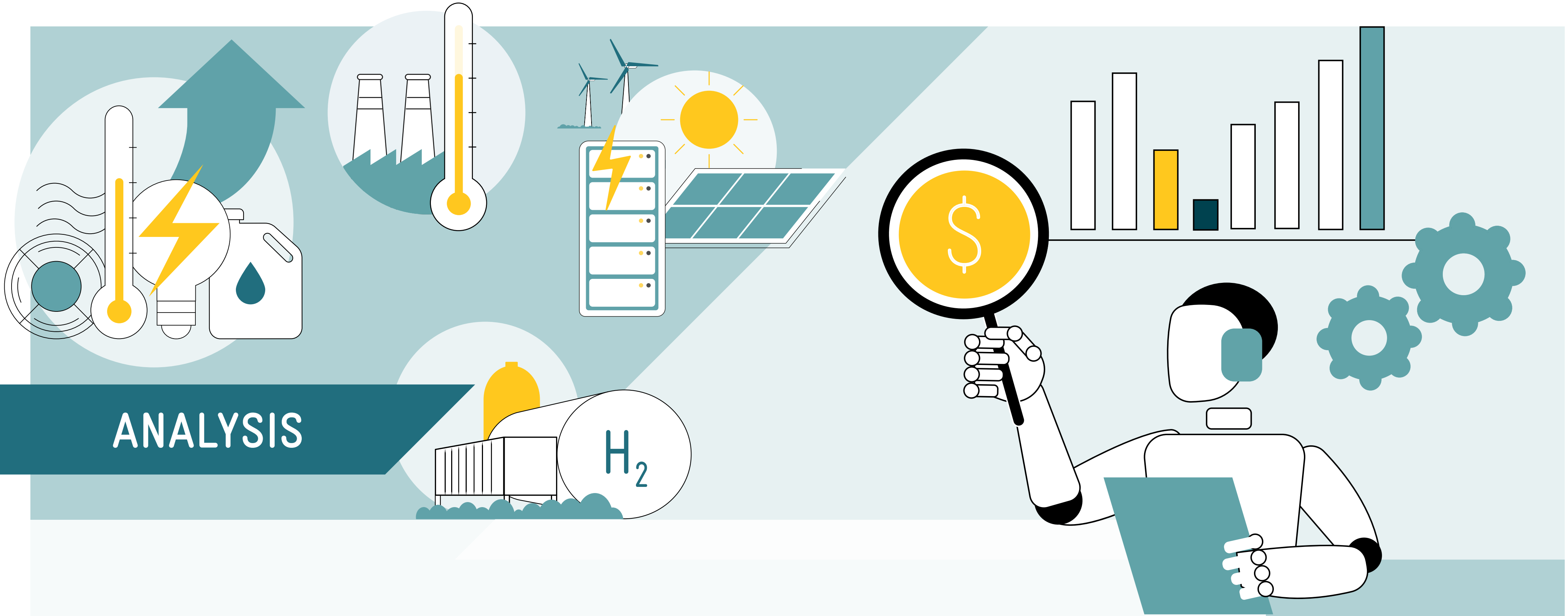

ANALYSIS

Leveraging AI to Improve Credit Risk Assessments in Frontier Markets

Deutsche Gesellschaft
für Internationale
Zusammenarbeit (GIZ) GmbH

This publication was commissioned by the German
Energy Solutions Initiative of the German Federal
Ministry for Economic Affairs and Energy (BMWE)

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Abbreviations/acronyms

ACS	Algorithmic credit scoring
AI	Artificial intelligence
API	Application programming interface
B2B	Business to business
BaFin	Germany's Federal Financial Supervisory Authority
CDP	Commission de Protection des Données Personnelles (Data Protection Commission)
CRA	Credit risk assessment
DPPA	Data Protection and Privacy Act
ERP	Enterprise resource planning
ESG	Environmental, social and governance
KYC/AML	Know your customer/ anti-money laundering
GDPR	General Data Protection Regulation
IoT	Internet of Things
IT	Information technology
LIME	Local interpretable model-agnostic explanations
LLM	Large language model
ML	Machine learning
MPS	Ministry of Public Security
NLP	Natural language processing
OCR	Optical character recognition
ODPC	Office of the Data Protection Commissioner
P2P	Peer-to-peer
PAYGO	Pay-as-you-go
PD	Probability of default
PDF	Portable document format
POS	Point of sale
RE	Renewable energy
SHAP	SHapley Additive exPlanations
SIM	Subscriber identity module
SME	Small and medium-sized enterprise
SMS	Short Message Service
TPO	Third-party ownership
XAI	Explainable AI
FI	Financial institution(s)

Currency units

EUR	Euro
KES	Kenyan Shilling
USD	United States dollar
VND	Vietnamese Dong

Date	EUR	
	Buy	Sell
18 Sep. 2025	143.909	144.051
18 Sep. 2025	143.056	143.301

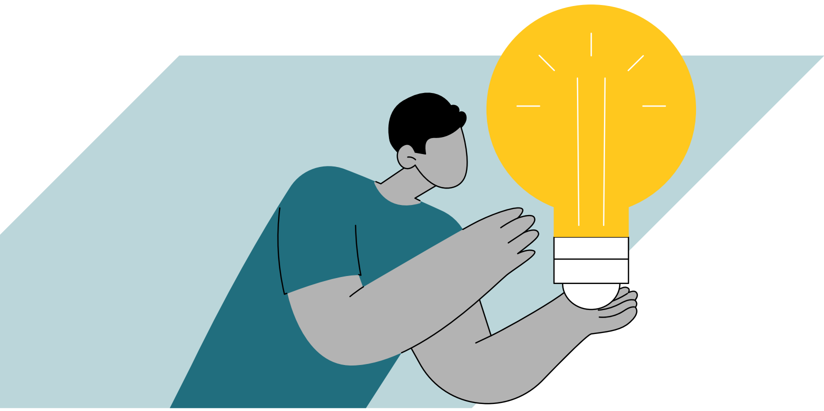
Conversion rate as of 01.05.2025

KES 1 = EUR 0.0068324

USD 1 = EUR 0.885442

VND 1 = EUR 0.0000340635

Source: https://www.xe.com/currencyconverter/



ENERGY SOLUTIONS – MADE IN GERMANY

The German Energy Solutions Initiative

The German Energy Solutions Initiative of the German Federal Ministry for Economic Affairs and Energy (BMWE) aims to globalise German technologies and expertise in climate-friendly energy solutions.

Years of promoting smart and sustainable energy solutions in Germany have led to a thriving industry known for world-class technologies. Thousands of specialised small and medium-sized enterprises (SMEs) focus on developing renewable energy systems, energy efficiency solutions, smart grids, and storage technologies. Cutting-edge energy solutions are also built on emerging technologies such as power-to-gas, fuel cells, and green hydrogen. The initiative's strategy is shaped around ongoing collaboration with the German business community.

The initiative creates benefits for Germany and the partner countries by:

- boosting global interest in sustainable energy solutions
- encouraging the use of renewables, energy efficiency technologies, smart grids, and storage technologies, while facilitating knowledge exchange and capacity building
- enhancing economic, technical and business cooperation between Germany and partner countries

THE PROJECT DEVELOPMENT PROGRAMME (PDP)

PDP is a key pillar of the German Energy Solutions Initiative and is implemented by the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH. It connects development cooperation with private-sector engagement and supports climate-friendly energy solutions in selected developing and emerging countries, enabling local businesses to adopt solutions in energy efficiency, electricity and heat supply, and hydrogen, while facilitating market access for German solution providers.

Developing and emerging economies offer promising business potential for climate-friendly energy solutions but also pose challenges for international business partners. The PDP team works closely with local industries to develop financially viable projects by providing technical expertise, financial guidance, and networking opportunities.

It identifies project leads, collects and analyses energy consumption data, and assesses projects from both a technical and economic perspective. This includes outlining the business case, calculating payback periods, and evaluating profitability. Companies can then choose to finance projects using their own funds or explore leasing and other financing options. PDP provides cost-free advice to local companies and connects them with German solution providers for project implementation.

Additionally, by offering training, organising reference project visits, and publishing studies on the potential of climate-friendly solutions and on navigating regulatory frameworks, the programme supports market development and fosters private-sector cooperation.

In the race to expand clean energy access across Africa and Asia, financing renewable energy projects remains a major hurdle, especially in frontier markets where the data is limited and risks are high. Traditional credit risk assessment tools often fall short when evaluating local companies because of the absence of formal financial histories, which makes it difficult for lenders and project developers to assess their financial viability confidently. Increased risk aversion and regulatory complexities further complicate access to funding, which slows down investments critical for achieving climate goals.

HOW AI IS CHANGING THIS LANDSCAPE

While credit risk assessment (CRA) is a major barrier to trade finance and to providing financing for third-party ownership (TPO) based business models by the German SME, the world is rapidly moving towards systems that have evolved beyond the traditional ones. Artificial intelligence (AI) is one of the tools that can be leveraged to both supplement and complement the traditional CRA process through multifaceted interventions.

Starting from easy first steps, e.g. parsing financial statements, to leveraging unconventional and alternative data sources for small companies, AI can significantly reduce the time and effort it takes to conduct a traditional CRA, while offering the reliability and complementarity of alternative data that adds more nuances to the traditional CRA. In addition, this provides lenders and investors with an improved understanding of project potential and borrower reliability. These insights allow for more accurate credit risk assessments, even with limited traditional financial documentation.

EFFECTIVE EXAMPLES IN RENEWABLE ENERGY

- In West Africa, satellite imagery combined with machine learning

Zusammenfassung

Im Wettlauf um den Ausbau des Zugangs zu sauberer Energie in Afrika und Asien ist die Finanzierung von Projekten zu erneuerbaren Energien ein zentrales Hindernis. Dies gilt insbesondere für Entwicklungs- und Schwellenländer, in denen die Daten begrenzt und die Risiken hoch sind. Herkömmliche Instrumente zur Kreditrisikobewertung stoßen bei der Bewertung lokaler Unternehmen häufig an ihre Grenzen, weil oftmals die Finanzdaten der Vergangenheit nicht vollständig sind. Das erschwert es Kreditgebern und Projektentwicklern, die Finanzkraft der Unternehmen zuverlässig einzuschätzen. Eine zunehmende Risikoaversion und komplexe regulatorische Rahmenbedingungen erschweren den Zugang zu Finanzierungen zusätzlich und verlangsamen Investitionen, die für das Erreichen der Klimaziele entscheidend sind.

WIE KI DIE MÖGLICHKEITEN VERÄNDERT

Während die Kreditrisikobewertung (CRA) sowohl für die Handelsfinanzierung als auch für die Finanzierung von Third-Party-Ownership (TPO)-Geschäftsmodellen deutscher KMU ein wesentliches Hindernis darstellt, bewegt sich die Welt rasant auf Systeme zu, die über traditionelle Ansätze hinausgehen. Künstliche Intelligenz (KI) ist eines der Werkzeuge, die genutzt werden können, um den traditionellen CRA-Prozess durch vielfältige Interventionen zu ergänzen und zu verbessern.

Beginnend mit einfachen ersten Schritten – zum Beispiel das Auslesen von Finanzberichten – bis hin zur Nutzung unkonventioneller und alternativer Datenquellen für kleinere Unternehmen kann KI den Zeit- und Arbeitsaufwand einer traditionellen CRA erheblich verringern. Gleichzeitig erhöhen die Zuverlässigkeit und die Ergänzung alternativer Daten die Detailtiefe der Bewertung. Dies verschafft Kreditgebern und identified suitable sites for off-grid solar installations, reducing site assessment costs and accelerating project financing.

- In East Africa, IoT (Internet of Things) sensors installed on solar systems provided real-time operational data, enabling lenders and project owners to monitor performance, pre-empt failures, and assess long-term repayment capacity with greater confidence.
- In South Asia, behavioural data from mobile money transactions helped users evaluate small solar energy providers operating without formal financial records to unlock access to finance and bridge funding gaps.

Although the overall data is scarce on the use of AI by medium-scale renewable energy (RE) companies, the impact on small-scale companies indicates a high potential and relevance for medium and large-scale interventions too, when implemented and used optimally and strategically.

REGULATIONS AND TRUST TO NAVIGATE THE LEGAL LANDSCAPE

German SMEs are already in a more favourable position due to the evolving regulatory environment, including the EU AI Act, the General Data Protection Regulation (GDPR), and local data laws which are generally similar to these two acts, which presents both challenges and opportunities. Embracing transparency, ensuring privacy, and building trust with stakeholders are therefore crucial for scalable AI deployment. Companies leading with responsible AI practices will gain competitive advantages and facilitate smoother cross-border collaborations.

CONCLUSION: A NEW ERA FOR GERMAN SMES AND INVESTORS

Investoren ein feineres Verständnis des Potenzials eines Projektes und der Verlässlichkeit von Kreditnehmern. Solche Einblicke ermöglichen genauere Kreditrisikobewertungen – selbst wenn traditionelle Finanzdokumentationen nur begrenzt verfügbar sind.

WIRKUNGSVOLLE BEISPIELE IM SEKTOR DER ERNEUERBAREN ENERGIEN

- In Westafrika wurden mithilfe von Satellitenbildern und Machine Learning geeignete Standorte für Off-Grid-Solaranlagen identifiziert. Dadurch konnten die Kosten für Standortbewertungen gesenkt und die Projektfinanzierung beschleunigt werden.
- In Ostafrika lieferten auf Solarsystemen installierte IoT-Sensoren (IoT – Internet of Things) Echtzeit-Betriebsdaten, die es Kreditgebern und Projektbetreibern ermöglichten, die Leistung zu überwachen, Ausfälle frühzeitig zu erkennen und die langfristige Rückzahlungsfähigkeit mit größerer Sicherheit einzuschätzen.
- In Südasien trugen Verhaltensdaten aus mobilen Zahlungstransaktionen dazu bei, kleine Solarenergieanbieter ohne formale Finanzunterlagen zu bewerten. So konnte der Zugang zu Finanzierungen eröffnet und Finanzierungslücken konnten geschlossen werden.

Obwohl die Gesamtdatenlage zur Nutzung von KI durch mittelgroße Unternehmen im Bereich der erneuerbaren Energien noch begrenzt ist, zeigt die Wirkung bei kleinen Unternehmen ein hohes Potenzial und eine klare Relevanz auch für mittel- und großskalige Anwendungen – vorausgesetzt, die Technologie wird optimal und strategisch implementiert und genutzt.

AI-enabled CRA models could significantly expand access to finance both for and by German SMEs by accurately assessing the risks of local companies, even in data-scarce environments. With financiers and German SMEs championing these innovations, investments will become more attractive, costs will decrease, and the pace of renewable energy deployment, and thus progress toward climate resilience, will accelerate in frontier markets.

REGULIERUNG UND VERTRAUEN IM RECHTLICHEN UMFELD

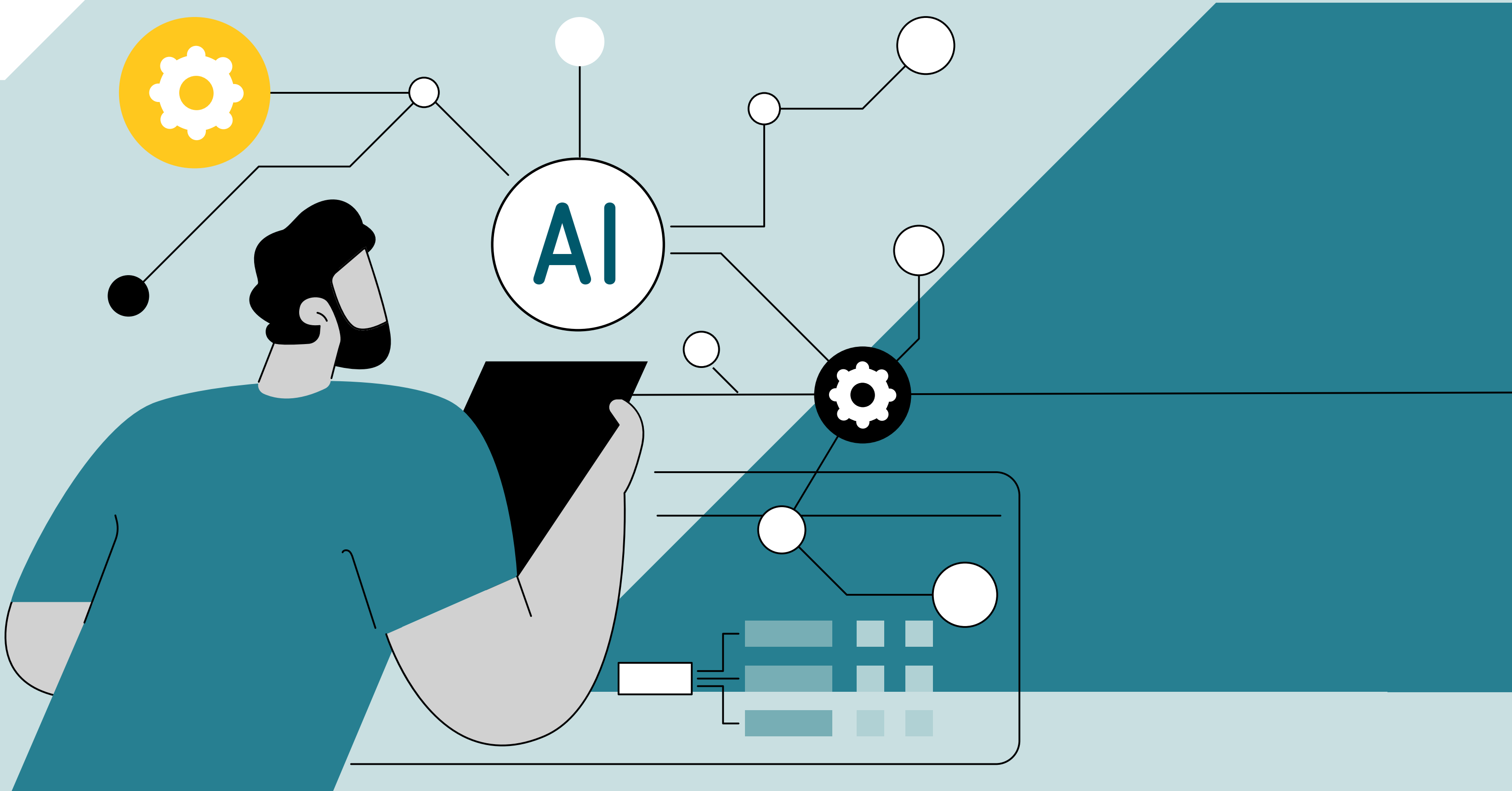
Deutsche KMU haben durch das sich entwickelnde regulatorische Umfeld bereits einen Vorsprung. Zu diesem Umfeld gehören unter anderem der EU AI Act, die Datenschutz-Grundverordnung (DSGVO) und die lokalen Datenschutzgesetze in den Entwicklungs- und Schwellenländern, die sich im Wesentlichen an diesen beiden Regelwerken orientieren. Dies bringt sowohl Herausforderungen als auch Chancen mit sich. Transparenz zu fördern, den Datenschutz zu gewährleisten und Vertrauen bei Stakeholdern aufzubauen ist daher entscheidend für den skalierbaren Einsatz von KI. Unternehmen, die verantwortungsbewusste KI-Praktiken vorantreiben, sichern sich Wettbewerbsvorteile und erleichtern reibungslosere grenzüberschreitende Kooperationen.

FAZIT: EINE NEUE ÄRA FÜR DEUTSCHE KMU UND INVESTOREN

KI-gestützte CRA-Modelle könnten den Zugang zu Finanzierungen sowohl für deutsche KMU als auch durch sie erheblich erweitern, indem sie die Risiken lokaler Unternehmen auch in datenarmen Umgebungen zuverlässig bewerten. Wenn Finanzierer und deutsche KMU diese Innovationen vorantreiben, werden Investitionen attraktiver, Kosten sinken und der Ausbau erneuerbarer Energien in Entwicklungs- und Schwellenländer beschleunigt – und damit der Fortschritt hin zu mehr Klimaresilienz.

1

Introduction



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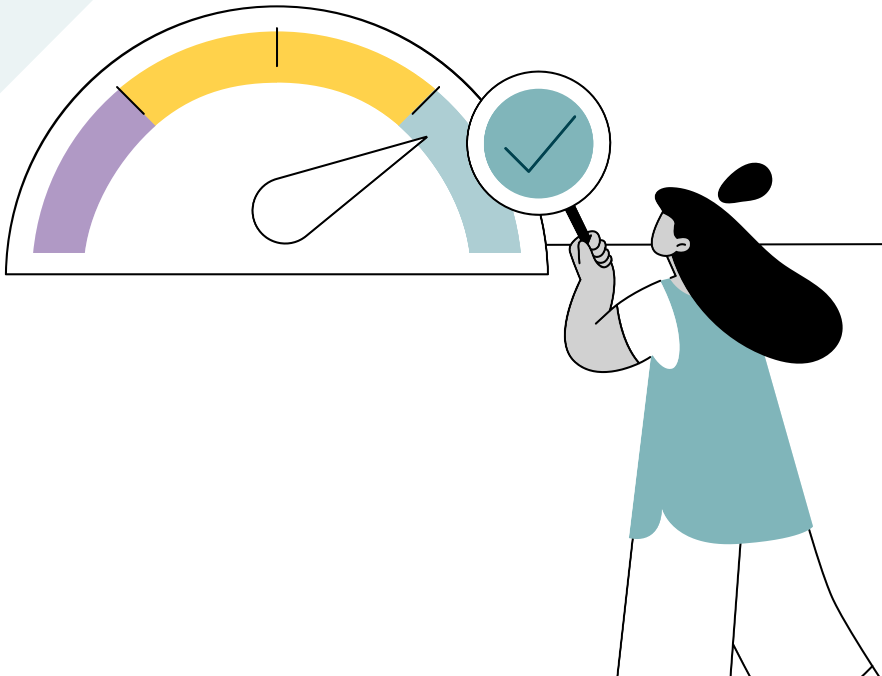
The objective of this research is to explore the use of artificial intelligence (AI) for the credit risk assessment (CRA) of local companies in frontier markets (specifically for this research Senegal, Viet Nam, Kenya, and Uganda). The study explores the market and looks at alternative indicators that have been used in the past and potentially can be used in the future to assess credit risk in different types of business models, especially trade finance. This will eventually enable German small and medium-sized enterprises (SMEs) working in the renewable energy (RE) sector to sell their products and services to local companies with greater confidence and expedite the financing process through public and private credit institutions.

Credit risk can be defined as the possibility that a counterparty fails to meet its obligations in accordance with the terms of the agreement (Brown & Moles, 2014). In the context of trade and commercial transactions, credit risk encompasses the (in)ability of a counterparty to meet its contractual commitments, which is essential in determining the viability of a transaction and the financial stability of the counterparty (Adefarati & Bansal, 2019).

1

Traditional credit risk models rely on statistical methods and historical data, specifically focusing on credit scores, income levels and debt-to-income ratios to predict the probability of default (PD) (Shittu, 2022). However, these models face significant challenges in assessing non-traditional or emerging credit profiles where small businesses or individuals do not have documented credit histories (Shittu, 2022). This problem manifests particularly in emerging markets where the underbanked sections, especially youth, women and small businesses, do not have traditional forms of collateral or identification that FI (financial institutions) require before they extend credit to them (Biallas & O'Neill, 2020).

To overcome this data scarcity challenge within CRA, alternative data collection methods can be sought. This data collection can be done in cooperation with various (local) data vendors. Besides the data scarcity challenge, there is a second challenge of low data quality, i.e. even when some financial data is available, it is usually not validated or audited. Therefore, outcome validation is a key point for ensuring high quality data. The third and final challenge is the lack of available data centres in the various frontier markets. Therefore, a move to cloud-based solutions is recommended. This research shows that with the deployment of AI tools, despite all its challenges, it is possible to make a sound and well-founded CRA.



1.1 Traditional CRA with financial institutions

The traditional CRA is an essential part of all kinds of financing, no matter whether it is a German SME or local private company applying for a trade credit, or a German SME offering financing itself to local private companies through various business models. The documentation requirements are extensive, calling for financials for a minimum of two to three years, comprehensive business plans with detailed export/import projections, tangible trade contracts or letters of intent, collateral documentation, management experience profiles, and thorough market analyses of the target countries. The traditional method relies heavily on historical financial performance data, credit rating based on conventional financial ratios, and industry-specific risk evaluation combined with environmental, social and governance (ESG) compliance checks.

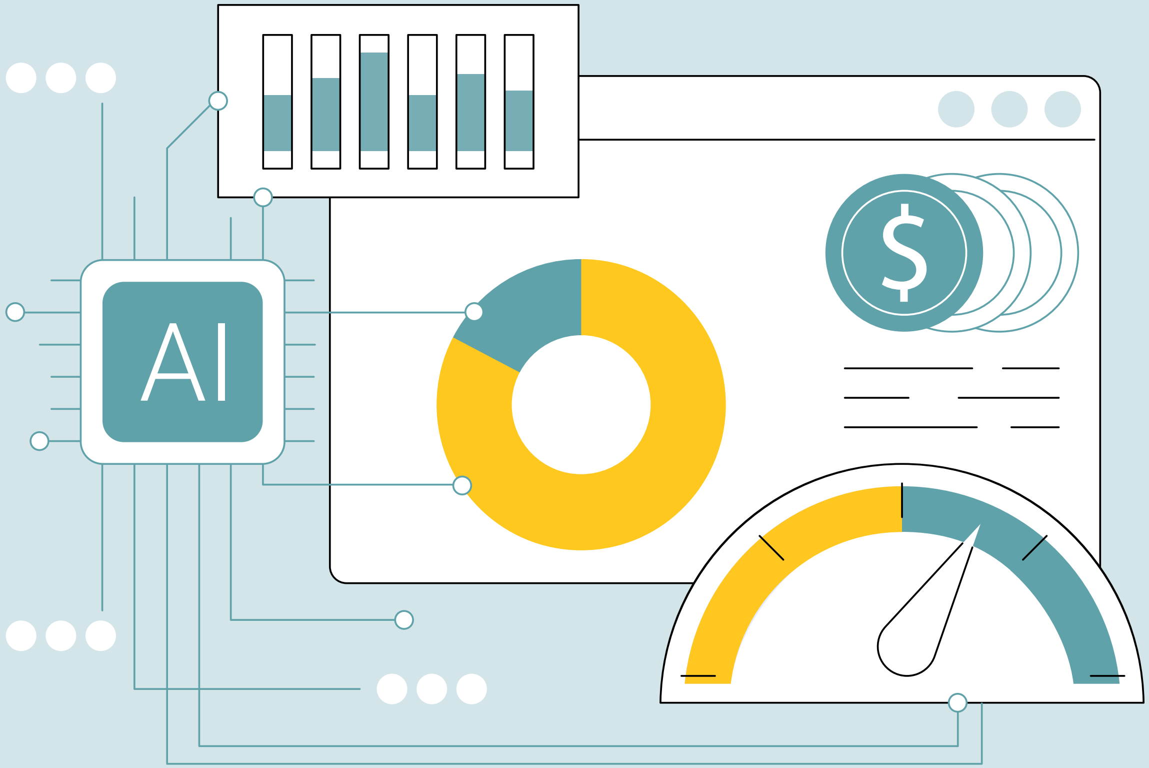
However, this established framework faces significant challenges that have intensified in the post-pandemic landscape. The most direct worry is the significantly increased risk aversion on the part of financial institutions, as over 32% of German SMEs reported restrictive bank lending conditions as of 2024, which exceeded the previous maximum since the introduction of the new survey methodology in 2017 (KfW Research, 2025). The costs of regulatory compliance have been particularly severe, with know your customer/anti-money laundering (KYC/AML) requirements appearing as a prominent rejection criterion for trade finance applications. Enhanced due diligence requirements for cross-border transactions, multi-layered sanctions screening, and time-consuming anti-money laundering documentation present significant challenges. Moreover, traditional loan models are ineffective in capturing SME finance risk since historical financial statements do not reflect current market conditions and a lack of real-time cash flow visibility hinders proper risk analysis and further loan approval.

These challenges become even more complex when German SMEs seek finance for transactions with companies in frontier markets where the fundamental data required for traditional CRA processes is often unavailable or unreliable. Country risk evaluation becomes significantly more stringent, currency risk analysis requires sophisticated modelling, and cross-border regulatory compliance verification demands extensive resources. The core problem lies in the severe scarcity of financial data from potential counterparts in these regions; the documentation that credit institutions require for their standard assessment procedures simply does not exist for vast segments of businesses. When financial information is available, its trustworthiness remains highly questionable as it typically lacks proper validation, auditing, or standardisation, which leads financiers to even more conservative approval decisions. This data quality crisis, combined with inadequate country-specific market intelligence and the absence of reliable data infrastructure, creates a major barrier to traditional CRA frameworks, and consequently to German SMEs aiming to expand into frontier markets.

This study is structured as follows. First, it describes the input data for CRA, and indicates where the data scarcity challenge arises and what alternative data sources exist. Second, the available AI tools are described. Next, the regulatory boundaries governing the use of AI are outlined, followed by a proposal for a set of improvements to the current CRA model. The paper concludes with key insights from the research and proposes potential next concrete steps.

2

Data for CRA in frontier markets



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This chapter focuses on the challenge of data scarcity during CRA in frontier markets. It will first describe various credit default risk factors applicable specifically to the RE sector, and then explore the challenges posed by unavailability or scarcity of data, leading to a discussion on how alternative data sources can help overcome this challenge.

2.1 Traditional CRA data input in frontier markets

Credit risk assessment typically begins with the analysis of traditional data sources such as financial statements, tax returns, credit bureau histories, public records and sectoral benchmarks. These inputs form the baseline for evaluating a borrower's financial health, creditworthiness, and capacity to repay. In well-documented environments, such data can offer sufficient insight into a company's risk profile. However, in many frontier markets and emerging sectors, such as decentralised RE, this information is often incomplete, outdated, or entirely unavailable. Nonetheless, reviewing financial statements, public records and sector data is always the first step in the credit risk assessment process before considering any alternative data sources.

2.1.1 Financial information

A German SME requesting a loan for international trade and operations is typically required to submit financial information that demonstrates the viability of its business model and the financial health of its local partners. A core component of credit risk assessment (CRA) is analysing transaction data, which offers insight into an SME's revenue streams, spending patterns, and overall liquidity.

When working with companies in frontier markets, the recommendation is to begin by reviewing formal financial figures from the past two to three years (Asah & Louw, 2021). However, in many cases, especially across sub-Saharan Africa and parts of Asia, such data is incomplete or entirely absent due to limited regulatory requirements for annual reporting and financial disclosures (Asah & Louw, 2021). In these situations, historic transaction data can serve as a valuable substitute for traditional financial statements.

This transaction data can be collected through:

- Exports from formal bank accounts, or
- Mobile money transaction records, when formal banking is unavailable.

In many African countries, the latter has become a primary source of financial activity. Mobile wallets have become a dominant financial tool, particularly in regions where formal banking penetration remains low. For example, just 54% of African adults have a bank account, but 61% own a mobile phone. Among SMEs, mobile money adoption is even more pronounced: 72% of SME transactions are conducted via mobile money platforms in markets like Kenya, Ghana and Nigeria, with 64% of SMEs in Africa now engaging with some form of digital banking (Brunett & Kinder, 2025).

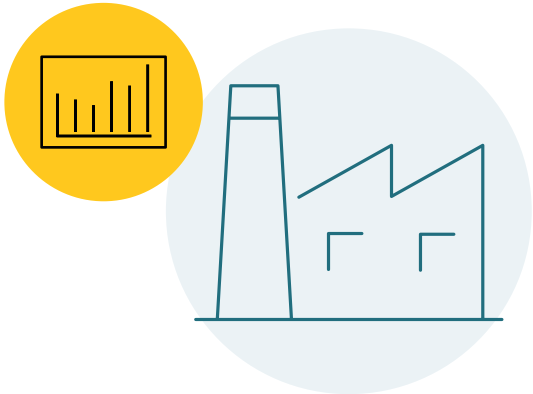
A leading example of this transformation is M-PESA, Kenya's widely adopted mobile money platform developed by Safaricom. M-PESA allows users, including micro and small businesses, to send and receive payments, pay utilities, manage savings, and even access credit. For many informal or semi-formal SMEs, M-PESA effectively functions as both a bank account and an accounting ledger. Lenders can analyse M-PESA transaction exports (with borrower consent) to assess income regularity, cash flow volume, frequency of payments to suppliers, and bill payment behaviour. This makes M-PESA data a powerful proxy for traditional financial statements, especially when evaluating SMEs in sectors like retail, energy distribution or last-mile services.

This shift toward digital financial ecosystems is reflected in broader mobile money trends. According to the 2023 GSMA State of the Industry Report on Mobile Money (GSMA, 2024), there were 1.75 billion registered mobile money accounts globally, with 435 million active accounts. Daily transaction volumes reached USD 3.8 billion, and monthly merchant payments totalled USD 4.1 billion, showing a 7% increase between September 2022 and June 2023. This surge demonstrates how mobile wallets are not only reshaping consumer finance but also forming the transactional backbone of small business operations in many frontier economies.

2.1.2 Public records

Public records provide crucial insights into effective CRA, and there is scope for utilising more of the available public records. These range from employment history consistency, income levels, legal proceedings and disputes (bankruptcy filings, foreclosure proceedings), court judgements for unpaid debts, tax payment history and records of tax liens (Alliance for Financial Inclusion, 2025). Credit reference bureaus in Kenya aggregate data from various public sources. Cross-institutional and cross-border sharing of data is supported through a policy where reciprocal arrangements have been established between relevant countries and institutions. These frameworks allow for the integration of unconventional indicators like telecom service usage (voice, data, mobile money) and mobile subscription duration, which are considered reliable non-traditional proxies for credit repayment (Alliance for Financial Inclusion, 2025).

Publicly accessible databases such as land registries, tax returns, court records and company registries can be searched or obtained from government portals where available. Research finds that banks and financial institutions in emerging markets are increasingly utilising publicly available sources of data such as utility bills, government databases and official records to supplement traditional credit evaluation methods. The World Bank's comprehensive 2025 report on alternative data in credit risk assessment shows that digitalisation has tremendously increased the size and variety of alternative data sources, enabling financial institutions to use structured and unstructured public data to assess creditworthiness (Alliance for Financial Inclusion, 2025). This should be done in a manner that fulfils the transparency and lawful access requirements of domestic legislation and the GDPR.



2.1.3 Sector data

Sector codes (like the United Nations' International Standard Industrial Classification of all Economic Activities (ISIC) codes) represent a standardised classification system for categorising companies based on their economic activity (United Nations, 2008). They play an important role in credit risk assessment by enabling lenders and financial institutions to analyse the economic environment in which a borrower operates. This is demonstrated by the bank industry regulations including the sector codes as pre-requisites for incorporation into the risk models (for instance, in the Basel II and Basel III frameworks, sector classification helps banks perform industry exposure analysis and sector concentration risk management (Basel Committee on Banking Supervision, 2011)). In the context of frontier markets, which is characterised by less developed financial systems, higher economic volatility and limited available data, sector codes can play an even more important role.

They offer a standardised framework for categorising the borrower's industry, facilitating comparisons between similar firms and sectors, and enabling risk analysts to identify industry-specific vulnerabilities and opportunities. By referencing sector codes, lenders can access sector-specific economic indicators, regulatory environments and historical performance data, which enhances the accuracy of credit scoring models. Furthermore, sector classification aids in stress testing and scenario analysis by modelling how sector-specific shocks might impact a borrower's ability to meet obligations. In frontier markets, where informal sectors and limited disclosure are common, applying standardised sector codes helps improve transparency and comparability, and serves as a foundation for risk mitigation strategies.

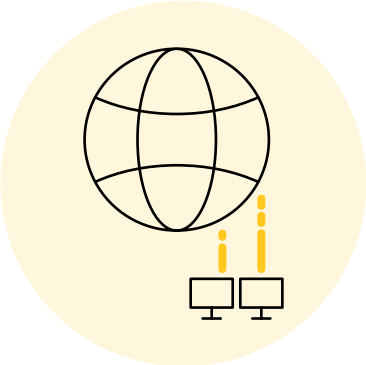
2.2 Alternative data sources and collection methods

The challenging funding journey of a German SME begins with gathering information so that a traditional banking score can be generated. In contexts where traditional data, such as financial statements or credit histories, is missing, unreliable, or insufficient, lenders increasingly turn to alternative data sources to assess credit risk. This is especially relevant for SMEs in frontier markets and emerging sectors like RE, where formal documentation is often limited. Alternative data can offer timely, contextual, and behaviour-based insights that improve risk visibility. These sources include mobile and telecom data, satellite imagery and geospatial analytics, IoT and sensor-based performance data, as well as psychometric and behavioural indicators.

There might be other indicators like relationships with suppliers, payment history with unregulated companies or institutions, etc., that could be used as alternative data sources for SMEs but they have not been explored here because they have not yet been piloted for use in AI-based credit risk assessment. Furthermore, while some of this information, particularly mobile phone metadata and psychometric profiles, may appear personal in nature, it is often used as a proxy for the reliability, financial behaviour or operational patterns of the entrepreneur or business owner, which directly influence the performance and risk profile of the SME. For most SMEs, the line between personal and business behaviour is often blurred due to the non-existent division between the firm's and owner's assets. Frequent transfers of funds between personal and business accounts, whether to simplify operations or obtain fiscal benefits, are common (Hernandez & Baltazar, 2020), thus making comprehensive data from both spheres valuable for holistic credit assessments.

2.2.1 Mobile and telecom metadata

This includes device and Subscriber Identity Module (SIM) metadata (e.g. phone type, operating system), airtime purchase patterns, Short Message Service (SMS) logs, call duration, frequency, geolocation data, and app usage. These signals offer behavioural proxies for financial stability and creditworthiness, particularly for informal SMEs with limited financial documentation. Mobile apps developed by lenders (e.g. Branch, JUMO, Begini) request permissions to access phone metadata and activity logs. This data is collected automatically once access is granted, and transmitted securely to backend scoring systems. Geolocation and device usage data are also collected passively during loan application and ongoing app use.



2.2.2 Satellite imagery and geospatial data

Satellite and geospatial data are used to analyse economic activity, infrastructure presence, population density, energy needs and land usage, which are crucial indicators for assessing SME viability in rural and peri-urban regions without formal data trails. Images are acquired either from public sources (e.g. Sentinel, Landsat) or from commercial providers (e.g. Planet, DigitalGlobe). AI systems like VIDA (Village Data Analytics) process this data using machine learning algorithms to extract features such as settlement patterns, building density, proximity to roads or transmission lines, and energy infrastructure suitability. These features inform credit decisioning models used by financiers or developers.

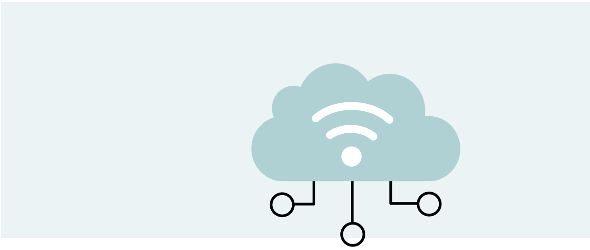
2.2.3 IoT and sensor-based data

IoT devices embedded in RE systems collect operational metrics such as real-time energy production, consumption, voltage fluctuations, uptime, fault occurrences, and load profiles. This data is essential for assessing project performance, reliability, and default risk in RE SMEs. IoT sensors are installed in solar panels, batteries, or smart meters. These devices transmit data using the publish/subscribe (pub/sub) communication pattern, which allows real-time data streaming without continuous polling. Data flows from the device to a centralised platform (often cloud-based), enabling lenders to track SME performance dynamically.

2.2.4 Psychometric and behavioural analytics

Psychometric data evaluates cognitive traits, decision-making tendencies, reliability, and personality characteristics. This is collected via structured questionnaires or gamified assessments and serves as a proxy for trustworthiness and risk behaviour, particularly for new or informal SMEs. SMEs complete surveys through mobile or web-based platforms. Behavioural traits are inferred from how individuals interact with the assessment, time to complete, consistency of responses, or engagement style. In some implementations, psychometric scores are combined with mobile metadata for a more holistic view.

2.3 Notable use cases



2.3.1 Kiu Global (Viet Nam & South-east Asia): SME transaction and financial behaviour data

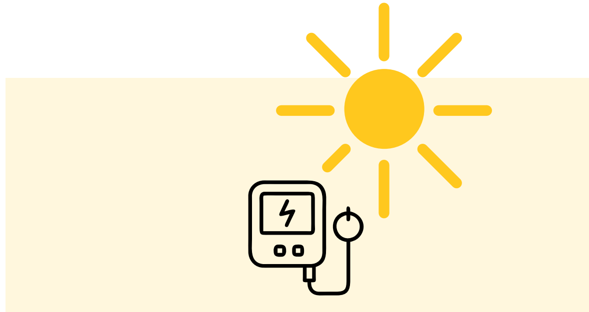
Kiu offers a cloud-based enterprise resource planning (ERP) and point of sale (POS) platform that collects daily transaction data about sales, expenses, vendor payments, and cash flow from SMEs. This data is automatically analysed by AI models to assess creditworthiness.

IMPACT:
Over 40,000 SMEs across South-east Asia have used Kiu's platform, many of them gaining first-time access to financing from local banks who rely on Kiu's AI-generated credit scores (Kiu Global, 2025).

2.3.2 VIDA/PowerGen (West Africa): Satellite imagery

VIDA (Village Data Analytics) uses machine learning on satellite images and demographic/geospatial data to identify viable sites for mini-grids and clean energy SMEs. It evaluates energy demand potential, proximity to roads/infrastructure, and population clusters.

IMPACT:
It was developed by TFE Energy to assess and pre-qualify off-grid communities for financing, thus reducing on-site survey costs and improving project bankability (TFE Energy, 2025).



2.3.3 Smart metering for solar SMEs: IoT data

Solar-powered SMEs in East and West Africa often operate with IoT-enabled smart meters that capture real-time data on energy usage, production and system performance. This data allows lenders to monitor business activity, detect faults, and determine payment capacity dynamically.

IMPACT:
It is used by financiers offering pay-as-you-go (PAYGO) or lease-to-own solar solutions. It enables performance-based lending and portfolio-level risk monitoring, especially for productive-use SMEs (Small City Mall Africa, 2025).

2.4 Concluding remarks

This chapter highlights the challenge of data scarcity in conducting CRA in frontier markets, especially for financing RE projects. It emphasises the fact that a traditional CRA relies heavily on available financial, public, and sector-specific data, which is often limited or unreliable in frontier markets. Alternative data, local data vendors and intermediaries can serve as key enablers, especially in remote or low-infrastructure regions, subject to governance of data handling by clear privacy policies, informed consent, and strong cybersecurity standards to foster trust and long-term sustainability.

The following section explains which AI techniques can leverage these alternative data sources, and how they work.

3

How can AI leverage alternative data to improve CRA in frontier markets?

3

As mentioned in the previous section, lenders in frontier markets face a dual challenge in credit risk assessment: not only is financial data often scarce, but what exists is frequently incomplete, inconsistent, or outdated. These conditions make it difficult to rely solely on traditional assessment models based on audited statements or credit bureau data. To overcome these limitations, artificial intelligence, particularly machine learning (ML), natural language processing (NLP) and explainable AI (XAI), offers powerful tools for building more adaptive, inclusive, and predictive credit models.

AI systems can analyse unconventional and alternative data sources such as mobile phone usage, transaction patterns, geolocation behaviour, and even unstructured data from digital communications and public records (Amarnadh & Moparthi, 2023; Biallas & O'Neill, 2020). By capturing real-world business activity and behavioural signals, these methods provide a more nuanced view of borrower risk, especially for small and medium enterprises (SMEs) and early-stage RE projects operating in low-data environments.

For German SMEs and their financing partners seeking to engage with local firms in these markets, AI-driven credit scoring creates new opportunities to expand trade and investment by reducing information asymmetries. This chapter explores the range of existing AI approaches used in frontier-market CRA, from classical statistical techniques to advanced ML models, NLP applications and XAI frameworks, and highlights tools, platforms and real-world success stories that are shaping the future of inclusive credit risk assessment.

3.1 Existing AI approaches and their impact

The integration of AI into CRA is transforming the financial landscape in frontier markets as it enhances decision-making power through innovative methodologies (Milojević & Redzepagic, 2021). Algorithmic credit scoring (ACS) is a key application of AI in this context, using ML and other techniques to assess creditworthiness. AI models are selected based on how effectively they can address these challenges and facilitate efficient credit decisions. Each model offers unique advantages, and this section briefly describes existing AI approaches that are in use for CRA.

3.1.1 Statistical models

Traditional statistical models like logistic and Lasso regression dominate the CRA landscape in frontier markets because of their simplicity and interpretability (İnal, 2023). Logistic regression is used in predicting binary outcomes such as default or non-default and is still the fundamental benchmark in CRA (Moscatelli, Parlapiano, Narizzano, & Viggiano, 2020). Small FI with limited IT infrastructure are more inclined to use these less complex models because of their fast training and ease of interpretation, though their limitation in handling nonlinear problems is acknowledged (Xia, Xu, Wei, Wei, & Tang, 2023).

3.1.2 ML algorithms

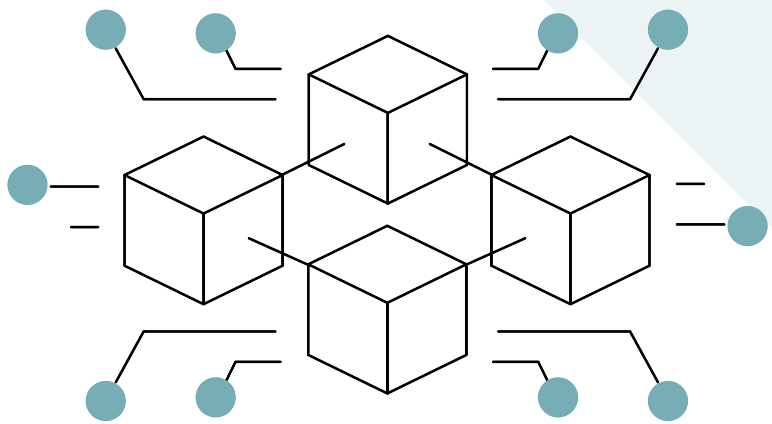
Several studies have proven that ML algorithms can significantly improve the accuracy of CRA models (Agu, et al., 2024). These AI models are essentially complex mathematical functions that aim to predict or classify a possible result (Y) given other related sources of known/recorded data (X). For example, they can model the probability of rain (Y), given weather forecast variables (Xs) like humidity, temperature, wind speed, etc. For this, they need to be trained with large datasets containing both X and Y, so they "learn" to minimise errors in their predictions, and iteratively finetune their function parameters. In the same way, ML models can be used in predicting the probability of default, PD (Y), by using transaction history or public records data variables (Xs). After successful training, the models can be used to accurately predict outcomes, e.g. default or non-default, PD or classifications like credit score labels. Ultimately, they allow us to model future unknown outcomes using known past data sources. They are being increasingly applied to financial modelling because of their ability to process vast amounts of unstructured data, such as transaction histories, mobile phone usage data and social media activity (Wang, 2024), and learn the intricate patterns linking those variables and default probabilities (Abdul-Azeez, Ihechere, & Idemudia, 2024; Agu, et al., 2024) which traditional CRA models may overlook. They thus provide a more accurate assessment of creditworthiness that surpasses conventional CRA techniques (Wang, 2024).

3.1.3 vXAI and model complexity

Studies have shown that model complexity does not always guarantee better performance: simpler models sometimes outperform more sophisticated ones depending on the quality of available data and the context (Mhlanga, 2021). ML models are essentially statistical models. They range from less complex models like logistic regression to others that are much more complex. Usually more complex models can capture more complex patterns in the data, so one might assume, since they are more "powerful", that they should be the best ones to use. However, in reality, the situation is different and very dependent on the context and data availability, and for simpler problems, less complex models may be the best option.

ML models can be successful at modelling complex behaviour patterns linking X and Y, and can generate accurate predictions, but for humans it may be hard to understand what these relations are and justify the model outcomes if they are unable to offer an explanation. If enough data records are given, the more complex models will provide more precision; however, it will be harder to explain. So, deciding which ML algorithm to use requires many considerations, and the best model varies from one case to another.

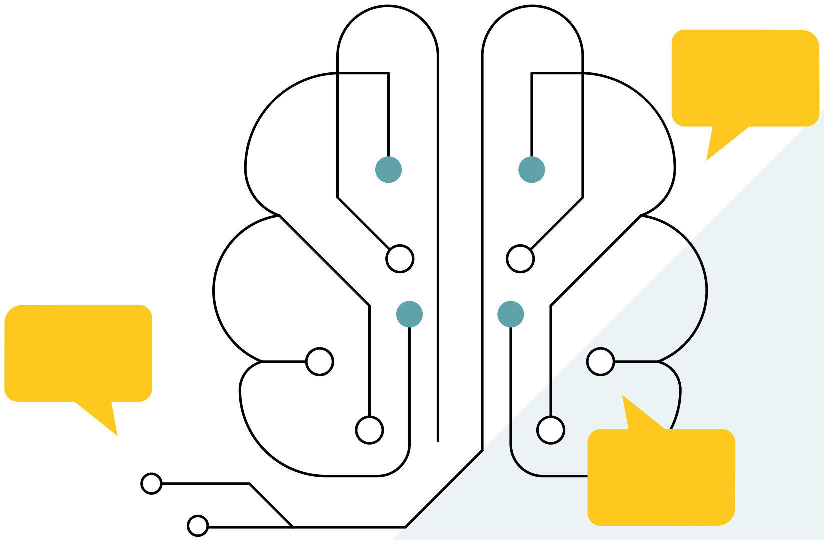
Given this, debates on the lack of transparency of advanced ML models have led to the emergence of XAI techniques. Abikoye and Agorbia-Atta (Abikoye & Agorbia-Atta, 2024) emphasise how 'explanatory AI can help bridge the gap between the complexity of ML models and the need for transparency in financial decision-making.' They specifically reference XAI techniques such as LIME (local interpretable model-agnostic explanations) and SHAP (SHapley Additive exPlanations) as methods that can help make ML models more transparent, allowing better justification of credit outcomes and increasing stakeholder trust (Akhigbe, 2024; Wang, 2024)



3.1.4 Natural language processing

Natural language processing (NLP) techniques are also on the horizon. Their biggest added value lies in ensuring the continuity of credit risk monitoring (Obiki-Osafiele, Agu, & Abhulimen, 2022). NLP algorithms achieve this through sustained analysis of unstructured data streams like news articles, company websites and social media. This allows users to identify creditworthiness signals of borrowers (Agu, et al., 2024). Research demonstrates that integrating generative AI into credit default prediction workflows enhanced model accuracy by improving the quality of unstructured financial text data. This data was an extract of key insights from corporate disclosures, loan application narratives, and company communications. These outputs were then transformed into vectorised embeddings using NLP techniques, and incorporated into a multi-modal machine alongside traditional structured data. The generative AI large language model (LLM) was able to capture semantic relationships and latent risk indicators such as uncertainty, management tone or default intentions as early warning signs of credit default (Wu, Dong, Li, & Shi, 2025).

As this section shows, there is a variety of AI tools available for CRA in frontier markets, ranging from interpretable traditional regression models to NLP algorithms capable of processing vast unstructured datasets. These techniques offer a more holistic picture of a company's risk profile compared to conventional approaches, thus transforming the credit decision making landscape, especially in frontier economies where large volumes of alternative data can be leveraged. The true measure of these AI methods, however, lies in their real-world implementation and impact. The following section examines how companies in frontier markets have successfully deployed these AI-driven credit assessment methods, thereby transforming theoretical capabilities into practical solutions that are reshaping access to credit for underserved populations.



3.2 Available tools and models for AI-driven CRA

To implement an AI-based CRA framework, a variety of existing tools and models that require minimal customisation can be leveraged. Open-source libraries such as scikit-learn, XGBoost, and LightGBM offer robust ML algorithms including logistic regression, and gradient-boosted models which are ideal for environments with limited resources and technical capacity. These tools are widely supported, cost-effective and well-documented, enabling small teams to build and test models efficiently.

On the commercial side, platforms such as Amazon SageMaker and Microsoft Azure Machine Learning provide comprehensive, end-to-end solutions. These systems offer built-in support for explainability (e.g. SHAP values), data pre-processing, model validation, and compliance auditing, which makes them especially useful in regulated financial environments.

Although many or a combination of the above can be deployed, the final choice between open-source or commercial options depends on technical resources, the available budget, and the intended scale of deployment. For early-stage pilots, open-source tools can offer a flexible and cost-effective starting point, while commercial solutions may be preferable for fully operational, large-scale implementations that require advanced automation, user interfaces and compliance support.

3.3 Limitations of commercially available tools in frontier markets

While AI-based CRA tools, both open-source and commercial, have advanced significantly in recent years, there remain notable areas where these systems can be improved to better serve underbanked and data-scarce environments like those in frontier markets. Below is an overview of the areas of improvement that have been identified.

3.3.1 Limited adaptability to low-data environments

Many commercial tools are optimised for high-volume, structured financial datasets typical of developed markets. These tools often perform poorly when formal credit histories are scarce. To improve adaptability, models could be retrained using local, alternative data sources like telecom metadata and trade transactions. Moreover, simplified versions of the model should be developed to enable operability with minimal input data.

3.3.2 Overreliance on proprietary black-box models

Several commercial platforms offer limited transparency concerning their scoring algorithms, which makes it difficult for users, especially FI and regulators, to understand, trust or audit credit decisions. Greater integration of explainability tools such as SHAP and LIME, or the option of toggling between black-box and interpretable models, would enhance accountability and regulatory compliance.

3.3.3 Incomplete integration of non-traditional data sources

Despite the proven value of alternative data, many CRA tools still do not take advantage of sources like utility payments, psychometric testing, and behavioural app usage. Expanding the data ingestion capabilities of these tools to incorporate non-financial data would allow them to reach a broader base of potential borrowers, particularly SMEs and informal businesses.

3.3.4 Limited localisation for frontier markets

Most CRA systems are built for general applicability and fail to take account of country-specific economic behaviours, regulatory requirements, or data availability. Tools could offer customisable modules or country-specific model templates that reflect the local context, especially in frontier markets where access to formal financial services is uneven.

3.3.5 High technical barriers and costs

Some commercial platforms are too expensive for smaller lenders or development programmes, while technical expertise is often required to deploy and maintain open-source tools. Creating lighter, more user-friendly versions, templates and interfaces would improve accessibility and promote wider adoption among FI in frontier markets.

3.4 Success stories: using AI in CRA tools

The following examples showcase how AI-based credit assessment transforms financial inclusion across frontier markets, showing the direct connection between alternative data sources and AI techniques, and their results.

AI-driven CRA is revolutionising the assessment of borrowers' creditworthiness in frontier economies where conventional financial information is scarce. Using alternative sources like behavioural patterns, remote payments, and unstructured data sources, AI models (ranging from explainable logistic regressions to more complex ML techniques) enable accurate, comprehensive, and dynamic lending analysis. Techniques such as XAI promote transparency and regulatory suitability while NLP enables early detection and distant process risk monitoring. FarmDrive, Yabx, and Branch are just a few cases where the multi-faceted use of AI with alternate sources is expanding financial inclusion, mitigating defaults, and increasing loan disbursement. This can be especially beneficial in the RE sector, where long-term investment risk can be mitigated.

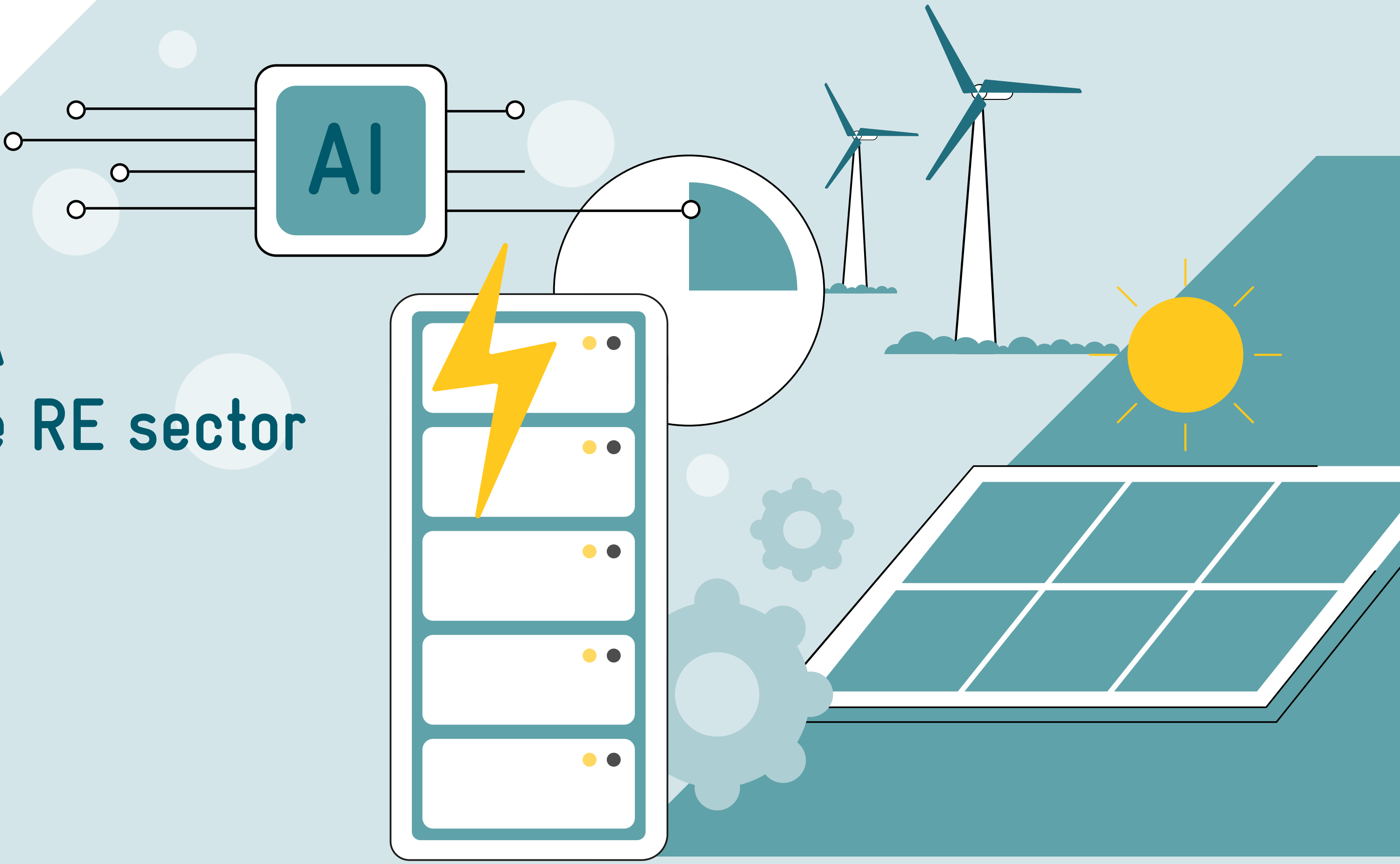
TABLE 1. Real implementation of AI-CRA in frontier markets

Source: Synechron Business Consulting B.V., Antonio Correia (2025), based on (Mhlanga, 2021; Lainez & Gardner, 2023; baobab, 2024; Benni, 2023; Dayal, 2024)

Company	Challenge	AI solution	Results
FarmDrive	Small-scale farmers with no credit history or collateral. Discouragement of financing and investment in the sector. Country: Kenya	ML algorithms processing agronomic, remote sensing data, market data and behavioural data (via text messages or smartphone applications)	USD 10+ million in loans, 100,000+ farmers served, 1.2 million farmers in digital registry
branch	71% use digital loans but 13.8% default rate Country: Kenya	Mobile behaviour + M-PESA activity data collection, ML techniques employed to analyse 200+ variables. Allowing offers of loans ranging from KES 1,000 to KES 300,000 with immediate approvals	A total of 15 million loans were provided to over three million customers in Kenya, Mexico, Nigeria, India and Tanzania, disbursing a total of USD 350 million since Branch's inception.
YABX	Large unbanked population limiting credit access Country: Uganda	ML algorithms process utility payments, telecom data, analysis of wallet behaviours	Number of eligible customers increased from 100,000 to 4 million within 12 months
FE CREDIT	Many Vietnamese people remain underbanked due to lack of formal credit histories and outdated manual assessment processes. Country: Viet Nam	ML algorithms processing demographic, income and behavioural data to create customised risk profiles	Around VND 66 trillion (approx. EUR 2.17 bn) disbursed in loans
baobab+	Lack of energy access, and financing barriers due to lack of credit history. Country: Senegal	Sophisticated 'rating algorithm' that processes customer data, transaction history and behavioural patterns to provide rapid credit assessments (within a few hours)	In 2023, EUR 1,140 bn in loans was disbursed in nine countries (Burkina Faso, China, Côte d'Ivoire, France (HQ), Madagascar, Mali, Nigeria, Democratic Republic of the Congo, Senegal).

4

AI-augmented CRA specifically for the RE sector



4.1 Key risk factors impacting RE companies' CRA input

RE projects are in general exposed to a wide range of risks, including those relating to financial viability, operational performance, regulatory compliance, and environmental sustainability (Akhigbe, 2024). These risks are condensed into four different categories in Table 2.

The risks mentioned above contribute to and hence increase the credit risk associated with RE projects. Traditional CRA is the go-to method for assessing the creditworthiness of typical partners in frontier economies. However, as traditional credit history is absent or minimal in these markets, leveraging non-traditional publicly available data sources is becoming more common by the day. This relies on alternative indicators to determine the creditworthiness of local businesses by analysing behavioural, transactional and social trends likely to reflect the counterparty's credit repayment capability.

TABLE 2. Comparative table of RE project risks Source: Synechron Business Consulting B.V., Simran Sandhu (2025), based on (Akhigbe, 2024)

Category	Description	Examples/ notes	Most affected models/entities
Financial risk	**Market/price volatility:** Fluctuations in energy prices, demand-supply dynamics and currency exchange rates cause instability. **Counterparty credit risk:** Risk if offtakers cannot make payments, or file for bankruptcy. **Long-term financial risk** involves variability in the cash flows needed to service debt over the project lifespan (about 15 years). **Dependence on project finance** increases risk, especially in asset-heavy models like utility or customer-sited projects. **Equipment and distributor risks** include inventory costs, buyer credit risks, and currency fluctuations.	Market price spikes, refinancing issues, asset performance decline, credit defaults	Utility-scale, renewable assets, equipment distributors, project developers, project financiers
Operational risk	**Technology failures:** Issues like mechanical failure, reduced efficiency or grid curtailment can diminish energy output, thus impacting revenue and investor confidence. **Wear and tear:** Long-term asset degradation due to poor maintenance or natural deterioration influences future profitability. Operational risks impact assets such as solar panels, wind turbines and storage systems; especially those tangible assets that are owned or managed.	Equipment failures, maintenance issues and site performance shortfalls.	Wind farms, solar projects, storage systems, utilities, project operators
Regulatory risk	**Policy and regulatory uncertainty:** Changes or removal of government policies, licences and standards can impact project approval, revenues and costs. Projects relying on long-term policies or subsidies are especially vulnerable to such situations. Permit delays or policy shifts may increase operational expenses or delay project schedules. Regulatory risks are pertinent to utility, rooftop and community solar projects, and device distributors.	Policy shifts, subsidy removals, permit bans, community opposition	Utility-scale projects, solar projects, wind projects, integrators, distributors
Environmental risk	**Physical climate risks:** Natural hazards such as storms, wildfires, soil issues and floods can damage infrastructure or delay projects. **Transition risks:** Regulatory actions or community opposition to fossil fuels or carbon-intensive projects can threaten existing assets or plans. Environmental risks particularly affect utility-scale facilities, field assets, and local distributed systems.	Natural disasters, climate change impact, community opposition, site contamination	Utility-scale facilities, distributed customer-sited assets, grid operators, distributors

4.2 Using AI to mitigate risk factors affecting RE business models

As shown in Table 2, multiple risk factors have been mentioned which impact RE projects from a credit risk perspective. These risks span four areas: financial (both short and long-term market volatility), operational (equipment and supply chain disruptions), regulatory (policy and compliance uncertainties), and environmental (climate-related impacts).

Following the exploration of various alternative data sources, their collection techniques, and the availability of different AI driven models, a list of AI techniques that effectively address these risks spanning different time horizons and business models is presented in Table 3. The choice of AI technique varies with each risk type and project model. For example, AI techniques like ML algorithms prove effective for short-term financial risk monitoring in customer-sited applications, while SHAP and LIME techniques provide regulatory transparency for utility-scale integrator projects. Each technique offers specific advantages in predicting, monitoring, and mitigating risks while enhancing overall project and offtaker creditworthiness assessments.

TABLE 3. Comparative table of AI techniques vs. risk type and horizon

Source: Synechron Business Consulting B.V., Aleksandar Shokolarov (2025)

Risk category	Risk horizon	AI technique	CRA contribution
Financial	Short term	ML algorithms like Random Forests and gradient boosting machines	Predicting market shocks, refining short-term credit decisions
Financial	Long term	Lasso regression, scenario modelling	Improving capital efficiency, simulating long-term viability underpricing fluctuation
Operational	Short term	ML algorithms, like gradient boosting machines and XGBoost	Predicting equipment failures, optimising maintenance and reducing default likelihood
Regulatory	Long term	XAI techniques, like SHAP and LIME	Ensuring model explainability under evolving data protection and subsidy regimes
Environmental	Long term	Neural networks (ML algorithm), climate simulations	Assessing resilience to climate impacts, integrating sustainability metrics
Regulatory/ financial	Short term	NLP and generative AI	Flagging sentiment changes which signal borrower or market instability

The risk profiles of the various RE business models demand more innovative and advanced tools to mitigate credit risk. Assessment of different RE models reveals that each of those models entails varying amounts of risk across operational, financial, regulatory and environmental dimensions. The time horizon of these risks also varies. It may show up as sudden market volatility or operational failures but may also unravel slowly in the form of long-drawn-out regulatory changes or chronic climate change. In this context, AI techniques offer considerable value as they can be customised to fit the structural and temporal features of different RE business models. These AI capabilities present an opportunity for German SMEs looking to participate in the RE sector in frontier markets.

4.3 How German SMEs in the RE sector can benefit from AI-based CRA

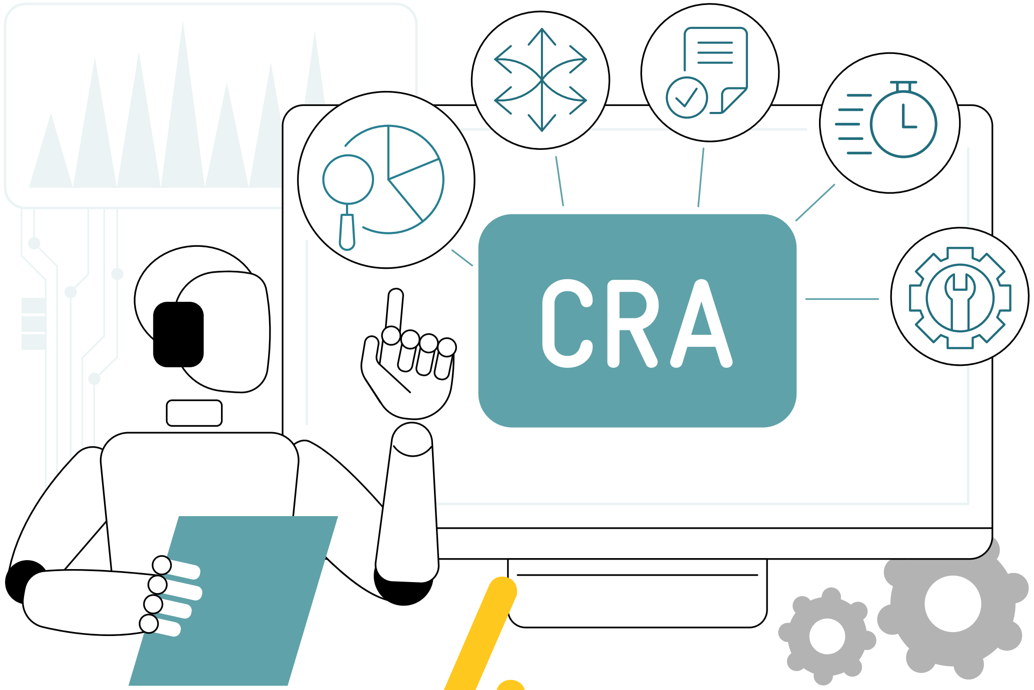
In frontier markets, financial institutions engaging in cross-border investment and trade are hindered by regulatory uncertainty, underdeveloped financial ecosystems and limited financial transparency. For German SMEs seeking financing support, these challenges translate into stricter lending conditions and higher rejection rates, while for the German SMEs seeking to offer financing for such projects involving third-party ownership (TPO) models, they are reflected in difficulties in making a final investment decision. In both the cases, financiers and German SMEs can assess counterparties, reduce default risks, and improve strategic decision-making with the help of AI-based CRA models, ultimately enabling them to offer more informed financing terms.

1

First, AI improves traditional credit evaluation methods by offering more precise and comprehensive risk profiles. It does this by using ML algorithms to analyse large volumes of unstructured alternative data such as mobile phone usage patterns, transaction histories, and social media activity. These models identify complex patterns among these alternative variables and the likelihood of default. As a result, third-party CRA tools enhanced by AI could more accurately predict repayment behaviour, reduce default rates, and extend trade-based credit to groups that were previously underserved. This helps mitigate issues like adverse selection and informational asymmetry. This enhanced accuracy enables financiers and German SMEs to confidently approve finance applications and TPO models respectively, which might previously have been rejected due to insufficient data about frontier market counterparties.

2

Second, AI allows for risk assessments that are customised to the specific structure and time horizon of different RE business models, thereby supporting the broader funding ecosystem in making informed investment decisions. For instance, utility-side and integrator models, which involve long-term asset ownership and infrastructure deployment, need evaluation tools that consider strategic risks such as recovering capital costs, technological obsolescence, and regulatory changes. AI facilitates tailored assessments that better reflect these unique risk factors and timeframes. AI tools like scenario modelling and Lasso regression can replicate long-term financial performance by combining historical project data, market trends and climate forecasts. This model-specific risk assessment allows financiers to offer more appropriate financing structures and terms to German SMEs that operate different RE business models, rather than applying one-size-fits-all credit criteria.



3

Third, AI-based CRA enhances compliance with ESG and transparency requirements. Using XAI techniques, AI-derived credit decisions can be better justified. This transparency not only helps German SMEs satisfy internal and external governance standards, thereby gaining trust with regional regulators and communities, but also enables them to meet ESG requirements for financing, and makes financiers more comfortable about extending credit when they can clearly justify their decisions to stakeholders.

4

Fourth, AI-enhanced systems can leverage NLP techniques to analyse unstructured data from news articles and social media to identify early indicators of financial or political distress to provide real-time credit monitoring. Such dynamic monitoring makes it possible for financiers and German SMEs to promptly modify contract terms and exposure, when engaged in ongoing trade or project finance, rather than rejecting applications outright due to uncertainty.

Lastly, AI-based CRA enhances access to financial instruments by producing structured, data-rich credit profiles. German SMEs frequently need concessional financing, guarantees or credit insurance when operating in high-risk frontier markets. AI-supported CRA outputs are becoming increasingly recognised as trustworthy by FI and export credit agencies, particularly when they come from systems that can be explained and audited (within the Netherlands, ING has been incorporating AI into their credit risk decision-making since 2018 (ING, 2018)). In addition to lowering the cost of capital, this makes it easier for financial institutions to approve financing for SMEs which would otherwise be rejected due to the high perceived risk of entering the market.

In summary, AI-based CRA addresses a critical bottleneck in frontier market financing by enabling financiers and German SMEs providing TPO to make informed credit decisions despite limited traditional data. This technological advancement directly benefits German SMEs by expanding their access to finance, reducing borrowing costs, and facilitating market entry into high-growth renewable energy sectors in emerging economies. As AI-CRA tools become more sophisticated and widely adopted, they represent a key enabler for German SME expansion into frontier markets.

5

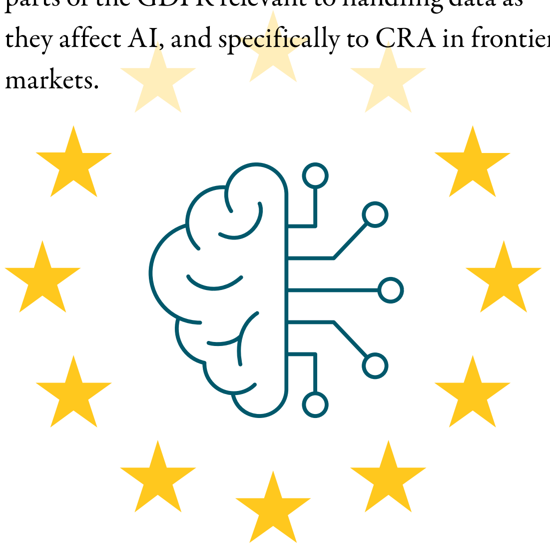
Boundaries of the regulatory playing field

5

AI-driven CRA tools cannot be deployed effectively if there is not a sufficient understanding of the legal frameworks that regulate data collection and processing. The third parties which German SMEs intend to use for AI-based CRA tools in frontier markets encounter a layered legal environment shaped by both domestic data protection laws in the target countries and the EU's legal regime in the form of the GDPR and the EU AI Act.

5.1 How do the existing laws and regulations in the EU govern the use of AI?

Two key regulations apply to using AI techniques in any form and handling personal data: the EU AI Act and the GDPR. The EU AI Act ensures that AI systems used within the EU are safe, transparent and respect the fundamental rights of their users. The GDPR is a data privacy law to protect the personal data and privacy rights of individuals within the EU and to create a uniform data protection framework across EU member states. This means that both these regulations concern the handling of personal data in a safe and transparent way. Because of this, there is overlap between the two regulations; the GDPR prevails for all matters related to the processing of personal data (European Union, 2016). Below we provide an explanation of the EU AI Act and the parts of the GDPR relevant to handling data as they affect AI, and specifically to CRA in frontier markets.



5.1.1 The EU AI Act

The overall approach of the EU AI Act can be summed up as a human-centric framework embracing the precautionary principle: it imposes ex ante obligations on AI systems that pose significant risks while simultaneously supporting the EU's AI competitiveness (Lee, Lee, Jeon, & Bae, 2024). The Act classifies AI systems used for evaluating a natural person's creditworthiness as high risk; however, uncertainty remains as to whether similar high-risk categorisation applies to B2B credit assessments, such as due diligence on corporate counterparties.

A key requirement for deploying high-risk AI systems under the Act is that providers must subject their systems to a conformity assessment to ensure compliance with certain specified requirements, which include aspects relating to safety, fairness, transparency, and robust governance. Sensitive AI systems handling critical decisions must undergo external evaluation by a notified body (an authorised third-party auditor) during this conformity assessment. This means that a CRA approach under the EU AI Act must have an external audit by notified bodies for high-risk AI systems. Beyond audits, these requirements include comprehensive documentation, continuous monitoring, and post-market surveillance to ensure ongoing compliance with the standards set forth in the regulation. This process ensures that an AI system meets the EU's stringent standards before being placed on the market or used within the EU.

Failure to comply with these requirements incurs administrative fines. Once implemented, the EU AI Act will enforce a technology-neutral yet strict compliance regime on banks and financial institutions deploying high-risk AI systems such as credit scoring or algorithmic trading systems, which will require rigorous pre-deployment vetting to protect EU citizens (European Union, 2024).

Furthermore, the Act's scope covers any AI system used or placed on the EU market, regardless of where it was developed or deployed, meaning that an EU-based SME using an AI tool, whether locally or through a foreign provider, is subject to its provisions. Importantly, outsourcing AI processing overseas does not exempt SMEs from compliance obligations; the Act's emphasis is on the actual use of AI within the EU (Hildebrand, 2024).

5.1.2 The General Data Protection Regulation (GDPR)

The GDPR imposes transparency obligations. When personal data is collected from individuals, the data subjects need to be informed that the data will be used for automated decision-making, including profiling (European Union, 2016). Two key articles relating to handling data for AI purposes are Articles 6 and 22.

Article 6 lays down the legal basis on which processing of personal data can be carried out by AI systems, based on individual's consent, or the data being required for a contract, a legal obligation, vital interests or a task in the public interest, or the controller's legitimate interest. Data involving special data (data revealing race, health, etc.) cannot be the basis for automated decisions unless an exception like explicit consent or substantial public interest exists under the law (European Union, 2016).

Article 22 is about the right of an individual to not be evaluated purely by a machine. If an AI system fully automates a decision that does not involve any human intervention, the data subject can refuse to be evaluated by such a system (European Union, 2016).

In sum, data protection law in the EU demands that FI using AI for automated decisions do so in an ccountable, fair and transparent manner with individuals retaining rights to know when AI is involved, to understand how it affects them, and to seek human review or remedies.

The GDPR has extensive geographical reach. It always applies to an EU-based controller (like a German SME) that handles any personal data, irrespective of where the data subject resides and where the processing takes place (DataGuidance, 2020). Practically, this means that even if a German corporation is gathering or evaluating personal data of individuals or SMEs in Africa or Asia, it must comply with the GDPR. The GDPR applies regardless of the country or place of residence; the person concerned does not need to be an EU resident (DataGuidance, 2020). Under Article 3(1) GDPR, (DataGuidance, 2020), the location of processing is irrelevant; so processing the data on servers in frontier markets does not evade GDPR control. Furthermore, the GDPR can potentially capture non-EU companies in specific circumstances (Article 3(2)) (DataGuidance, 2020), but in our situation the important aspect is that an EU-established controller is engaged. To put it simply, the German SMEs are subject to GDPR obligations globally and cannot avoid them by operating overseas or depending on foreign partners.

The table below gives an overview of how the GDPR works coherently with local laws. For explanation purposes, four countries within Africa and Southeast Asia have been selected as a sample group: Senegal, Uganda, Kenya, and Viet Nam.

TABLE 4. Data collection: direct vs. via local intermediary

Source: Synechron Business Consulting B.V., Aynur Yozlem (2025), based on (DataGuidance, 2020)

Data collection method	Legal role of German SME	Local law exposure	GDPR obligations	Cross-border transfer considerations
1. Direct collection from foreign SME or Individuals	Primary data controller (under GDPR and local law)	Subject to Senegalese, Ugandan, Kenyan, and Vietnamese data laws	Must provide Article 13 notices; establish lawful basis (legitimate interest, contract necessity or consent); conduct legitimate interest assessments	Transfer is regulated under local law; must comply with EU & host-country rules; consent likely needed
2. Collection via local intermediary that acts as processor	SME is controller, intermediary is processor	Local partner must complies with local laws (e.g. consent, registration); SME is liable for processor behaviour	SME must sign Article 28 GDPR contract with partner; ensure data is used as instructed; remain responsible for lawfulness	SME needs to impose GDPR-compliant safeguards; data transfer is governed by GDPR & local laws; local approval may be needed
3. Collection via local intermediary that acts as independent controller	SME is downstream controller or joint controller	Partner must ensure data sharing complies with national law (e.g. Kenya requires consent or adequacy)	SME must check data was lawfully obtained; provide Article 14 notices (unless exempt); confirm lawfulness of use	SME must ensure transparency for data subjects; local laws may require notification or consent to transfer

5.2 Implications for organisations deploying AI technologies

As mentioned above, the implications of the EU regulations (the GDPR and the EU AI Act) are far-reaching. Besides EU supervision being applicable, local authorities also apply local laws to companies using AI tools and personal (company) data. Table 5 gives an overview of the means of supervision which the EU and local authorities can use.

TABLE 5. Compliance requirements and implications for organisations

Source: Synechron Business Consulting B.V., Aynur Yozlem (2025, based on (DataGuidance, 2020)

Risk / obligation	EU (GDPR/AI Act)	East Africa	Central Africa	West Africa	South-east Asia
Regulatory fines	Fines up to EUR 20 m (GDPR), EUR 35 m (AI Act). Applies even if data is non-EU.	Fines up to EUR 40,000 or 1% of turnover. ODPC actively enforces.	Fines up to 2% of turnover. Officers can face jail sentences.	Fines up to EUR 150,000 + criminal sanctions. CDP enforces.	Fines are currently small, but MPS can block or suspend operations.
Registration	No general registration but processing must be documented and high-risk AI must be registered.	Registration with ODPC is required before data is collected and processed.	Registration with the Data Protection Office is required.	Notification or approval is required before processing.	Notification of MPS in the case of sensitive data or cross-border transfers
AI documentation	Log AI decisions, assess risks, document training data and outcomes.	Ensure data minimisation and fairness. Keep records.	Document how AI uses data, perform impact assessments.	Explain AI decisions. Log and monitor outcomes.	Consent and impact assessments are essential.
Data protection	Use legal basis (e.g. legitimate interest) and obtain consent when needed.	Consent is key. Use data only for agreed purposes.	Clear consent is needed. Avoid using sensitive data.	Consent is needed. Sensitive data needs extra approval.	Obtain consent. Sensitive data needs extra steps.
Breach notification	Report breaches within 72 h to authorities and individuals if risky.	Report breaches within 72 h. Notify ODPC and affected persons.	Report breaches within 72 h. non-reporting results in fines or jail.	Notify CDP and data subjects as soon as possible after the breach.	Notify MPS within 72 h of breach. Document all the details.
Cross-border transfers	Use standard contractual clauses. Assess third-country protection.	Transfers need consent or proof of safeguards. Notify ODPC.	Transfers need consent or 'adequate' protections.	Data must not leave Senegal without CDP approval.	Transfer impact assessment and MPS approval are required.
Local oversight	Data processing authority can audit, fine or demand changes.	ODPC can audit or impose fines. Active in fintech cases.	Regulators may inspect or escalate to court.	CDP can suspend processing or prosecute for breaches.	MPS may inspect, suspend, or question activities.

5.3 What potential opportunities emerge from the regulatory landscape?

5.3.1 Regulatory harmonisation and clarity

The GDPR is the pioneering regulatory framework, and many nations, including the target countries, follow its principles. This trend benefits German SMEs because Kenya and Senegal can leverage their EU compliance toolbox. Kenya's Data Protection Act closely resembles the GDPR, so a German SME that is already GDPR-compliant will just need to register with the Kenyan authority or adapt its consent forms (Otanga, 2021). The data controller must prove that the transfer site has adequate data safeguards for cross-border transmission. Since the GDPR is the foundation of data protection and regulation, showing GDPR-level safeguards helps build trust with foreign regulators. The AI Act could become the international standard, appearing before AI rules in other countries. Thus, investing early in AI Act compliance may give German SMEs a competitive edge as the legislation catches up in the future.

5.3.2 Regulatory sandboxes and innovation-friendly policies

Recognising the need to promote innovation, the target countries have introduced regulatory sandboxes in fintech and AI. These sandboxes allow companies to pilot new technologies. For example, the Bank of Uganda launched its first regulatory sandbox in 2021, inviting fintech innovators to test solutions in a controlled environment which included AI-driven credit scoring for financial inclusion (The Republic of Uganda, 2021). Similarly, Kenya's Capital Markets Authority launched a fintech sandbox, and its central bank has shown openness to innovative credit scoring models under its watch (Ngari, 2021). In Senegal, while no formal sandbox has been established, the Government has been working with development agencies to promote digital financial services. (UN Capital Development Fund, 2020). Viet Nam is similarly exploring sandbox regulations for fintech (covering areas like P2P (peer-to-peer) lending and credit scoring) as part of its strategy to boost innovation (Wong, 2025). By engaging in these programmes, German companies might benefit from temporary regulatory relief or exceptions.

5.3.3 Competitive advantage through compliance and trust

German SMEs that proactively adhere to high ethical and legal standards in AI can differentiate themselves in the market. Organisations that build trust with data subjects and regulators may gain easier access to data and clients. Research indicates that consumers (and by extension, businesses) are far more willing to share data with an entity they trust, and this trust translates into a competitive advantage in data-driven industries (Good Corporation, 2019). For example, if an African regulator in a year's time demands algorithmic transparency or impact assessments for credit scoring algorithms, a German SME that already conducts bias audits and keeps thorough documentation (as per the EU AI Act) can readily provide this, whereas competitors might struggle.

5.4 Potential challenges emerging from the regulatory landscape

5.4.1 Data localisation and access restrictions

Several host countries require personal or financial data to remain within their borders. For example, in Viet Nam, there is a compliance burden of local storage or bureaucratic approval before transferring data abroad (Interesse, 2024). If critical credit data (like financial statements, credit histories, payment data) cannot be transmitted to Germany, the SMEs might need to invest in local data centres or work through local processors. In Kenya and Uganda, while data can be transferred, this depends on the provision of adequate protection and on obtaining consent from each party. There is also the risk that data needed for a comprehensive credit model cannot leave the country due to government restrictions (for instance, credit bureau data might not be shareable with foreign entities). These localisation challenges can lead to gaps in the AI model's inputs, potentially reducing its effectiveness across borders. Third-party CRA tools may be compelled to work with a licensed local partner or invest in in-country data processing infrastructure.

5.4.2 Divergent privacy regulations

One of the primary challenges for deploying AI in CRA across multiple jurisdictions is the fragmentation of privacy laws. What qualifies personal or sensitive data and how it can be lawfully processed varies between these jurisdictions. Uganda's Data Protection and Privacy Act (DPPA) classifies financial information as sensitive personal data requiring stricter handling. Under the EU's GDPR, financial data is not inherently sensitive and may sometimes be processed under a legitimate interest basis without explicit consent.

This discrepancy directly impacts AI-driven credit scoring. A model legally trained and deployed in Germany on the basis of a legitimate interest may violate local laws if used in Kenya or Uganda, where explicit consent to or prior approval of such profiling is required from the Office of the Data Protection Commissioner (ODPC) or the Personal Data Protection Office (PDPO), respectively (The Republic of Kenya, 2019). Overlapping or conflicting legal requirements can make it difficult for companies to develop scalable and compliant AI systems.

5.4.3 Consent and data subject rights management

Third-party CRA tools need efficient mechanisms for managing consent, withdrawal of consent and access requests. If a Kenyan business owner requests information used in an AI-based CRA (right to access under Kenya's law or under the GDPR), the SME must provide the relevant data across borders (Otanga, 2021). This is complicated, as alternative credit models might use unconventional data (mobile phone records, utility payments, social data) that could originate from various third parties. Additionally, handling objections to automated decisions can be tricky as a Ugandan company that is scored poorly might invoke its right to have a human review under Uganda's domestic law. These requirements demand a human-in-the-loop process and a client support function that small tech-focused firms may not initially have.

5.4.4 Model validity and bias concerns

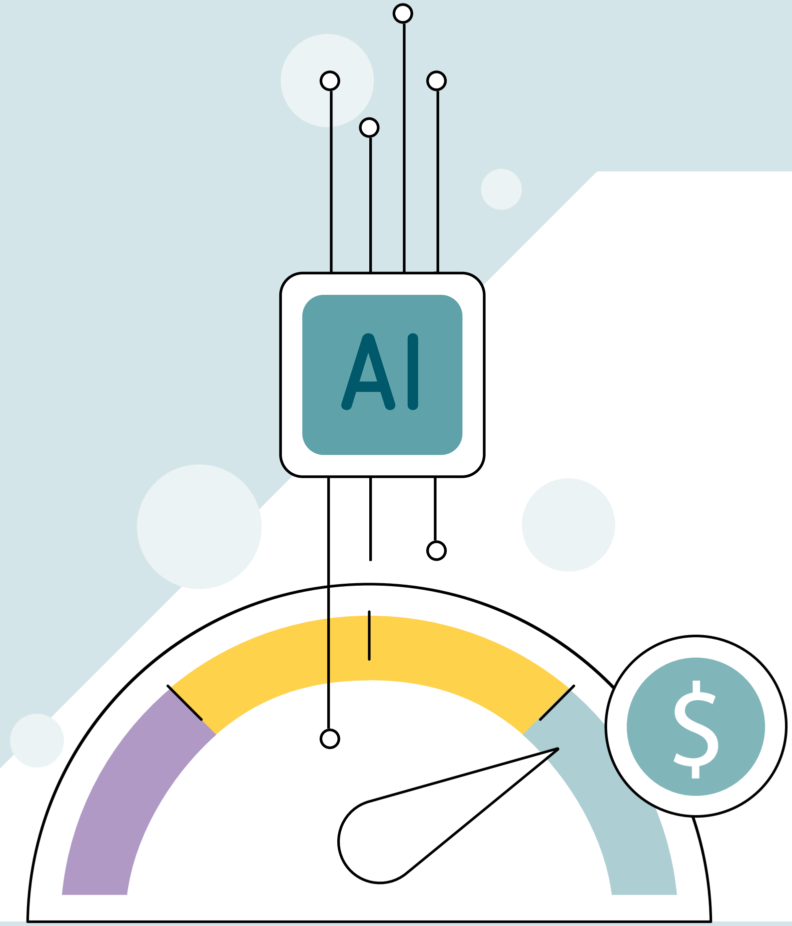
Applying an AI model that is trained in one context to another context can create accuracy and fairness problems. German law and Germany's Federal Financial Supervisory Authority (BaFin) guidelines stipulate that models must use valid predictors and avoid unjust bias (Albers, Fahrenwaldt, Kuhn-Stojic, & Schneider, 2024). But in frontier markets, traditional credit data is usually sparse, which necessitates the use of proxies such as geolocation, utility bill payment patterns and social network data. These proxies can correlate with sensitive attributes like ethnicity or gender in ways that regulators consider discriminatory. The SMEs face the challenge of developing AI models that are predictive and non-discriminatory in a range of environments.

5.4.5 Local regulatory engagement and licensing

Operating in regulated financial sectors abroad may force German SMEs to engage with foreign regulators directly. For example, to obtain approval for data transfers or to join a regulatory sandbox, forms must be submitted and fees paid in-country. If a country like Kenya decides that what the SME is doing amounts to a credit bureau service, the SME might be required to either obtain a local licence or cease that activity. Licensing can be onerous (involving financial, capital requirements, ongoing compliance reports) and may not be feasible for an SME (Kenya, 2020).

6

Integrating AI into the traditional CRA process



6

Following evaluation of the regulatory landscape and considering compliance with EU and local laws, this section consolidates a list of recommendations to enhance the CRA process for German SMEs operating in the RE sector across frontier markets. These recommendations build on static Excel-based traditional CRA tools and regulatory alignment.

6.1 How can the insights and findings be effectively integrated into the existing legal frameworks?

As showcased in the previous chapter, rapid advancements in AI have enabled the usage of alternative data sources to complement the traditional CRA process and make it more efficient and context-specific for the frontier markets. ML models supported by XAI techniques can be utilised to improve the accuracy of CRA in markets with limited financial information, especially given the unique nature of business models within the RE sector. However, these AI or ML models do not operate in a vacuum. They are governed by the regulatory environment in which they operate. In this case, it is the EU's AI Act and the GDPR, and the relevant data protection laws that apply within the target countries.

Building on the specific legal aspects discussed above, AI methodologies would have to satisfy the following minimum requirements to avoid any regulatory problems:

- **Consent is fundamental:**
  Both the EU and target countries require informed, specific and freely given consent. There may be azdditional restrictions for sensitive data in some cases, including financial information.
- **Cross-border data flows:**
  AI models in Germany using data collected from outside the EU require adequate safeguards under both EU legislation and local laws. In Viet Nam and Senegal, the local laws impose stricter impact assessment rules.
- **Explainability and fairness:**
  Kenya and Uganda demand that automated decisions are reviewable and explainable. For standard B2B lending there is no specific requirement, but general principles of fairness and transparency are encouraged, especially for high-risk models. Viet Nam and Senegal do not impose specific obligations but expect general principles to be upheld.
- **Integrated compliance strategy:**
  The GDPR, the AI Act and local laws must be harmonised to avoid friction and so that companies can demonstrate trustworthiness to data subjects and regulators alike.

The key AI methodologies identified include:

- Integration of ML algorithms (Random Forests, XGBoost, neural networks) with alternative data sources
- XAI tools (SHAP, LIME)
- Generative AI and NLP for real-time risk monitoring.

To integrate these methodologies into the existing legal framework, financiers and German SMEs offering TPO models to local private companies should focus on the following:

- **Data collection and processing:** Securing explicit and informed consent for all data sources including cases where alternative and behavioural data is involved. The data minimisation principle should also be incorporated, i.e. only collecting information that is essential for credit risk evaluation.
- **Cross-border data transfers:** Ensuring adequate safeguards for data transferred to or from the EU, aligning with the GDPR, the AI Act and local requirements.
- **Algorithmic decision making:** Using XAI techniques (SHAP, LIME) to support credit decisions that can be explained to customers and regulators. Financiers should also ensure that enough mechanisms are provided to both German and local SMEs to challenge or request human review of automated decisions in line with the GDPR and similar provisions in the target markets.
- **Compliance with AI systems:** Conducting conformity assessments and maintaining technical documentation for AI systems should be a priority as required under the EU AI Act.

6.2 Three-pillar approach to improve CRA models

To address the identified limitations of ML models mentioned in chapter 3.3, a strategic three-pillar implementation framework is proposed, focusing on improving predictive accuracy through systematic data collection, expanding counterparty coverage via alternative data integration, and increasing operational efficiency through automation and infrastructure modernisation.

6.2.1 Improving accuracy through outcome data collection and validation

To improve accuracy through outcome data collection and validation, the foremost priority is to begin collecting labelled outcome data of financial repayments from past and future projects. This will enable proper training and validation of supervised learning models. A centralised follow-up system should be established to track borrower performance at regular intervals. Additionally, partnerships with local credit bureaus and fintechs should be pursued to access external repayment data and expand the historical dataset. Two or three local partners should be identified for the initial data-sharing discussions. Prioritisation of gnuGrid in Uganda and Creditinfo in Kenya is recommended, based on the previous research findings. Moreover, setting accuracy improvement targets is also recommended to track prediction rates against performance of existing models as a feedback loop to improve the CRA process.

6.2.2 Enhancing the completeness of counterparty coverage using alternative data

To enhance the completeness of counterparty coverage using alternative data, AI adoption should be integrated with alternative data sources that reflect the financial behaviour of SMEs and informal enterprises not covered by conventional credit assessments. This includes establishing data-sharing agreements with mobile money providers, telecom operators, and utility companies. Pilot studies should be launched in countries with mature digital ecosystems, such as Kenya and Viet Nam, to test the performance of alternative data in expanding reach and scoring accuracy. These two countries are recommended because of their mature digital ecosystems. After this, a pilot framework could be set up to test alternative data scoring on a sample of several SMEs. For this, setting coverage expansion goals is recommended to track the increase in the assessable SME population through alternative data sources.

6.2.3 Increasing efficiency through automation and infrastructure upgrades

To increase efficiency through automation and infrastructure upgrades, manual Excel-based tools must transition to a cloud-hosted, database-driven infrastructure. The introduction of automated tools is recommended to streamline input gathering and minimise human error. A lightweight interface can be developed for local users to upload documents, receive risk scores instantly, and trigger automatic alerts for high-risk profiles. An initial technical assessment of manual Excel-based workflows is recommended to identify automation opportunities. Thereafter an implementation plan can be developed that prioritises document digitalisation (using optical character recognition, OCR) as the first step. Target percentages for efficiency gains should be set from the beginning.

6.3 Strategic implementation: integrating open-source and commercial solutions to enhance the existing CRA process

The traditional CRA model employed by financial institutions follows a rigorous, document-heavy structure. However, this model often proves insufficient in frontier markets, where data is either unavailable or unreliable, and where SMEs and their local partners frequently lack standardised financial documentation.

Strategic implementation must therefore recognise the dual necessity of adhering to the traditional CRA protocols while enhancing their viability through AI-driven upgrades. This calls for a modular integration strategy that overlays AI and alternative data techniques onto the traditional assessment backbone, thereby improving coverage, trustworthiness and the speed of decision-making in markets with high data friction. The recommended strategy involves three primary focus areas: accuracy, completeness concerning counterparties, and efficiency.

6.3.1 Accuracy

To improve accuracy, the recommendation is to prioritise the use of supervised learning models such as logistic regression and gradient-boosted trees, which have proven effective in credit scoring tasks. Open-source libraries like scikit-learn, XGBoost and LightGBM provide strong foundations for these models, especially when combined with labelled repayment data. However, achieving high predictive accuracy depends on access to quality outcome data. Therefore, the recommended strategy is collection of labelled data through follow-up surveys and outcome tracking for credit offers while simultaneously engaging local credit bureaus such as gnuGrid or Creditinfo to access historical repayment data. For more scalable implementation, cloud-based platforms like Amazon SageMaker or Azure Machine Learning can support model training, validation, and deployment, with integrated tools for accuracy monitoring and explainability.

6.3.2 Completeness concerning counterparties

To achieve completeness concerning counterparties, particularly SMEs and informal businesses that lack formal financial documentation, tools that support alternative data can be leveraged. Fintech-focused platforms like CredoLab, Trusting Social and LenddoEFL specialise in credit scoring using behavioural data, mobile usage patterns, and psychometric testing. These can be accessed and deployed in parallel with traditional CRA tools to extend coverage of thin-file borrowers. On the open-source side, models built using mobile money and utility payment data (processed through flexible libraries like scikit-learn and TensorFlow) can be tailored to each country's data environment. Integrating such data sources will require local partnerships with telecom operators, e-wallet providers and utility companies, particularly in frontier markets.

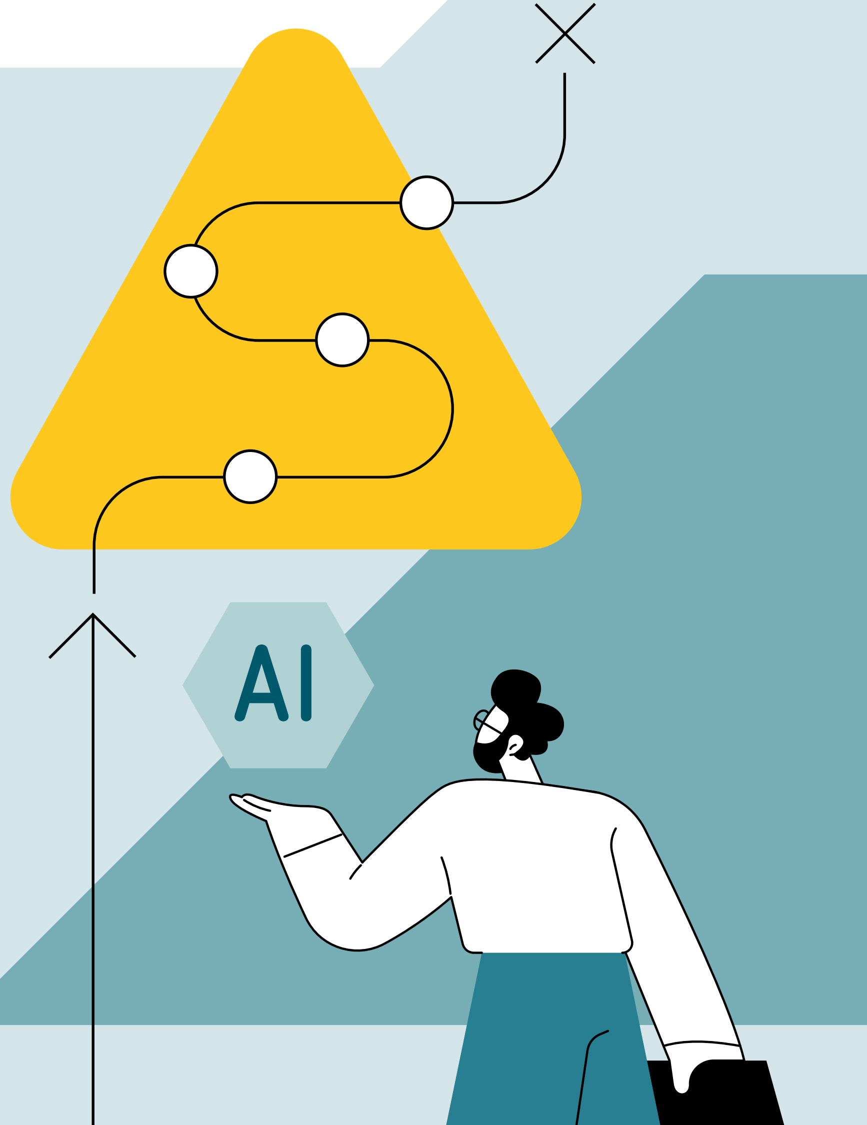
6.3.3 Efficiency

For greater efficiency, the digitalisation of manual Excel-based scoring tools is recommended, along with the adoption of cloud-based, automated workflows. Tools like OCR engines (e.g. Google's Document AI, Amazon's Textract) can extract financial information from PDF (portable document format) files and scanned documents, thus reducing the workload involved in data gathering. Meanwhile, ML platforms such as FICO Blaze Advisor can help to make the process more efficient, from data ingestion to risk scoring. These systems often include pre-built dashboards, application programming interface (API) integrations and compliance features, thereby enabling faster, more reliable assessments on a larger scale.

By strategically combining open-source flexibility with commercial platform functionality, a modular, scalable AI toolkit can be built that enhances accuracy, widens the pool of scorable counterparties, and streamlines the CRA process across partner countries.

7

Focused practical steps towards AI-enabled CRA



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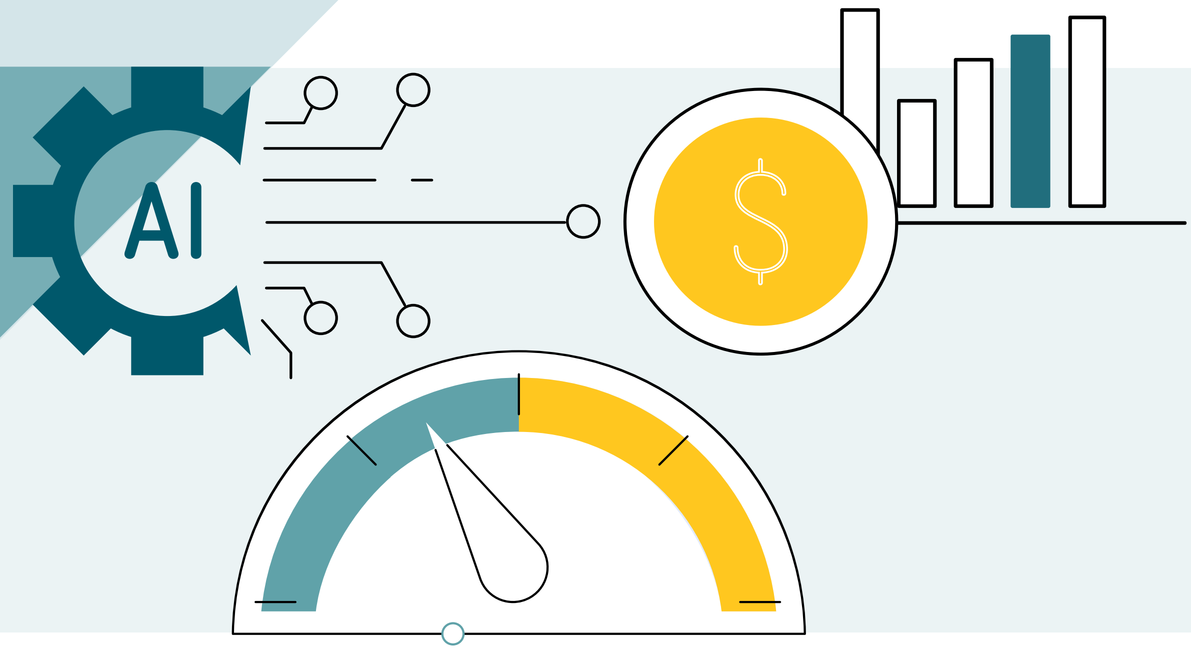


The aim of this study is to make it easier for German companies to implement renewable energy projects through improved access to finance in the long term. To overcome the major hurdle of accurate risk assessment in that process, a scalable, adaptable, transparent, explainable AI-enabled CRA system that is aligned with international standards can facilitate easy borrowing across multiple markets. However, achieving this vision requires incremental steps, starting with foundational capabilities that address current gaps in consistency, automation and data quality.

Initial efforts should focus on developing a baseline platform that incorporates basic AI functionalities such as document parsing and risk flagging to enable early deployment and validation across diverse contexts. Simultaneously, enhancing data sharing, ensuring model transparency and explainability, and alignment with international standards are essential to building a resilient and trusted infrastructure. This phased approach aims to demonstrate early value while laying the groundwork for a future-proof, comprehensive AI-driven CRA system.

7.1 Recommended roadmap

To build momentum and demonstrate early value in establishing a comprehensive AI-enabled CRA infrastructure, the following immediate actions are recommended:

1. **Establish a web-based modular CRA**
Transition to an automated web-based platform that uses traditional scoring logic, enhanced with basic AI functions such as document parsing and risk flagging. Target usability and consistency in country offices to facilitate adoption and iterative improvements.

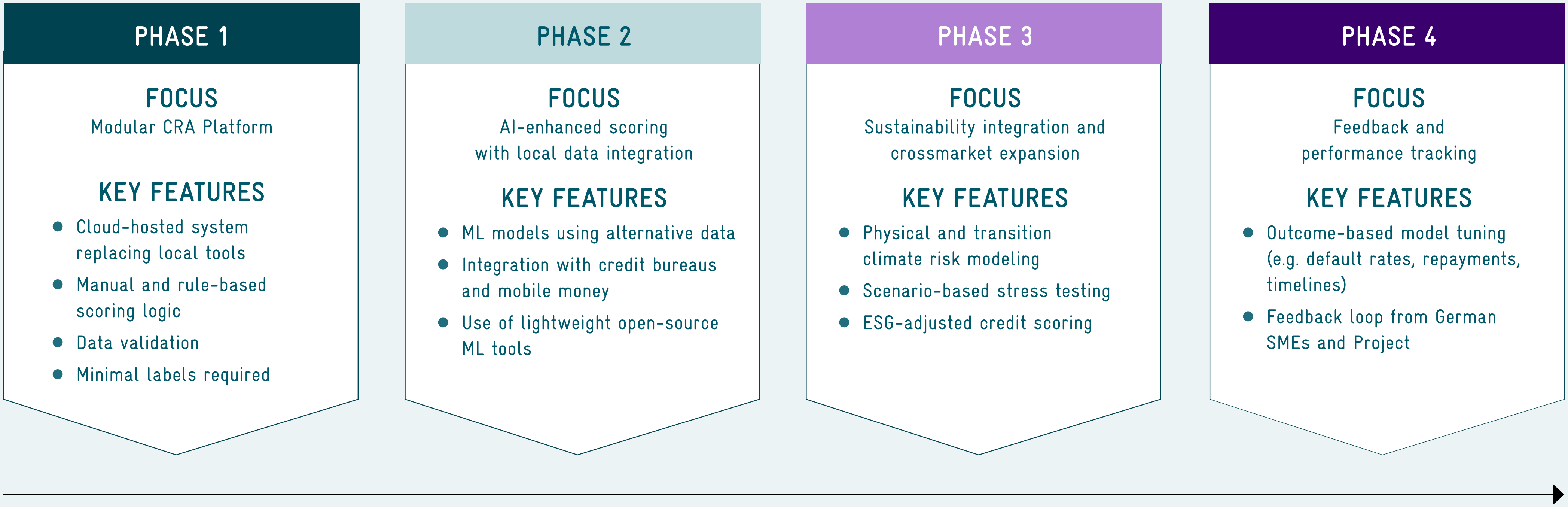
2. **Initiate data sharing discussions**
Engage with local credit bureaus, fintech platforms and utility providers to establish pilot data access agreements in one or two markets. Securing diverse data sources early will enable further AI model development and validation.

3. **Ensure compatibility with traditional CRA frameworks**
Ensure that AI-driven assessments complement traditional CRA evaluation criteria, such as financial projections, ESG compliance and collateral documentation. Translating alternative data insights into formats familiar to financiers will improve funding prospects and build trust with risk-averse lenders.

4. **Introduce an outcome tracking framework**
Start collecting structured feedback on local companies' repayment behaviour and project performance through surveys or field visits. This will support ongoing model validation and calibration over time.

5. **Define technical architecture and budget**
Draft an initial platform design incorporating a feedback framework and AI-enhanced scoring capable of local data integrations that clearly outlines scope, data flows, and approximate costs. This will help support procurement processes and future scalability.

FIGURE 1. Roadmap showcasing the four implementation phases Source: Synechron Business Consulting B.V., Aleksandar Shokolarov (2025)



A phased implementation approach as outlined in Figure 1 provides a structured pathway for advancing these initiatives. It details the focus, key features, and dependencies associated with each stage of development, starting from the creation of an initial platform and gradually advancing toward more sophisticated AI integration, risk modelling and sustainability considerations. This approach ensures that efforts are manageable, measurable and aligned with strategic objectives.

A successful transition to a modern CRA platform will depend on the selection of a feasible starting point, one that combines technically achievable, cost-effective and strategic alignment. Research indicates that initial efforts can leverage open-source tools, existing components and phased investments to build a scalable, transparent and adaptable system.

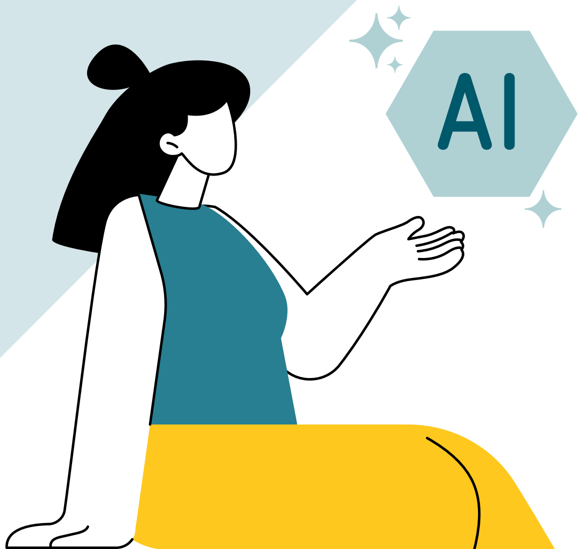
Technical viability can be supported by a modular architecture, initially hosting rule-based scoring and progressively layered with AI models, which will enable phased development and adaptation. The availability of open-source tools like scikit-learn and SHAP will ensure transparent and explainable modelling, while commercial cloud solutions such as SageMaker can support compliance requirements with built-in explainability and audit capabilities. The early system can rely on easily accessible data such as cash flows, business registration details, and utility information, thus minimising the need for extensive new data collection at the beginning.

Financial feasibility benefits from a phased investment strategy that reduces upfront costs and fosters learning through each stage. Additionally, deploying cost-effective automation solutions like AI OCR (e.g. Amazon's Textract), chatbots and NLP tools can substantially reduce the manual workload at minimal cost, thereby supporting scalable progress without requiring large initial investments.

Since it is both replication of efforts multiplied many times if every German SME tries to implement this approach by itself as well as a high cost, it is recommended that the implementation be done by an organization or institution, which can combine this effort for the German SMEs and provide them access to such a tool. The potential proponents could be a German ministry, an industrial or commercial association, or a public bank, subject to availability of budget. As a CRA is a part and parcel of all trade and financing transaction, and involves manual input and update of data, benefiting from AI and digitalization here all but makes sense.

8

Conclusion



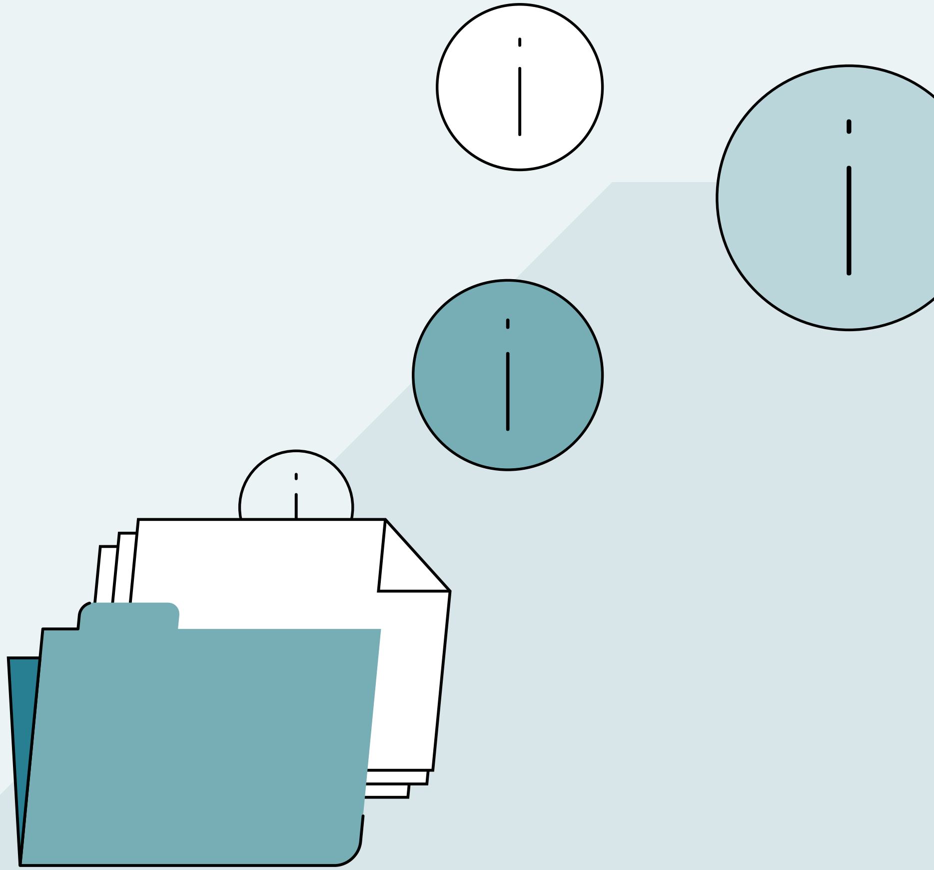
This study demonstrates that integrating AI-driven infrastructure into CRA offers significant advantages for German SMEs operating in frontier markets. Transitioning from static, Excel-based tools to scalable, cloud-enabled systems enhances accuracy, minimises human error, and enables dynamic, real-time risk evaluation, particularly where financial data is scarce or unreliable.

Importantly, these AI-enhanced models should not replace traditional CRA methods used by financial institutions but rather supplement them. By aligning alternative data analytics and machine learning outputs with the documentation standards and evaluation criteria that traditional financial institutions expect, SMEs can increase the credibility of their assessments and improve their access to finance.

Leveraging AI tools, such as explainable machine learning models, NLP, and reputational data analysis, allows for more inclusive and predictive credit scoring. This not only mitigates default risk but also expands access to finance for underserved segments, supporting broader goals of financial inclusion and sustainable growth.

Ultimately, combining technological innovation with regulatory compliance and alignment to institutional financing structures offers a practical, future-ready roadmap for improving CRA in frontier markets. This integrated approach enables German SMEs to build trust with lenders, reduce financial exposure, and scale renewable energy initiatives with greater confidence.

Annexes



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