NUS National University of Singapore | Asian Institute of Digital Finance

Seeing Through the Black Box:

TRACE: An Interpretable, High-Performance MSME Credit Risk Assessment Framework

A Whitepaper by NUS Asian Institute of Digital Finance

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CRI Credit Research Initiative

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1. Executive Summary

Bridging the MSME Financing Gap. Micro, Small, and Medium Enterprises (MSMEs) are the backbone of economic growth and innovation globally. Yet, they face a persistent financing gap driven by limited transparency and inconsistent reporting. In the ASEAN region specifically, fewer than 30% of firms obtain bank credit (World Bank, 2025a), leaving a vast share of viable businesses disconnected from the formal financial system.

The Core Challenge: The Performance-Transparency Trade-off. The structural challenges of MSME data make reliable credit assessment inherently difficult. Financial institutions currently face a paralyzing dilemma between two imperfect approaches: employing transparent but over-simplified scorecards, or adopting high-performance but opaque 'Black Box' AI. Consequently, the industry is forced to trade off transparency for performance, lacking a widely adopted method that reconciles both needs for the MSME context.

A Legacy of Credit Innovation. To bridge this gap, the Asian Institute of Digital Finance (AIDF) draws on a deep history of credit risk research. Through our Credit Research Initiative (CRI), we have developed a globally recognized, forward-looking credit assessment framework since 2009. While this framework has become a standard for publicly listed corporations, our research underscores the urgent need to extend this rigorous, interpretable evaluation to the heterogeneous MSME sector.

The Solution. We have developed the Toolkit for MSME Risk Assessment & Credit Evaluation (TRACE). TRACE is designed to resolve the long-standing trade-off by combining econometrically interpretable models with advanced machine learning under an explainable, governance-ready structure.

Strategic Value for the Ecosystem. TRACE serves as foundational infrastructure for responsible, scalable credit expansion:

- **Intelligent Data Integration:** Fuses traditional financials with alternative signals (e.g., telecom, macro data) using AI to overcome data sparsity.
- **'Glass Box' Modelling:** Delivers high-performance AI prediction while ensuring the auditability, stability, and supervisory comfort required by regulators.
- **Regulatory Alignment:** Deploys a GenAI-Driven Scenario Lab to stress-test models against 'edge cases', ensuring robustness and responsible AI governance.
- **Proven Impact:** Battle-tested across Southeast Asia—from Vietnam to Singapore—proving it can unlock MSME lending without compromising risk management.

Key Capabilities of the TRACE Framework

Intelligent Data Integration

TRACE framework integrates diverse alternative data sources, such as location data, public records, news articles and so on, with traditional financials. Its strength lies not merely in aggregating non-traditional data, but in **using AI to identify, prioritize, and structure credit-relevant information**. The framework transforms fragmented and unstructured inputs into a coherent, multi-dimensional profile of each enterprise. This **data fabric** forms the foundation on which reliable and high-resolution MSME credit assessments can be built.

AI-Powered Pre-Model Development

TRACE framework converts irregular MSME data into reliable and interpretable inputs through a coordinated set of AI agents. These agents apply accounting-based inference to responsibly fill data gaps and restore structure in records that would otherwise be discarded in traditional assessments. They also extract economically meaningful signals and automate complex financial analysis under accounting integrity constraints, followed by feature construction and selection to retain the most predictive and industry-relevant variables.

'Glass Box' Modelling

TRACE framework operates within a configurable governance and explainability framework that adapts to different market and supervisory requirements. It includes an interpretable statistical forward-intensity model, which estimates default risk across multiple horizons within a single calibration, consistent with CRI's methodology for listed firms. At the same time, TRACE can incorporate advanced ML/AI models through a dedicated explainability layer that makes model outputs auditable and decision traceable.

GenAI-Driven Validation Layer (Scenario Lab)

In addition to conventional validation, TRACE introduces an optional GenAI-driven scenario lab that generates rare or boundary cases to probe robustness – checking sensitivity, monotonicity, and threshold stability. This strengthens responsible-AI governance by revealing edge-case behaviours and ensuring that policy bands and reason codes behave consistently under controlled perturbations.

Battle-Tested Across Southeast Asia

Through collaborative research with industry partners, TRACE has been iteratively refined to reflect market-specific data realities and governance needs across Southeast Asia. Our key pilots were instrumental in developing and battle-testing the specific components of the framework.

Vietnam

Challenge: Extreme financial data sparsity & incompleteness

Capabilities Tested:

- ✓ Intelligent Data Integration
- ✓ AI-Powered Pre-Model Development
- ✓ 'Glass Box' Modelling
- GenAI-Driven Validation

Singapore

Challenge: High regulatory & governance needs

Capabilities Tested:

- Intelligent Data Integration
- AI-Powered Pre-Model Development
- ✓ 'Glass Box' Modelling
- ✓ GenAI-Driven Validation

Indonesia

Challenge: Absence of historical default labels (unlabelled data)

Capabilities Tested:

- ✓ Intelligent Data Integration
- ✓ AI-Powered Pre-Model Development
- 'Glass Box' Modelling
- GenAI-Driven Validation

Designed from the ground up for institutions serving MSMEs, particularly in data-constrained emerging markets, TRACE has been proven through these real-world engagements.

By addressing the performance-interpretability trade-off, TRACE framework is particularly valuable for banks, development finance institutions, and fintech companies seeking to expand MSME lending while maintaining robust risk management practices.

2. Background

2.1. The MSME Credit Assessment Challenge

MSME credit assessment presents a fundamental unit-economics challenge for lenders. Frameworks designed for large corporates rely on standardized, audited financial reporting. When applied to smaller firms, these models struggle with incomplete documentation, highly variable reporting practices, and distinct sectoral heterogeneity. These frictions create persistent information asymmetries, making it prohibitively expensive for banks to verify creditworthiness manually. This dynamic drives the multi-trillion-dollar MSME finance gap, currently estimated at roughly $5.7 trillion globally (IFC, 2017; IFC, 2025).

Core obstacles faced by lenders include:

Data sparsity and quality constraints
Thin files, incomplete statements, and limited credit histories reduce the effectiveness of conventional models; information opacity is a first-order challenge (Berger & Udell, 2006), exacerbated by the fact that a large share of firms in emerging markets lack externally audited financial statements (WBES, 2025b).

Operational heterogeneity
Unlike large firms, MSME business models vary wildly—from high-growth startups to cash-based retailers. Scorecards designed for homogeneous borrowers often fail when applied across these diverse segments.

Prevalence of informal practices
Heavy reliance on cash transactions and non-standard documentation creates a verification blind spot. With a material share of MSME activity remaining outside formal financial reporting (WBES, 2025), traditional models effectively look at an incomplete picture of the firm's health.

Information asymmetries and pricing effects
The difficulty in assessing risk leads to defensive pricing. MSMEs face higher rejection rates and interest rates as lenders price in the risks. This implies that many viable businesses are excluded simply because their risk cannot be transparently quantified (Berger & Udell, 2006).

2.2. The Innovation Gap in MSME Credit Assessment

Despite advances in financial technology, MSME credit assessment remains stuck in a 'bimodal' trap. Lenders are currently forced to choose between two imperfect approaches, creating a persistent innovation gap in the sector:

Simplified Scorecard

Transparent and governance-friendly, but often under-fit heterogeneous MSME portfolios and miss non-linearities (EBA, 2020)

The Failure: These models operate on rigid rules that often 'under-fit' the complex, heterogeneous reality of MSMEs. They fail to capture non-linear risk signals, resulting in higher rejection rates for viable but non-standard businesses.

Complex 'Black-Box' Model

Typically achieve higher discrimination than single-scorecard baselines, yet face adoption hurdles due to explainability and auditability requirements (EBA, 2020)

The Failure: These systems are 'Black Boxes'. In regulated commercial lending, they face immense adoption hurdles due to explainability and auditability requirements (EBA, 2020). Loan officers cannot intuitively validate the output, leading to a lack of trust.

The Consequence:

This trade-off creates a paralyzing operational friction. When using simplified scorecards, lenders are forced into overly conservative limits to compensate for the model's blind spots. Conversely, when attempting to deploy complex models, approval processes stall under credit-committee scrutiny and prolonged model-risk validation cycles.

The industry effectively lacks a middle ground: a solution that delivers the high performance of AI with the transparency required for regulatory confidence.

2.3. Critical Need for Interpretability with High Performance

The demand for solutions that deliver both interpretability and high performance is particularly acute in MSME finance. While 'Black Box' approaches are sometimes tolerated in high-volume consumer lending (relied upon with post-hoc explanations), commercial credit decisions operate under different constraints.

This business reality, coupled with supervisory expectations, creates an imperative for 'Glass Box' models — approaches that maintain full interpretability without materially sacrificing predictive power.

Achieving this balance is a critical innovation frontier in MSME credit assessment, with the potential to meaningfully narrow the finance gap noted above.

The AIDF TRACE framework emerges as a direct response to this need. As detailed in the following sections, TRACE unifies three core capabilities into a system:

1. **Expert-Guided Data Sourcing**
2. **AI-Powered Pre-Model Development**
3. **'Glass Box' Modelling**

3. The AIDF TRACE Framework

MSMEs frequently lack complete financial records, operate informally, and vary widely in their structure and operations. Our TRACE framework combines AI technology with industry expertise to create a balanced approach that works with diverse data sources, fills in missing information gaps, and produces easy-to-understand risk assessments without sacrificing accuracy. This makes TRACE particularly valuable for financial institutions, development banks, and fintech companies seeking reliable, transparent, and scalable lending solutions.

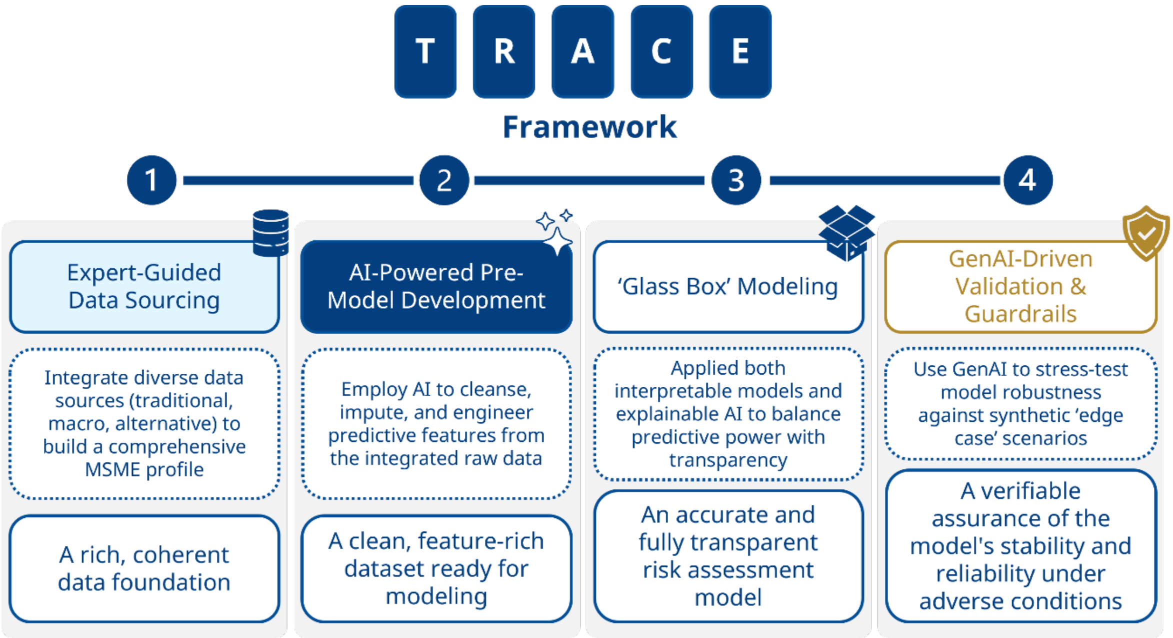

Figure 1: The AIDF TRACE Framework: A unified approach for high-performance, transparent MSME credit assessment.

3.1. Intelligent Data Integration: Fusing Diverse Sources

This component of the framework focuses on fusing diverse, unstructured, and alternative data sources to create a coherent profile. The core challenge in MSME assessment is not just a lack of data, but the sheer diversity and unstructured nature of available information.

TRACE's distinction lies in its 'know-how': it moves beyond generic data collection to intelligently map specific data sources to a risk profile. This is the ability to understand precisely *what* information to look for (e.g., signals of operational stability or real-time business activity), *where* to find it (e.g., in location data or telecommunications patterns), and *how* to integrate it to assess a specific aspect of creditworthiness.

This integration capability allows us to fuse:

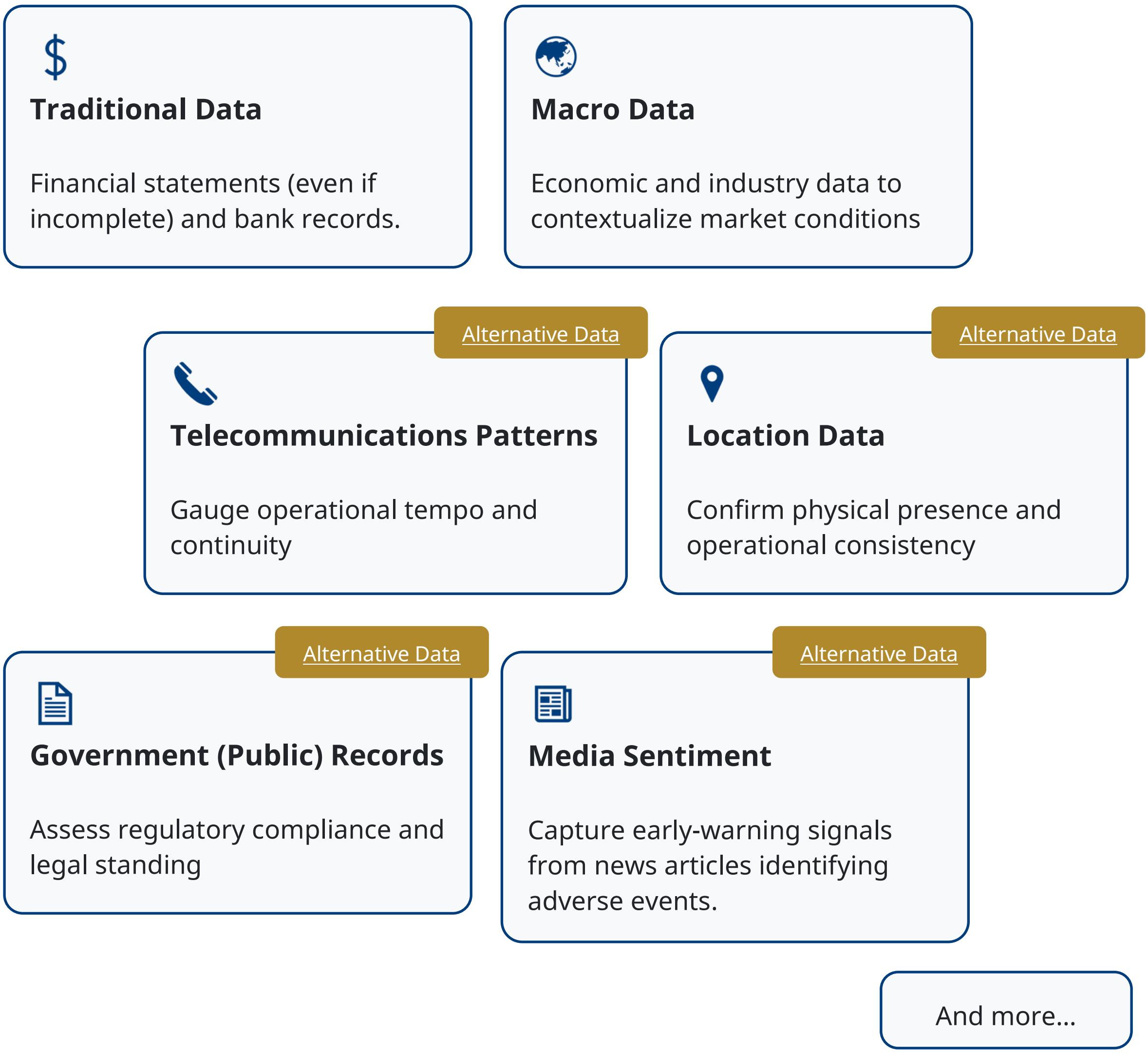

Figure 2: Intelligent Data Integration: Fusing traditional and alternative signals to construct a coherent risk profile.

We also connect business owners' personal credit histories when available, adding behavioural data when the firm information is limited.

TRACE's intelligent data integration - the 'know-how' - creates the rich data foundation required for high-accuracy risk assessment for MSMEs.

3.2. AI-Powered Pre-Model Development: Creating Predictive Features

TRACE leverages AI to cleanse, impute, and refine the integrated data, transforming raw or incomplete inputs into high-quality, predictive features. Raw MSME data, even after integration, is often hindered by sparsity, inconsistencies, and 'noise'. Simply feeding this raw data into a model leads to poor performance. TRACE's toolkit at the pre-model development phase is designed to conquer this complexity, using AI to transform incomplete or 'dirty' data into high-quality, predictive features.

This is not a single tool, but a suite of AI-powered solutions.

01

AI-Driven Data Imputation

TRACE intelligently fills data gaps by applying accounting principles and industry benchmarks. It ensures data consistency and reliability even when businesses provide incomplete information.

02

AI-Generated Features and Smart Selection

TRACE automatically transforms raw business information into meaningful credit indicators. It then employs smart feature selection to ensure only the most relevant indicators are used. This approach adapts to changing economic conditions and immediately captures industry shifts.

03

AI-Automated Financial Analysis

TRACE includes AI agents to automate complex financial analysis, such as statement spreading and ratio calculation, while maintaining full accounting integrity.

Figure 3: AI-Powered Pre-Model Development: Transforming sparse, unstructured inputs into high-quality predictive features.

TRACE's AI-powered pre-model development toolkit ensures that the models are trained on high-quality and feature-rich information, which is essential for boosting predictive accuracy.

3.3. ‘Glass Box’ Modelling: Balancing Performance with Transparency

TRACE’s ‘Glass Box’ approach resolves the performance-transparency trade-off by providing flexible modelling strategies. It ensures that high-performance predictions are always accompanied by clear, auditable, and economically grounded reasoning.

3.3.1. Inherently Interpretable Models

TRACE deploys a set of interpretable models built on established financial theory, providing clear mathematical formulas. These models are valued for their strong theoretical grounding and transparency, though they typically require specific, financial data features as inputs. Examples include:

- **Forward-Looking Default Model:** TRACE utilizes variants of AIDF’s flagship forward-intensity default model, which have been specifically adapted for the MSME context. The underlying flagship model is already well-recognized in the industry and has been adopted by numerous financial institutions for its proven high precision and full interpretability. Unlike traditional point-in-time assessments, it projects credit risk across multiple future time periods, giving lenders insight into how a business's risk profile may evolve.
- **Proxy Distance to Default (DTD) for MSMEs:** We have adapted sophisticated credit risk measurements typically used for public companies to work for small businesses without market data. This provides a practical, formula-based measure of bankruptcy risk using available financial information (Merton, 1974).

3.3.2. Advanced ML/AI with ‘Reverse Black Box’ Explainability

For cases requiring maximum predictive power, TRACE’s breakthrough approach pairs advanced ML/AI models with a unique distillation-based explainability layer (Hinton, Vinyals, & Dean, 2015). While these advanced models process diverse data streams to produce highly accurate risk predictions, our approach symbolically translates these ‘Black Box’ results into clear rationales and simplified mathematical formulas. These formulas reveal the economic reasoning behind each assessment while maintaining virtually the same predictive power, satisfying both performance and regulatory requirements. Examples include:

- **Symbolic Regression (SR):** It distils teacher outputs into a sparse closed-form, yielding standardized reason codes and enforcing economically sensible directions—useful for threshold design and audit (Udrescu & Tegmark, 2020).

- **Monotone GA2M / EBM (Additive Surrogate):** It fits a shape-constrained additive model to teacher logits; provides smooth global effects and policy-friendly thresholds, often matching teacher rankings with far greater transparency (Caruana et al., 2015).

For comparison, we also consider post-hoc explainability methods such as SHAP (Lundberg & Lee, 2017); however, to meet governance and auditability requirements a distillation + symbolic-regression 'Reverse Black-Box' approach is chosen as the primary explainability layer within TRACE.

In sum, TRACE's dual approach allows financial institutions to achieve superior predictive accuracy while maintaining the full transparency required for robust risk management and regulatory compliance (EBA, 2020; Basel Committee on Banking Supervision, 2015).

3.4. GenAI-Driven Validation: Scenario Lab

This optional component, the 'Scenario Lab', complements conventional validation by using Generative AI to stress-test model robustness. It actively probes for 'edge case' behaviours by creating targeted, synthetic scenarios that are not present in the original dataset. The lab systematically checks model integrity, including *sensitivity* (how much outputs change with small input changes), *monotonicity* (e.g., ensuring risk always increases as a negative factor worsens), and *threshold stability* (analysing behaviour near key decision cut-offs).

Sensitivity Testing

Measure how model outputs respond to small changes in input variables, ensuring stable and predictable behaviour across the input space

Monotonicity Verification

Confirm that risk assessments move in economically sensible directions as key factors change, preventing counterintuitive predictions

Threshold Stability Analysis

Examine model behaviour near critical decision boundaries to ensure consistent and reliable classification across policy bands

Edge Case Generation

Create synthetic scenarios representing rare or extreme conditions to validate model robustness under adverse circumstances

This validation layer provides verifiable assurance of model robustness and alignment with governance principles, even under adverse or unseen conditions (EBA, 2020; Basel Committee on Banking Supervision, 2015).

4. Application Highlights

TRACE provides flexible solutions for assessing credit risk across diverse economic environments. The framework has been successfully implemented and refined through pilots in Southeast Asia, including Vietnam, Singapore, and Indonesia.

These engagements are essential for battle-testing the framework against real-world market conditions and data limitations. The following subsections demonstrate how each pilot was designed to develop, test, and validate the core capabilities of TRACE.

4.1. Pilot 1: Mastering Sparse Financial Data in Vietnam

This pilot is a foundational test of TRACE's *Intelligent Data Integration*, *AI-Powered Pre-Model Development* and *'Glass Box' Modelling* capabilities.

In collaboration with Vietnam Credit Rating JSC (VNCR), we applied the AIDF TRACE framework to the Vietnamese SME financial statement datasets (2016–2023), demonstrating estimation procedures, predictive performance, and parameter insights. Particularly, we examined two Vietnamese SMEs whose credit profiles deteriorated sharply in the months before their respective credit events. Both companies exhibited stable one-year PDs below 100 bps until the model detected sustained increases, providing a valuable multi-month early-warning window.

160K	14K	83%
Unique SMEs Analysed	**Observed Defaults**	**Dynamic AUC**

4.1.1. Data and Methodology

The empirical analysis covers 160,490 unique SMEs domiciled in Vietnam over January 2016–December 2023, yielding 14,295 observed defaults and 5,429 other exit events after data-cleaning.

Considering the export-driven country of Vietnam, we incorporated 5 macro-financial indicators (e.g., GDP growth rate, exchange rate, commodity price indices) alongside 22 firm-specific predictors derived from annual financial statements—spanning liquidity, profitability, efficiency, cash-flow, solvency, and taxation. After around 200 initial features were generated, LightGBM's built-in importance ranking was used to pare the set down to the 25 most influential predictors. A subsequent manual review merged conceptually related variables to balance statistical relevance with economic interpretability.

4.1.2. Predictive Performance

Model discrimination was evaluated using the dynamic AUC across horizons. For the medium-size segment, the dynamic AUC averaged 83% over the full 24-month range. Small and micro segments exhibited dynamic AUCs of 81.6% and 76.5%, respectively. These metrics underscored robust, stable ranking power across SME scales and forecast horizons.

4.1.3. Company Alpha: Pre-Liquidation Signal

In mid-2022, Company Alpha maintained a one-year PD of under 50 bps, reflecting stable operations. Beginning in Q4 2022, however, the model registered a gradual uptick in forward PD, accelerating sharply six months before its formal liquidation announcement on 21 November 2023. By July 2023, the one-year PD had climbed above 300 bps—six times its baseline—highlighting mounting financial strain. This early warning window could have facilitated credit line reviews or restructuring discussions well before the default event.

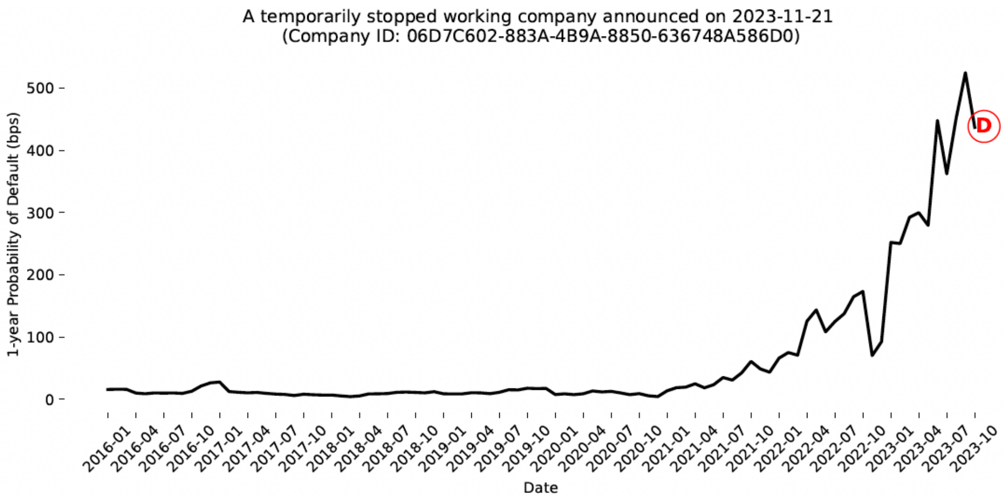

Figure 4: Early Warning Signal: TRACE detected escalating risk for 'Company Alpha' six months prior to liquidation.

4.1.4. Company Beta: Rehabilitation Trajectory

Company Beta's risk trajectory followed a similar pattern: stable sub-100 bps PD through 2021, followed by a sustained rise in early 2022. By March 2023—six months prior to its rehabilitation filing on 4 September 2023—the model projected a one-year PD above 400 bps. The dynamic PD term-structure not only flagged the deteriorating credit profile but also quantified the speed and magnitude of risk escalation, enabling targeted monitoring and tailored mitigation strategies.

Figure 5: Rehabilitation Trajectory: Monitoring risk escalation and recovery potential for 'Company Beta' (Rehabilitation Case).

4.2. Pilot 2: Proving the 'Glass Box' in a High-Compliance Market

This pilot is a critical test of TRACE's advanced capabilities, focusing on the *'Glass Box' Modelling* and the *GenAI-Driven Validation*.

The primary goal is to prove that TRACE could ingest massive, non-traditional datasets and produce a high-performing model that remains fully transparent, auditable, and compliant with high regulatory standards.

4.2.1. Data & Context

This pilot assessed MSME credit risk in a context where firm-level risk was gauged by fusing a massive amount of data from diverse sources, such as traditional registry data, digital footprints, macroeconomic indicators.

The core challenge was that fusing such high-dimensional, non-traditional data often created a powerful but opaque 'black box' model. This approach was difficult to reconcile with the needs of a high-compliance market like Singapore, requiring full model transparency and robust governance.

4.2.2. Methodology

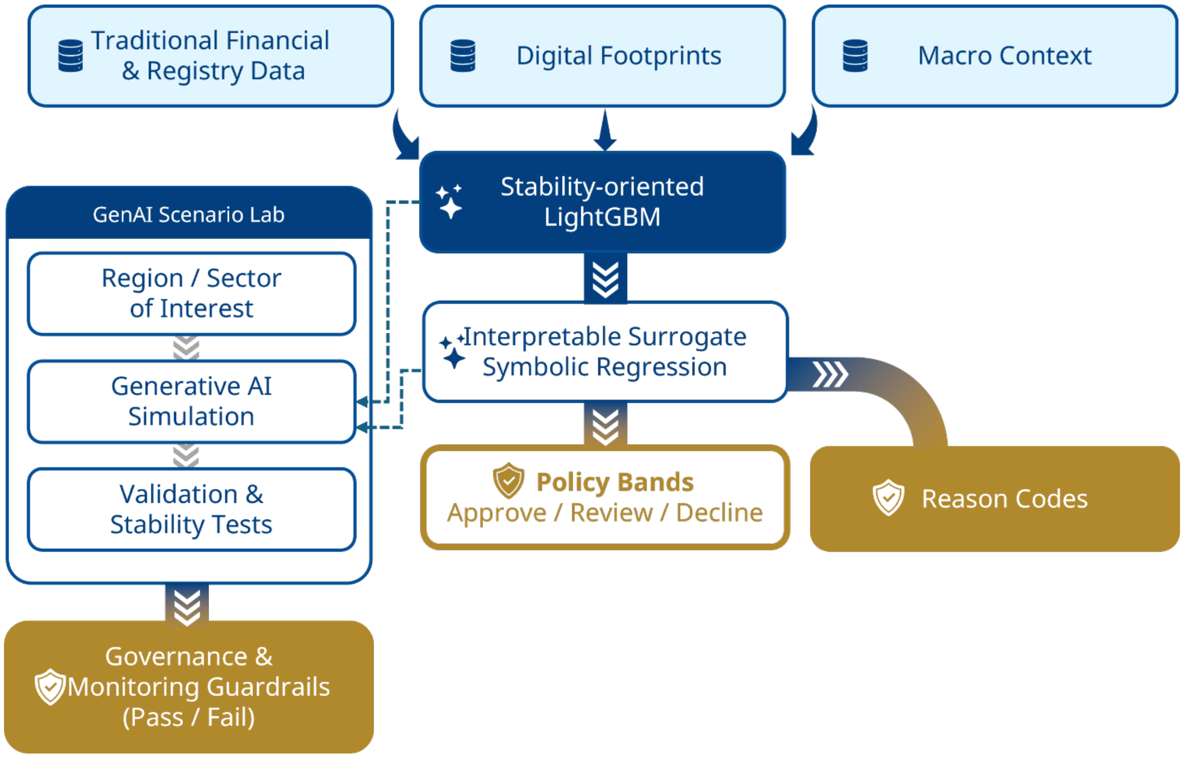

Figure 6: The 'Glass Box' Architecture: Distilling complex AI into auditable, policy-compliant reason codes.

To solve this, we implemented a sophisticated, multi-stage methodology focused on auditability.

Validation protocol. We adopted a forward time-split cross-validation with anchored windows. All features were computed using only information available at the decision time of each fold. Performance was reported out-of-time (OOT) and by key segments to assess temporal and cohort stability.

Teacher–student modelling. A ML teacher model (e.g., LightGBM) was trained under stability-oriented settings (early stopping, conservative regularization, and business-consistent constraints where applicable). We then distilled the teacher into a sparse symbolic-regression (SR) student that approximated the teacher's non-linear decision surface with a compact, auditable formula. The SR model yielded reason codes, preserved economically sensible directions, and supported transparent policy mapping.

Imbalance and thresholds. Given low default prevalence, we prioritized class-weighting and decision-threshold tuning over aggressive resampling. Evaluation emphasized discrimination and calibration rather than raw recall at extreme base rates.

Generative scenario lab. We validated this transparent 'student' model using our 'Scenario Lab'. Rather than replacing observed data or being treated as ground truth, we implemented a GAN-based generator. This allowed us to examine edge cases (e.g., abrupt shifts in a small set of key signals) and confirm that the model's policy bands and reason codes behaved consistently and intuitively under controlled perturbations.

4.2.3. Predictive Performance

Across out-of-time folds, the model delivered a clear lift over a strong baseline on rank-based metrics. The transparent 'student' model retained most of the 'teacher's' predictive power. The results showed that top-tier performance and full, auditable transparency were not mutually exclusive. (Results were reported as relative and qualitative due to confidentiality constraints.)

4.3. Pilot 3: Overcoming Unlabelled Data in Indonesia

This pilot is mainly to solve the 'cold start' problem, directly testing TRACE's capabilities of *Intelligent Data Integration* and *AI-Driven Pre-Model Development*.

In this context, we addressed one of the most significant challenges in emerging markets: building a credit risk model when no historical default labels were available. We were tasked with assessing Indonesian MSMEs using only bank statement data. The complete absence of labelled outcomes (i.e., 'default' vs. 'non-default') required an innovative, multi-step strategy to generate reliable proxy targets and create a path for long-term model improvement.

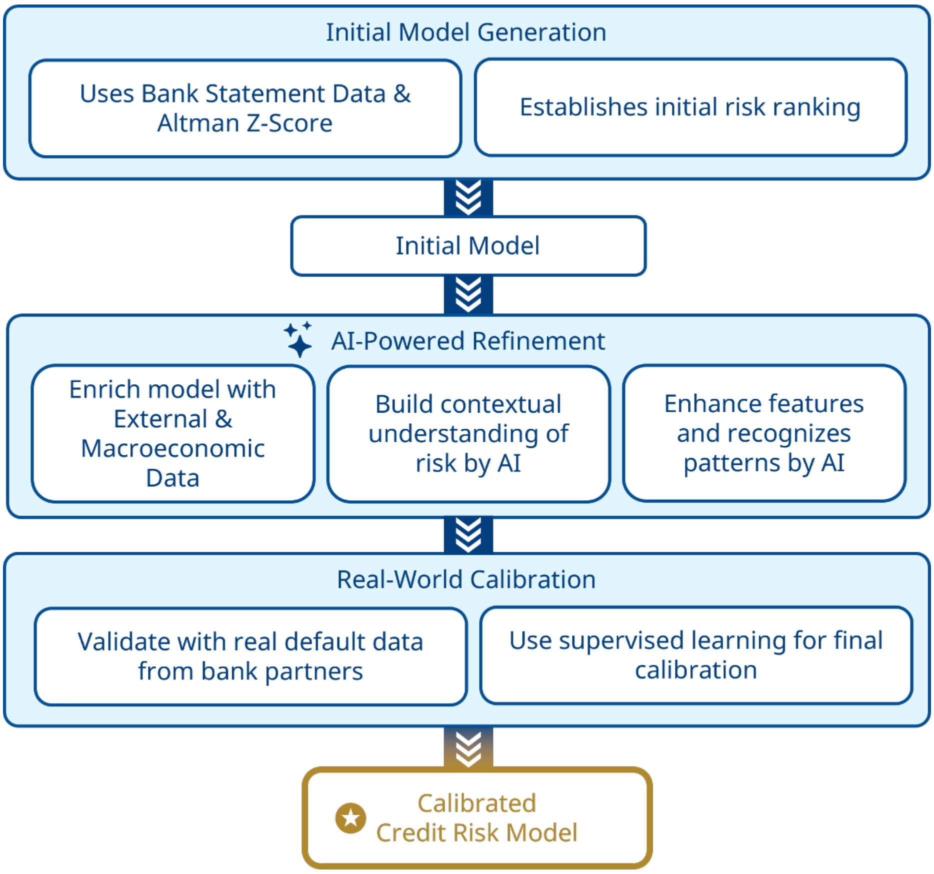

Figure 7: Overcoming the 'Cold Start': Iterative model refinement using proxy labelling and external data enrichment.

4.3.1. Step 1: Proxy Labelling with Altman Z-Score and Heuristic Assumptions

Without historical default labels, we developed a credit risk model using bank statement data to derive financial indicators. We began by deriving financial features from SME bank statements in the absence of traditional financial statements. To construct a proxy for creditworthiness, we adapted the Altman Z-score framework, typically reliant on structured financial data, and inferred its components (e.g., liquidity, leverage, and cash flow proxies) from transaction-level patterns within the bank statements. (Altman, E. I., 1968)

Given the lack of actual default labels, we assumed a baseline default rate of 10% and labelled the bottom 10% of SMEs (ranked by the inferred Z-score) as defaulters. This heuristic labelling formed the foundation of the initial training dataset for risk modelling.

4.3.2. Step 2: Iterative Model Refinement Using LLMs and External Data

We then enhanced the initial model through iterative optimization powered by LLMs and by integrating additional external data sources. These included macroeconomic signals, sectoral risk trends, and regional financial indicators, which collectively helped contextualize bank transaction behaviour and improve predictive accuracy.

4.3.3. Step 3: Collaboration with FIs for Ground Truth Labels

To further validate and calibrate the model, we established partnerships with financial institutions (FIs) to obtain real default data. This enabled supervised learning on verified outcomes and significantly improved the model's precision and reliability in practical deployment scenarios.

5. Conclusion

The AIDF TRACE offers a transformative approach to credit assessment for MSMEs. It empowers financial institutions with powerful analytical tools that are accurate and transparent, translating complex modelling into deployable, governance-ready credit policy.

As demonstrated by our real-world pilots, the TRACE framework is not a theoretical model but a battle-tested solution. Its key, proven advantages include:

Readiness for Real-World Data

TRACE is proven to work in diverse, data-constrained environments. By intelligently fusing traditional financials with alternative data (Intelligent Data Integration) and using AI to prepare sparse, "noisy" inputs (AI-Powered Pre-Model Development), it generates high-precision insights.

Performance with Full Transparency

The framework's "Glass Box" Modelling definitively addresses the performance-interpretability trade-off. It delivers top-tier predictive power using methods (like the forward-intensity model or symbolic regression) that remain fully auditable, economically intuitive, and explainable.

A Commitment to Responsible AI

With the optional GenAI-Driven Validation layer, TRACE enables institutions to stress-test models for edge-case behaviours, ensuring robustness and alignment with responsible AI principles.

6. Call to Action

AIDF is committed to advancing MSME credit assessment methodologies. We invite you to engage with us in two ways, whether you're seeking collaborative research opportunities or immediate implementation solutions.

Collaborate on Research

As a research institute, we invite financial institutions, regulatory bodies, and fellow researchers to join our collaborative network.

We welcome opportunities for joint research initiatives, knowledge exchange programs, and customized implementation partnerships.

Adopt the Framework

For organizations seeking immediate solutions, the TRACE framework is available for adoption with comprehensive support:

- Full technical documentation and implementation guidance
- Ongoing methodological support from our expert team
- Training programs for your credit risk professionals
- Customization services to adapt TRACE to your specific portfolio

By combining our collective expertise, we can accelerate progress in this critical field and create more inclusive financial systems.

Contact us to explore collaboration opportunities or to discuss how the TRACE framework can strengthen your institution's MSME financing capabilities.

7. References

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance, 23*(4), 589–609.

Basel Committee on Banking Supervision. (2015). *Guidance on credit risk and accounting for expected credit losses.* Bank for International Settlements.

Berger, A. N., & Udell, G. F. (2006). A more complete conceptual framework for SME finance. *Journal of Banking & Finance, 30*(11), 2945–2966.

Caruana, R., Lou, Y., Gehrke, J., Koch, P., Sturm, M., & Elhadad, N. (2015). Intelligible models for healthcare: Predicting pneumonia risk and hospital 30-day readmission. In *Proceedings of the 21st ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1721–1730). Association for Computing Machinery.

European Banking Authority. (2020). *Final report on big data and advanced analytics* (EBA/REP/2020/01).

Hinton, G., Vinyals, O., & Dean, J. (2015). Distilling the knowledge in a neural network. *arXiv*. https://arxiv.org/abs/1503.02531

International Finance Corporation. (2017). *MSME finance gap: Assessment of the shortfalls and opportunities in financing micro, small and medium enterprises in emerging markets.* World Bank Group.

International Finance Corporation. (2025). *Micro, small & medium enterprises (MSMEs) – Factsheet.*

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. In *Advances in Neural Information Processing Systems* (Vol. 30, pp. 4765–4774).

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance, 29*(2), 449–470.

Udrescu, T.-M., & Tegmark, M. (2020). AI Feynman: A physics-inspired method for symbolic regression. *Science Advances, 6*(16), eaay2631.

World Bank. (2025a). *Enterprise surveys—Firms with a bank loan/line of credit (% of firms).*

World Bank. (2025b). *Enterprise surveys—Indicator descriptions: Percent of firms with annual financial statement reviewed by an external auditor.*

8. About the Authors

Associate Professor Huang Ke-Wei is the Executive Director of Asian Institute of Digital Finance (AIDF) at the National University of Singapore (NUS), and an Associate Professor in the Department of Information Systems and Analytics at NUS

Ms. Helena Zhang is a Director of Operations at Asian Institute of Digital Finance.

Dr. Yao Xuan is a Research Fellow at AIDF.

Dr. Tan Tianhui is a Senior Research Scientist at AIDF.

Ms. Zhang Yihang is a Research Analyst at AIDF.

Mr. Li Sirui is a Research Associate at AIDF.

For collaboration inquiries, implementation discussions, or research partnerships, please reach out to our team:

Email

nuscri@nus.edu.sg

Visit our website

https://www.aidf.nus.edu.sg/
https://nuscri.org/

Asian Institute of Digital Finance
National University of Singapore
Innovation 4 (i4.0) Building,
3 Research Link, #04-03,
Singapore 117602

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