing structure, funding cost and applicable policy.
Ongoing monitoring	Track ageing, partial settlements, disputes, credit notes, concentration and changes in payment patterns.

Table 5. Proposed use of credit intelligence in risk-based financing decisions.

Buyer-led expansion

Madad's reverse-factoring concept centres on an approved buyer limit. Confirmed supplier invoices become proposed drawdowns subject to programme terms and duplicate-financing controls. Supplier and transaction assessment still apply. Payment undertakings, documentation, reconciliation and relevant Shariah approval underpin the financing structure.

9. From invoice records to underwriting evidence

How linked SME, buyer and receivable records support the trust layer

Madad's platform data covers 426 invoice records across 21 SMEs and 42 buyers, with invoice amounts ranging from QAR 73.18 to QAR 408,333.33. Each record identifies the invoice, its dates, the SME, the buyer, the amount and its status in the underwriting workflow.

Portfolio descriptor	Reported value	Interpretation
Invoice records	426	Invoices submitted to the platform's underwriting workflow.
SMEs	21	Distinct SMEs submitting invoices.
Buyers	42	Distinct buyers (paymasters) named on invoices.
Invoice amount range	QAR 73.18 to QAR 408,333.33	Range of individual invoice values.

Table 6. Madad platform invoice data.

From a document to a financeable receivable

The value of the platform lies in connecting records which otherwise sit separately. An invoice links an SME, a named buyer, an amount and contractual evidence. Where buyer confirmation is completed, the financing partner gains an additional record of the obligation. Combining this record with SME financial information, buyer payment history and transaction checks provides a fuller basis for underwriting.

Together, these records form a network of SME-buyer relationships that a lender would not otherwise see. Confirmation, eligibility, financing and repayment are then established record by record. The buyer behind the invoice broadens the credit assessment rather than replacing the assessment of the SME.

Verification before capital commitment

The workflow is designed to establish identity, invoice authenticity, buyer confirmation and credit eligibility before funding. Unverified and unqualified records mark points needing further evidence or an eligibility decision, so issues surface before capital is committed. The underwriting value comes from the evidence and decisions recorded at each stage.

What this evidence contributes

Linked receivables records give financing partners a way to examine buyer exposure, invoice size, concentration and confirmation status alongside the SME's finances. Reconciled SOAs add observed payment patterns and exceptions. This is the practical trust-layer proposition: organise, verify and interpret commercial evidence before assigning risk or committing capital.

10. Validating payment behaviour as underwriting evidence

A forward-looking study of SOA-based payment forecasts and later settlement outcomes

Pulse's payment-timing model has been developed using historical statements of account: invoice-by-invoice records of how buyers paid SMEs. The next phase broadens the training base with additional customer SOAs and tests whether observed behaviour helps predict later settlement timing. These are customer-supplied accounting records, distinct from financing transactions originated or serviced on Madad.

Validation of forecasting across new SMEs is the focus of the next phase, combining a broader customer sample with chronological testing and simple benchmarks.

Separate payment timing from default risk

The payment-timing study should define its target explicitly: settlement date, elapsed days from invoice issuance, or days late relative to the contractual due date. Partial payments require an agreed allocation and settlement definition. Default analysis is a separate study requiring a defined adverse event, a suitable observation period and verified outcomes. An outstanding or disputed invoice is not, by itself, proof of default.

The next validation phase

Additional SOAs should cover more SMEs and buyers, with invoice, due-date and payment records reconciled before analysis. Where available, disputes, credit notes, partial payments and changes in terms should accompany the history. The study should preserve the information available at the prediction date and compare forecasts with later observed settlements.

Workstream	Question	Evidence to report
Data breadth and reconciliation	Does the sample represent more than a small set of customer relationships?	Customer and buyer coverage, concentration, periods covered, exclusions and reconciliation rules.
Later-invoice testing	Do forecasts perform on invoices occurring after model development?	Identical eligible observations, later outcomes and comparison with simple timing benchmarks.
New-SME testing	Does performance carry over to customers outside the training data?	Held-out-SME results and SME-balanced reporting alongside pooled results.
Payment-timing performance	How close are predictions to realised settlements?	Absolute timing error, predictions within defined tolerances and uncertainty-interval coverage.
Separate default assessment	Is there sufficient evidence to study a defined credit loss or default event?	Outcome definitions, event counts, observation periods, discrimination and calibration where supported.

Table 7. Proposed validation programme.

From validation to integration

The intended end state connects to permissioned customer ERP or accounting systems so reconciled financial and payment records feed the assessment on an ongoing basis. Bank integrations would then deliver authorised scoring outputs and supporting evidence to financing partners. This is a development objective.

Validation would inform the use of payment behaviour in tenor, repayment terms, exposure and monitoring. Credit Risk will define acceptable use and limitations. Weak results should narrow permitted use.

11. An action agenda for GCC and ASEAN stakeholders

Build the infrastructure that turns SME activity into financeable evidence

Stakeholder	Priority actions
Regulators	Define permissioned data-sharing rules; support common identifiers and consent; clarify receivables registration and platform responsibilities; establish proportionate AI and model-risk expectations.
Banks and Islamic banks	Support permissioned financial and SOA data. Apply the integrated SME, paymaster and transaction framework. Agree pilot outcomes, share settlement feedback, retain credit-policy approval and use approved Shariah structures where relevant.
Development institutions	Fund shared infrastructure and independent validation; support guarantees and risk-sharing where market failures persist; publish consistent SME finance statistics.
Large buyers and anchors	Confirm invoices digitally; provide structured payables and dispute status; sponsor supplier programmes; support timely settlement data and authorised-user controls.
Fintechs and platforms	Design for provenance, privacy, versioning and auditability; avoid unsupported AI claims; build registry and bank interoperability; report outcomes and limitations.
Data and technology providers	Provide data lineage, availability timestamps, service resilience and test environments; support privacy-preserving matching and independent assurance.
Investors and capital providers	Assess infrastructure quality, not only origination volume; fund assets where verification and servicing controls are clear; require transparent portfolio reporting.

Table 8. Proposed action agenda.

A GCC-ASEAN collaboration programme

The strongest cross-regional opportunity is not a generic memorandum on fintech cooperation. It is a set of practical workstreams: cross-border trade-data connectivity; common invoice and receivable identifiers; registry interoperability; consent and corporate identity standards; Shariah governance for digital SME finance; independent model-validation methods; bank-fintech pilot templates; and investor channels for verified SME assets.

SFF 2026 is designed around the coming rewiring of the financial system through technology, geoeconomics, capital, talent and policy. SME credit sits at the intersection of all five forces. The technology is data and AI. The geoeconomic opportunity is the GCC-ASEAN trade corridor. The capital question is how to fund verified assets. The talent requirement is stronger credit, data and model-risk capability. The policy task is to enable innovation without weakening trust. [21]

12. Conclusion

SME finance needs better infrastructure for deploying capital

The missing middle persists because many profitable firms remain difficult to observe, verify and underwrite at acceptable cost. The answer is not to lower credit standards or replace credit officers with a black-box model. It is to improve the evidence available to lenders and the efficiency with which that evidence becomes a decision.

A credible SME credit stack begins with permissioned identity and business data, connects to verified trade and receivables, prevents duplicate financing, combines policy rules with validated statistical models, preserves human accountability, and feeds actual outcomes back into the system. This stack supports conventional and Shariah-compliant products, bank balance sheets, marketplace models, crowdfunding and institutional capital. The final contract and risk allocation may differ. The trust infrastructure is reusable.

Madad's implementation case connects verified receivables, financial standardisation, configurable credit policy and buyer behaviour. The intended value is better risk identification and more informed financing terms. The proposed SOA-based study will test how far payment histories support forecasts on later invoices and new SMEs.

> **Closing proposition**
>
> Capital reaches SMEs at scale when trusted data, sound credit judgment, responsible technology and appropriate funding structures operate as one system.

A. Appendix: evidence boundaries

Item	Limitation or treatment
Madad invoice export	426 records, 21 SMEs and 42 buyers. These are submitted invoice records, not counts of verified or funded receivables.
Status values	Snapshot values: qualified, unverified, withdrawn, validated, unqualified and paid. They are not treated as a sequential funnel without event history.
Paid status	Not treated as proof of financed and fully repaid performance. Financing and settlement fields are required.
Traction snapshot	November 2026 figures. Offer value, financing approval, disbursement and repayment are distinct measures.
Payment-timing model	Validation of forecasting across new SMEs is the focus of the next phase.
Cross-country chart	Uses reported official or OECD-collated figures with different definitions and years. It is directional, not a harmonized ranking.
Product capability	Based on Madad product documentation as of November 2026.
Shariah discussion	General governance and design considerations only. Not a fatwa or legal opinion.

B. Appendix: references

Public references

[1] International Monetary Fund. Gulf Cooperation Council (GCC): Enhancing Resilience to Global Shocks: Economic Prospects and Policy Challenges for the GCC Countries. IMF Policy Paper No. 2025/043, December 2025, Annex V. Source

[2] Qatar Development Bank and Qatar Central Bank. SME Lending Status in Qatar 2023. Source

[3] Asian Development Bank. Asia Small and Medium-Sized Enterprise Monitor 2025. Source

[4] OECD. Financing SMEs and Entrepreneurs 2026: Malaysia. Source

[5] OECD. Financing SMEs and Entrepreneurs 2026: Indonesia. Source

[6] Singapore Department of Statistics / MAS. Percentage of Business Loans to SMEs, annual series. Source

[7] Bangko Sentral ng Pilipinas. Report on the Philippine Financial System, Second Semester 2024. Source

[8] International Finance Corporation. Cracking the Credit Code: Alternative Data and AI for Financial Inclusion, 2026. Source

[9] Bank for International Settlements. How far can digital innovation improve credit to small firms in emerging market economies? BIS Bulletin 99. Source

[10] Bank for International Settlements. The impact of fintech lending on credit access for U.S. small businesses, Working Paper 1041. Source

[11] Association of Banks in Singapore. Trade Finance Registry. Source

[12] Association of Banks in Singapore. ABS launches Trade Finance Registry to counter trade finance fraud, 2023. Source

[13] Hong Kong Monetary Authority. CargoX Pilot Programme and Commercial Data Interchange, 2026. Source

[14] Reserve Bank of India. Trade Receivables Discounting System FAQs. Source

[15] Reserve Bank of India. Registration of Assignment of Receivables Regulations, 2022. Source

[16] Monetary Authority of Singapore. Guidelines on Artificial Intelligence Risk Management for Financial Institutions, 2026. Source

[17] Federal Reserve, FDIC and OCC. Supervisory Guidance on Model Risk Management, April 2026. Source

[18] European Central Bank. Revised Guide to Internal Models, 2025. Source

[19] Islamic Financial Services Board. Islamic Financial Services Industry Stability Report 2025. Source

[20] AAOIFI. Shari'ah Standards.

[21] Singapore FinTech Festival. SFF 2026: The Coming Rewiring of the Financial System. Source

[22] Huang, Y., Zhang, L., Li, Z., Qiu, H., Sun, T. and Wang, X. Fintech Credit Risk Assessment for SMEs: Evidence from China. IMF Working Paper WP/20/193, September 2020. Table 4, p. 22. Source

[23] Gambacorta, L., Huang, Y., Qiu, H. and Wang, J. How do machine learning and non-traditional data affect credit scoring? New evidence from a Chinese fintech firm. BIS Working Paper 834, December 2019. Source

Madad data

Madad figures and product descriptions are drawn from Madad's internal operating data and product documentation, as of 15 November 2026.