The Case for Re-inventing the Credit Decisioning Approach

An RPG Company

Introduction

The importance of credit decisioning in the success of a credit business cannot be overemphasized. Credit businesses are heavily dependent on their business rules, mathematical models, and data to make profitable decisions. Customer behavior and expectations have been irrevocably transformed as a result of the pandemic, and the use of alternative credit products such as BNPL, peer-to-peer lending, point-of-sale financing, and embedded credit has proliferated. At the same time, financial institutions now have access to unprecedented amounts of data owing to a digital footprint across all transactions. These factors combined with developments in AI/ML and analytics, are shaping a new battleground for financial institutions. They not only have to grapple with financial, structural, and regulatory changes but also compete with nimble new-age start-ups with next-gen decision models offering lower customer acquisition costs, faster turnaround times, and frequent feature releases. All of which makes it imperative for financial institutions to upgrade their systems and capabilities across the credit suite to make robust credit decisions. These challenges also present an opportunity to leverage new-age decisioning models based on AI and ML, tap into alternative data, and harness the power of cloud to create lasting competitive advantage.

In this white paper, we take a look at new developments in the credit decisioning world, major concerns and challenges facing banks today with respect to credit decisioning, and the building blocks of credit decisioning platforms created for the future.

We also propose a reference architecture and discuss various options available to approach credit platform modernization efforts.

First, let us look at what credit decisioning entails.

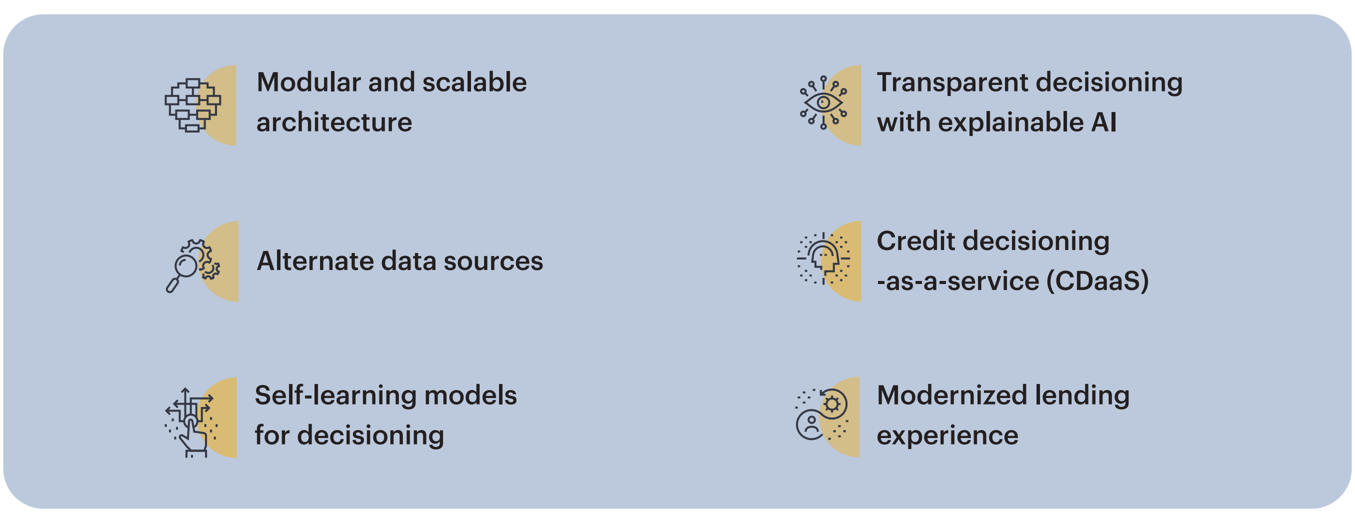


Figure 1: Building blocks for a credit decisioning platform built for the future

What is credit decisioning?

Credit plays a critical role in the modern economy. It is the key to fulfilling aspirations, building wealth, and growing the market economy. There was a time when common lending was done by local shopkeepers. We have come a long way since then through banks, credit unions, and organized retail lending. The most important part of the organized credit business is precise credit assessment. It is the process of determining the creditworthiness of borrowers by quantifying the risk of loss that the lender is exposed to.

There was no standard way of determining the creditworthiness of a person until 1956, when the first credit bureau FICO (Fair, Isaac, and Company, initially) was founded by engineer Bill Fair and mathematician Earl Isaac. FICO was working toward creating a standardized, impartial credit scoring system for over 20 years. Eventually, in 1989, FICO and Equifax launched the first modern credit score called BEACON. This credit score was derived from the credit history of a person. Credit history is the record of how a person has managed their credit in the past, including total debt load, number of credit lines, and timeliness of payment. Lenders look at a potential customer's credit history to decide whether to offer a new line of credit and to help set the terms of the loan.

Credit scoring facilitated the move from relationship-based lending to transactional lending. Decisions started being made through predictive statistics instead of personal judgments and rules. The Big Three credit bureaus in the US, viz. TransUnion, Equifax, and Experian today use their own calculation methods to arrive at the FICO scores of customers. The FICO score has long been the dominant determinant of retail credit decisions, but its influence is tapering off in favor of banks' own proprietary scores and bespoke models. [1]

[1] FICO Score's Hold on the Credit Market Is Slipping - WSJ

Facets of credit decisioning

Credit risk assessment process

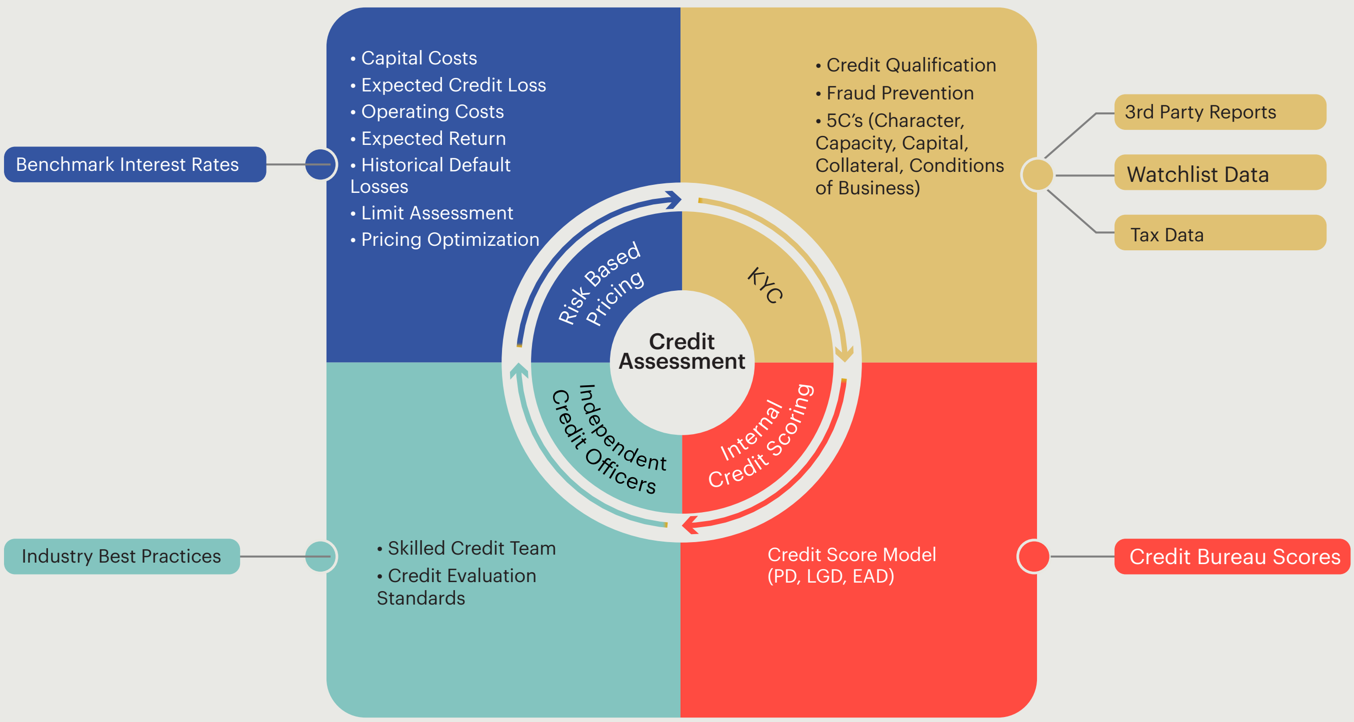


Figure 2: Credit risk assessment process

The credit risk assessment process involves numerous entities and pieces of information sourced from customer applications, credit bureaus, open banking data, and increasingly, even other third parties. Financial institutions feed all this data into internal scoring models. The decisions yielded by the statistical or AI models are further evaluated by skilled credit analysts to arrive at final approve-or-decline decisions and limits, rates, and terms, if applicable. Post-account origination, transactional data, behavioral scores, and other account performance data are used for making account management decisions, such as limit modifications and consequent product offerings.

Credit decision engine capability

A credit decision engine is a rules-driven platform that leverages credit policies and rules to arrive at a credit decision. The logic behind the decision is codified in the strategies and scoring models. The decision provided by the credit decision engine can be overruled by an expert or credit analyst and may also require an expert decision at times. Decision engines can be attached to a financial institution's existing credit processes since they are parameterized.

Credit risk scorecard model building

Credit ratings or scores are assigned to individuals and entities by empirical models referred to as scorecards. The two traditionally popular methods to create scorecards are decision trees and logistic regression. Increasingly, AI methods such as deep neural networks, random forests, and gradient boosting are being used for credit risk management. Models based on AI and ML can consume a far larger number of attributes than traditional models and derive more detailed conclusions. The credit decision is then arrived at through a combination of the credit scores, regulations, and the prior experience of the financial institution.

Credit risk analytics

Credit risk analytics involves the creation and deployment of risk and scoring models. The field of credit risk analytics has undergone a sea change over the past few years with the advent of big data and machine learning. Now, it not only helps make robust credit decisions but also leverages customer intelligence to create better credit products, improve customer acquisition, and construct a well-balanced credit portfolio.

Regulatory compliance

The regulatory landscape for credit risk and decisioning is becoming increasingly complex. There are a multitude of laws and regulations [2] that financial institutions need to adhere to, such as:

Privacy	Anti-discrimination
• Fair Credit Reporting Act (1970)	• Equal Credit Opportunity Act (1974)
• OECD Guidelines	• EU Artificial Intelligence Act (2022)
• General Data Protection Regulation	• Consumer Credit Protection Act (1968)

Credit provisioning and accounting	Capital adequacy requirements
• CECL	• Basel II (BCBS 239), III, and IV
• IFRS 9	• Dodd-Frank Act
• IFRS 17	

[2] Anderson, Raymond A. Credit Intelligence and Modelling: Many Paths Through the Forest of Credit Rating and Scoring. Oxford University Press, 2022

Credit industry today

New developments

Improved decisioning with alternative data

The increase in internet usage and the resultant digitization of cash transactions has led to the creation of numerous types of informational collateral. This alt-data includes alternative sources such as digital footprint, social media behavior, cashflows, utility payments, geolocation, telco usage, etc. Alt data can act as a leading indicator and augment credit risk management. A larger number of diverse data sources are now accessible to financial institutions to make credit and other financial decisions. A joint study by Experian and Oliver Wyman found that the combination of expanded data and analytics has the potential to improve credit access for close to 50 million American consumers who are credit invisible or cannot be scored[3].

A 2018 paper on the rise of FinTechs and Usage of Digital Footprint by Manju Puri et al demonstrated that digital footprint variables like email domain and type of device had a better chance than the traditional credit bureau scores at predicting whether a borrower would repay the loan[4]. The paper goes on to argue that a lender that consumes both traditional credit scores and digital footprint of the borrower in its models arrives at a better credit decision. New data sources have the potential to enable financial institutions to expand credit access without compromising on loan quality. Additionally, this data presents a more up-to-date picture of a customer's financial position. Several fintech firms like Kabbage and Tala have already been using alternative data to make credit decisions with success. According to a study, 35 percent of the surveyed lenders consider leveraging alternative data sources in credit risk assessment [5] (Figure 3).

What are your organization's top priorities for credit risk assessment and management over the next 12 months?

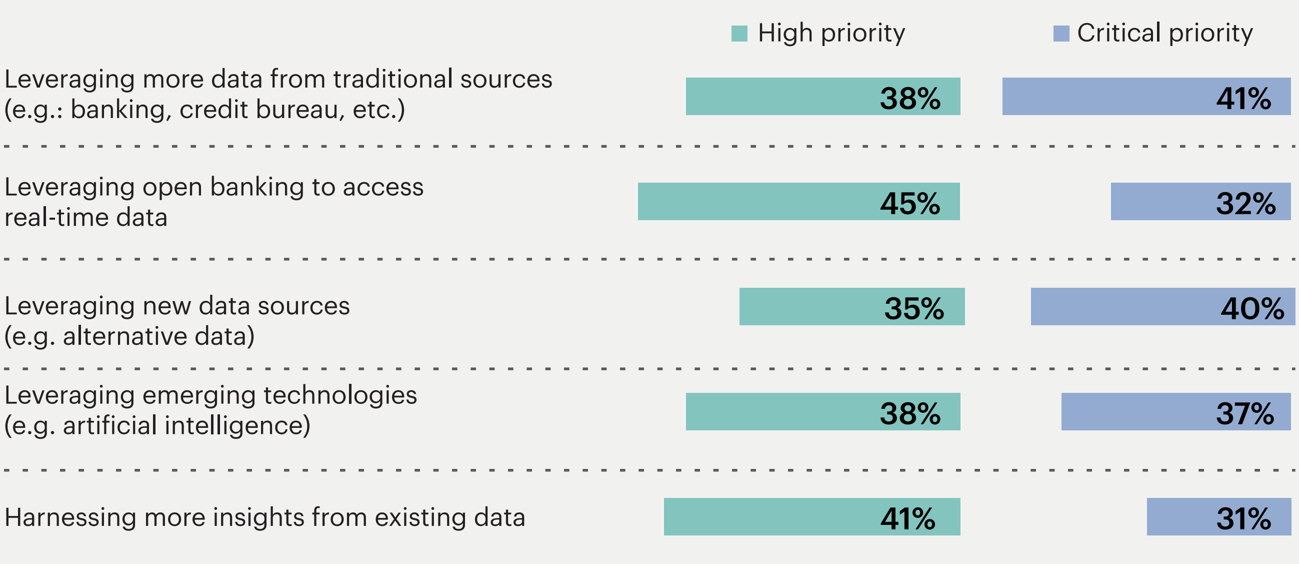


Figure 3 Data augmentation remains a top priority for credit risk assessment. Source: Forrester

[3]Experian plc - Experian and Oliver Wyman find expanded data and advanced analytics can improve access to credit for nearly 50 million credit invisible and unscoreable Americans

[4]Berg, Tobias, Andreas Fuster, and Manju Puri. "Fintech lending." Annual Review of Financial Economics 14 (2022): 187-207.

[5]Experian-Forrester Study on Credit Decisioning and Alternative Data Use | Experian (experiansolutions.in)

However, there is an important caveat to incorporating alternative data in credit decision-making. Financial institutions must make sure that collection of such data and subsequent incorporation into credit decisioning models do not contravene fair lending and data privacy regulations.

More accurate risk assessments with open banking data

Open banking legislation has ensured that the data on individuals' balances and transactions is easily accessible to financial institutions. It has several upsides for credit decisioning and lending at large. Augmented access to customer data makes credit assessment and credit decisioning more robust while also making it easier to validate the details provided by the customer for fraud prevention. Consumer-permissioned data such as assets income, cash flow, transaction data, etc., can complement credit scores and application data to determine creditworthiness more accurately. On the flip side, the legislation also creates a challenge for banks and other financial institutions since it effectively annuls their control of customer data and the resultant competitive advantage.

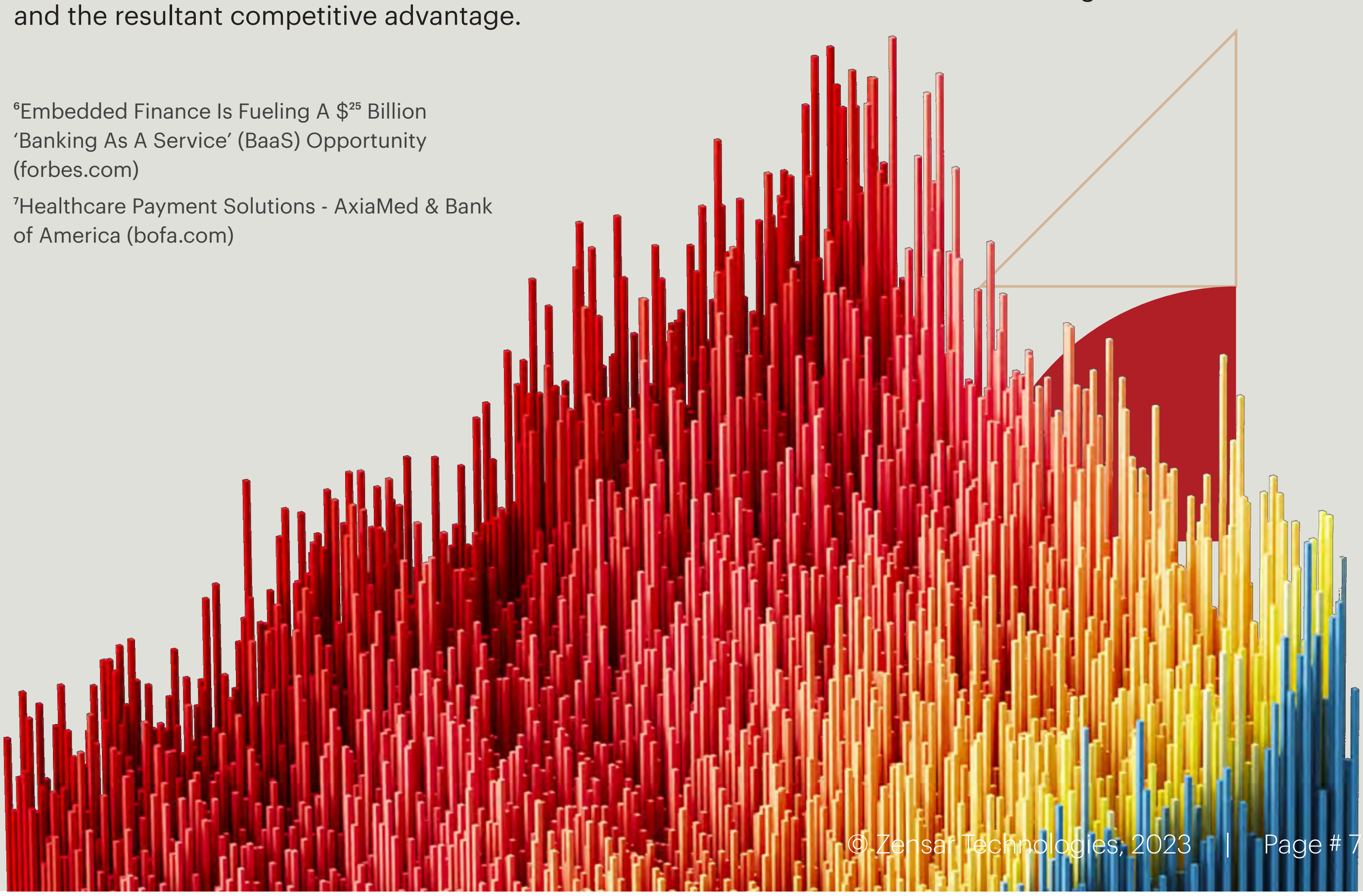
Credit decisioning on embedded lending platforms

According to Lightyear Capital Research, embedded consumer lending, which includes BNPL and other point of sale (PoS) financing options, will grow from $1.7 billion in 2020 to $15.5 billion in 2025 at a CAGR of 62 percent[6]. E-commerce platforms and the retail industry are said to be one of the first adopters of embedded credit at the point of sale. A number of other industries ranging from healthcare to hospitality, have now embedded credit on their digital platforms. For instance, FinTech firms such as Clarify Health and BofA-owned AxiaMed have started offering integrated financing solutions on healthcare platforms[7].

Assessing a customer's risk profile in the context of BNPL is not easy. Performance of the loan portfolio is of paramount importance for BNPL players. Therefore, approve/decline decisions have to not only be instantaneous but also as accurate as possible. Alternative data like telecom, utility bills payment, and other metadata are fed into machine learning models to arrive at a decision for a BNPL transaction instead of running credit checks.

[6]Embedded Finance Is Fueling A $25 Billion 'Banking As A Service' (BaaS) Opportunity (forbes.com)

[7]Healthcare Payment Solutions - AxiaMed & Bank of America (bofa.com)



Alternate credit decision process for green projects/ESG commitments

There is growing pressure on banks and financial institutions from governments and regulators to pay closer attention to their climate impact and analyze the role of ESG in credit risk management[8] (Figure 4). In keeping with the COP26 goals, banks across the world have committed to reach net zero carbon emissions by decarbonizing their loan and investment portfolios. The transition to net zero will also require banks to assess and modify their credit risk evaluation processes and overall risk management. More accommodative credit scoring and assessments may be needed for green projects as banks transition to less carbon-intensive exposure in their portfolios. Banks will have to aggregate data points and run portfolio analytics to arrive at portfolio allocation decisions in line with the COP26 goals. However, carbon footprint data is often difficult to obtain from corporate customers[9]. A number of alternative datasets focused on ESG are already being used as proxies in the financial services industry to assess climate risk.

Role ESG plays in credit risk management today	All	AMER	EMEA	APAC
It is playing a growing role	57%	59%	56%	55%
It has become integral to much that we do and play a major role in our decision-making	**26%**	**22%**	**33%**	27%
It plays a minor role	13%	14%	11%	16%
We are not considering ESG at this time	4%	5%	0%	2%

Figure 4 Role ESG plays in credit risk management
Source: Credit Risk and ESG Integration | ETF Trends

[8]Credit Risk and ESG Integration | ETF Trends
[9]Road to Net Zero: Using Data and Analytics for Portfolio Intelligence (garp.org)

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Key challenges with current credit decision models

Legacy IT systems with fragmented data

Due to a fragmented IT landscape, customer data is often siloed between different departments and products. A bank may have various exposures to the same customer via different credit products. However, barriers to accessing data across the firm prevent the bank from connecting the exposures to one single customer. Consolidating customer data split across different siloes and forming a holistic 360° view of the customer is one of the biggest challenges for financial institutions today. Data quality remains poor in the absence of a single source of truth and data governance policies. Thus, the outdated IT processes and out-of-date data make risk management and credit decisioning inefficient.

Legacy mainframe-based systems are monolithic. Their incompatibility with modern plug-and-play API-based products makes integration difficult in these systems. Development cycles to add in new upgrades require significant planning and are often prohibitively long.

Lack of transparency and prevalence of bias

Banks are increasingly using advanced AI models to make credit decisions. However, no matter how accurate a model is, it is not prudent to rely entirely on the output without considering the ethical aspects. There is a strong possibility that these models can learn the bias inherent in the historical data and perpetuate it further. Limited or faulty data can exacerbate this problem. Additionally, it is often impossible to explain how a neural network model arrived at a decision or what variables influenced the decision the most. Little wonder that regulators are turning their lens on the black box nature of the AI models used for credit decisioning and making it a requirement for financial institutions to provide a reason for declining a potential borrower. According to a recent circular released by the Consumer Financial Protection Bureau, federal anti-discrimination law makes it a requirement for creditors to explain why an adverse credit decision was made, no matter if it is a rule-based decision or an AI-based decision[10]

Overt emphasis on past repayments

The variables which factor into FICO scores are mostly dependent on the borrower's past record of debt repayment and length of credit history. This creates a chicken-and-egg problem for those who have little to no credit history and are seeking credit, while simultaneously limiting the total available market for the lenders. FICO, in partnership with Finicity and Experian, launched the UltraFICO[11] score in 2019, which allows customers with low or no FICO scores to include the data from their savings, checking, or money market accounts for enhancing their FICO scores. Including such data can not only address banks' concerns about a limited lending market but also drive financial inclusion.

Big Tech entering lending

Big Tech like Google, Apple, and Amazon have a large recognition and wide userbase, which they can immediately capitalize on. They also have access to an enormous amount of customer data, leading-edge infrastructure, and the top engineering talent to glean insights from the said data and make more accurate credit decisions. A number of Big Tech companies already have payment products which are quickly being followed by lending plays.

For instance, Apple has big aspirations for lending. It recently acquired UK-based credit decisioning start-up Credit Kudos after its launch of Apple Card (virtual as well as physical credit card) in partnership with Goldman Sachs in 2019. Credit Kudos uses open banking to provide affordability and risk assessment in the lending decision-making process. Predictive insights are built by combining transaction and loan outcome data[12]. Similarly, Amazon has also forayed into lending through its seller lending program and consumer lending through its Prime credit card.

[10]CFPB Acts to Protect the Public from Black-Box Credit Models Using Complex Algorithms | Consumer Financial Protection Bureau (consumerfinance.gov)

[11]Introducing the UltraFICO™ Score | Ultrafico

[12]Why Apple Acquired An 'Open Banking' Fintech (forbes.com)

Predictions for the future

Modular and scalable architecture

Credit decisioning architecture needs to be built with a high degree of flexibility and modularity. Business and technological environments are highly volatile, and new data sources, AI models, and credit policies keep emerging. Thus, the credit risk infrastructure should be built on the premise that requirements are bound to evolve. A cloud-based platform allows financial institutions to meet variable workload requirements and improve response times while improving availability and resilience.

Another non-negotiable component of a credit decisioning infrastructure is API front ends to ensure that internal decision systems can interact with third-party technologies and data sources. A centralized data lake must be created to aggregate internal and external data from both conventional and unconventional sources. This aggregation will allow banks to make customer-level decisions instead of account-level decisions.

Tap into newer data sources

Data can be an effective moat in today's world. The more the data, the more accurate the AI models are. Data augmentation by tapping into non-traditional sources such as the internet and social media usage, utility payments, subscriptions, etc., can enable businesses to assess their credit risk better by enhancing customer knowledge and improving risk scoring. Alternative data sourcing can be enabled through python-based scripts and APIs. Even combining all the internal customer data from within the enterprise, for instance, from different geographies and product lines, can lead to more accurate risk models, better risk discriminations, and consequently, higher profitability.

The market for alternative datasets is flourishing[13] (Figure 5). Combining these alternative datasets with internal data will require changes in the existing data infrastructure to ensure optimal performance.

Types of alternative datasets

Source: Neudata Scout; current as of 8 Apr 2022. N=1643. Note that some datasets are counted in multiple categories

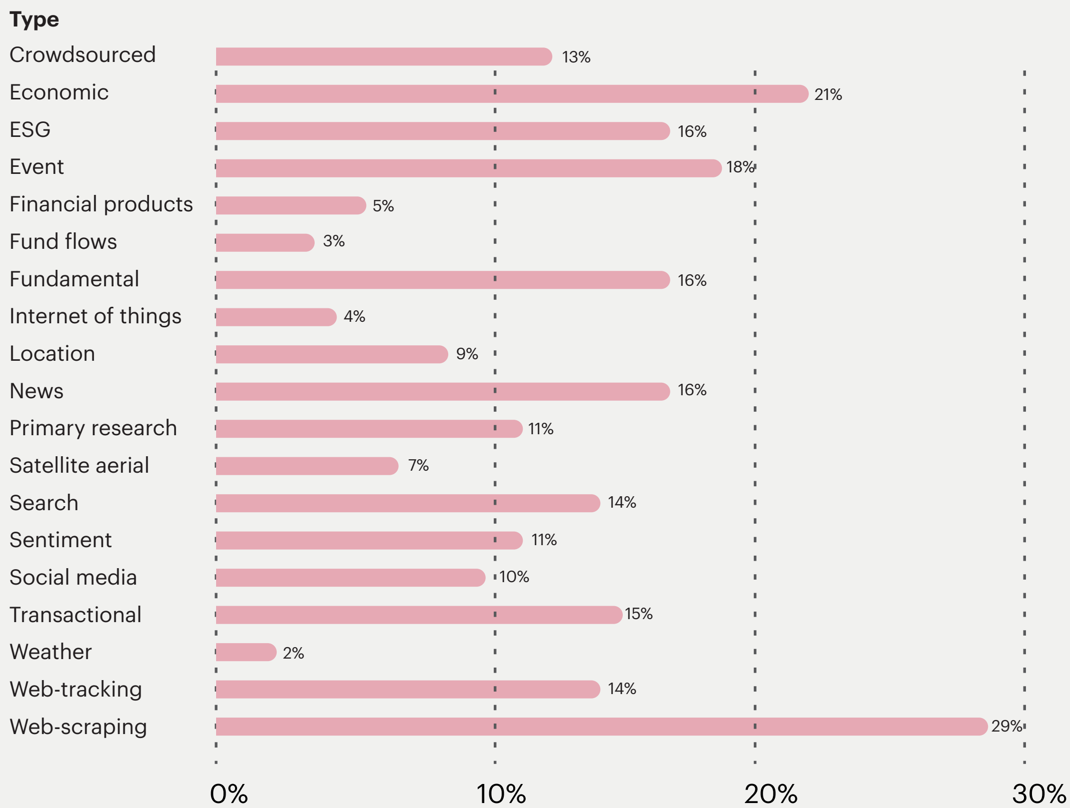

Figure 5: Categorization of alternative datasets in the market

AI/ML-based credit decisioning models

There will be aggressive advances in the algorithms and models trying to predict defaults on loan applications, trying to reduce the bad assets and losses for the lender. While denying loans to such borrowers, the models also need to look at the opportunity loss through false positives. This can only be done by improving the input data and establishing the correct correlation between the constituent factors. The data would not only be financial but also non-financial correlation, especially for unbanked or underbanked customers that do not have sufficient history. It will take extensive use of self-learning code/machine learning to allow such credit decisioning for the origination of new-age loans, viz. BNPL lending.

[13]Press Resources | Neudata

However, the role of advanced credit decisioning does not end at origination; it will require further advancement to predict early warning for loans in servicing that are about to go delinquent. Let us imagine a system that is able to read through social media about a genuinely traumatized customer and give early warning to the lender. The lender can then plan to provide moratorium or restructure of the outstanding loan proactively to such a customer. This could avoid delinquency for the customer (saving his credit history) and prevent bad assets on books of the lender. This is easier said than done however. How do you separate a genuine case from potential frauds? Here again we will have to rely heavily on advanced AI/ML models that can help us in monitoring risks in real time and identifying warning signals.

ML models can ingest far more attributes – both structured and unstructured – than traditional statistical models and identify patterns to arrive at actionable insights. Ensemble methods such as random forests and XGBoost have consistently performed better than traditional methods in credit risk prediction14. An area that has recently captured the attention of the world is generative AI. FICO, by its own admission, has been using generative AI for years to create synthetic data and conduct scenario testing for AI model development15.
We know that it can create fake customer records and transactions for testing purposes, but we are yet to see whether it can write decisioning rules and develop risk models on its own. These are early days for the technology, and we will have to keep a close watch on how it transforms credit decisioning as we know it today.

Furthermore, drastic shifts in consumer behavior, default rates, and macroeconomic variables in a post-pandemic world demonstrate the importance of continuous retraining of credit risk models. Financial institutions do not usually monitor their models to identify drifts and covariant shifts, and space out their model validations over long periods. It is important, therefore, to monitor and train ML models in production to avoid data and concept drift.

Glass box models for greater transparency

Explainable artificial intelligence is the solution to the black-box nature of AI. The complexity of AI-based models has increased exponentially over time in a bid to improve the accuracy of the results. However, there has been little focus on ensuring that the results are interpretable and explainable. AI helps identify specific explanatory factors for the conclusion that the AI model arrives at. It helps all the stakeholders – credit analyst, business manager, customer, and regulator – understand the basis of the credit decision and builds trust in the process.

Responsible AI is also an important component of an entity's ESG policy. It is important to ensure that the ML models are fair and inclusive. Regulators are already increasing scrutiny on artificial intelligence to combat systemic risk and ensure fairness and transparency. The European Commission's Artificial Intelligence Act (AI Act) and Blueprint for an AI Bill of Rights from the White House are cases in point. Public scrutiny is sure to follow. Explainability will, therefore, need to be adopted as a key tenet of building AI-based credit models going forward.

A number of tools and frameworks, such as Microsoft's Fairlearn and Google's What-If Tool, are being developed around the world to ensure bias-free decisions are being made. Zensar's AI4DI tool is another such initiative in this direction, which debiases HR-related decisions.

[14] Gunnarsson, Björn Rafn, et al. "Deep learning for credit scoring: Do or don't?." European Journal of Operational Research 295.1 (2021): 292-305.

[15] 4 AI Predictions for 2023: From the Great Correction to Practical AI (fico.com)

Credit decisioning as a service

There is huge disparity between the IT budgets of global banks and smaller regional banks and credit unions. However, all institutions that disburse credit in any shape or form, require efficient and responsive credit infrastructure to thrive in a volatile and fast-paced environment. Credit decisioning as a service allows financial institutions to access the credit decisioning technology without having to build the credit decisioning infrastructure on premises. Financial institutions can retain control of their underwriting and risk management personnel, risk policies, and servicing while the underwriting, incorporation of alternative data sources, fraud screening, and credit decisioning and analytics capabilities are furnished by the decisioning-as-a-service provider.

The provider also manages issues related to security, updates, and regulatory compliance while the financial institution can access leading-edge decisioning technology at an affordable cost. Services can also be extended to help financial institutions throughout the customer life cycle, from prospect qualification to compliance-related requirements. This will help financial institutions reduce their overhead costs and complexity and increase their agility, responsiveness, scalability, and competitiveness. Also, platforms that provide BNPL and other PoS financing as payment options can greatly benefit from this service.

Additionally, with the advent of technologies such as quantum computing, cloud-native platforms, and 5G networks, new-age credit decision platforms will have the formidable advantage of speed, resilience, and flexibility.

Key benefits of migrating to newer models

Better underwriting and risk-returns

Incorporation of alternative data and enriching the risk models can help financial institutions extend safer and higher number of loans that have a higher probability of being repaid. Efficiency in credit decisioning leads to more accurate modeling of credit risk and expected loss and reduction in non-performing assets and default rates. Research suggests that AI models can lead to a performance lift of 10 to 15% [16], decrease of 20 to 40% in credit losses,[17] and a reduction of 25% in exposure to risky customers.[18]

Growth in revenue

Apart from better risk-returns and increase in acceptance rate, newer models also have the potential to improve customer experience. An automated and intuitive credit process with shorter turnaround time with STP ensures better customer experience and can reduce churn. Cross-selling can also be augmented by leveraging a customer 360° view instead of account view and making hyperpersonalized offers.

Operational efficiency

Credit life cycle management is a resource-intensive process. Several tasks and workflows in the credit decisioning process can be easily automated or reengineered with adoption of new-gen platforms equipped with intelligent automation and AI/ML tools, to save manual time and effort. FinTechs which make systemic use of AI are able to process loan applications around 20% faster as compared to other lenders.[19] Accurate credit risk assessment also ensures that financial institutions can slash expenses on efforts to recoup bad loans.

Better compliance

The regulatory environment for banks and other financial institutions keeps shifting, resulting in frequent software change requirements, which are hard to implement in a fragmented IT landscape. New-age credit decisioning products are often continuously updated by vendors to reflect changes in global, regional, and local regulations, enabling financial institutions to remain compliant and reducing their compliance spends.

[16] The Future of AI in Lending - Experian Insights

[17] Designing next-generation credit decisioning models (mckinsey.com)

[18] AI-Driven Credit Risk Decisioning: What You Need to Know - Experian Insights

[19] Fuster, Andreas, et al. "The role of technology in mortgage lending." The Review of Financial Studies 32.5 (2019): 1854-1899.

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The roadmap to a transformed credit decisioning infrastructure

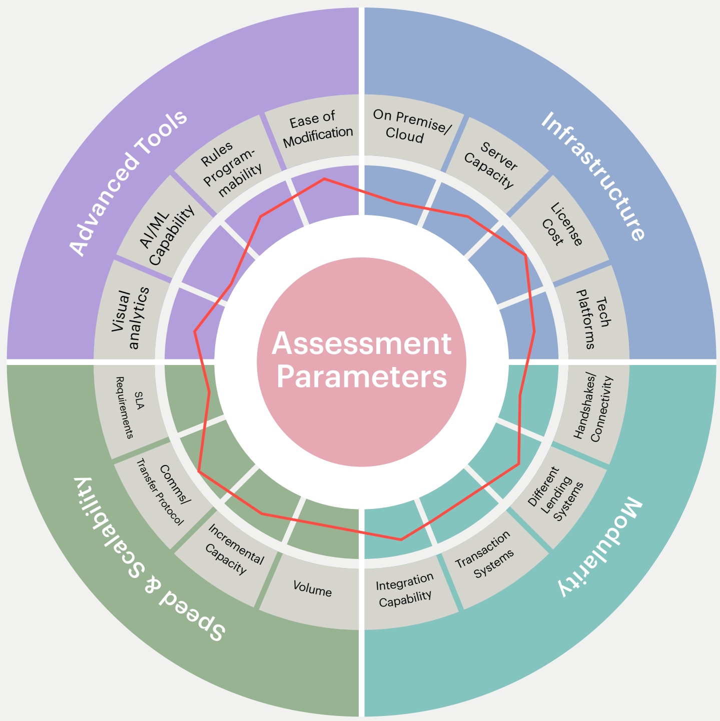

Figure 6: Evaluation framework to assess the maturity of a credit decisioning platform

Top global banks have started evolving their decisioning systems from static logistical regression-based models to dynamic ML models deployed across the customer lifecycle. Increasingly, top banks are also setting up centralized data lakes and analytics hub to create a holistic customer view and make personalized credit decisions in real-time. For instance, ING has deployed big data technologies to track and collate customer data from both internal and external sources in multiple data lakes to make better and data-driven decisions across the customer lifecycle[20]. ING also invested in a credit decisioning startup, named Flowcast, to augment and reinvent its credit decisioning capabilities. Flowcast makes use of machine learning algorithms and creates predictive models to reduce risk and improve acceptance rates[21]. Another pertinent example is U.S. Bancorp which has chosen to aggregate alternative data along with performance and account data to make better decisions[22].

Fintech firms such as Credit Kudos, Noble, LenddoEFL, Upstart API, etc. are utilizing cutting-edge technology to create credit decisioning tools. A number of innovative products have also been launched by established players such as FICO and Experian among others. Off-the-shelf decisioning platforms such as

[20]How ING engages customers with Big Data and the Internet of Things (internetofbusiness.com)

[21]The Asia-Pacific trade finance ecosystem, challenges and opportunities - Interview with ING Labs - ThePaypers

[22]Lenders find more uses for alternative credit data | Credit Union Journal | American Banker

SAS Viya and IBM Operational Decision Manager are becoming primary choice for banks in their modernization efforts. These platforms combine advanced analytics and machine learning with business rules to make better and faster enterprise decisions, ranging from customer outreach to credit decisioning, fraud detection, and pricing, in real-time. The business experts author the business rules and decision logic, which are enhanced by machine learning, predictive analytics, impact modeling, and optimization. Instead of decision-making logic being embedded in disparate applications scattered across the organization, these platforms act as a centralized repository for rules, which applications can invoke as needed. They also make it easy for the nontechnical users to write and edit rules, test the results using simulation, and deploy decision strategies, reducing the dependence on IT teams.

There are several models currently available for upgrading the credit decisioning infrastructure – fully outsourced, hybrid outsourced, proprietary model building or decisioning-as-a-service. The maturity of the current platform can be assessed using the framework like the one depicted in figure 6 above to decide which model is best suited for a financial institution's requirements.

This, although, will only help in benchmarking the existing legacy decision system. There would be lot more analysis required to arrive at a decision of whether to build an inhouse decision system that the time demands or simply purchase from a plethora of new age COTS products already available in the market. The scalable platforms with well-designed bases will not only help them tap into newer market segments but also meet GRC requirements effectively leading to significantly more competitive and profitable lending processes. But they will come with possibly steep license cost along with customization required while implementing as a replacement for the legacy system.

There will be a lot of deliberation in the Bank's management on which option to go with, although one thing is quite sure that status quo is not an option anymore!

Conclusion

In the era of embedded finance, the credit lending opportunities are omnipresent across industries at the last mile of delivery – retail, ecommerce, insurance, automobiles, healthcare etc. It is imperative for banks & financial institutions to have real time decision capabilities to tap into these opportunities while making right credit decisions to both maximize revenue opportunities and minimizing default & fraud.

Additionally, we live in the digital era today where the data availability has pivoted from limited data to overwhelming amounts of data. The need of the hour is to be able to filter out the data from noise and translate the data to information & actionable insights. There is also an opportunity to leverage the advances in the field of AI-ML technology to leverage social data and intelligent models in the decision-making process.

As competition intensifies in the credit market, banks require an API-driven credit decisioning system which can consume data from both conventional and alternative data sources, make more accurate decisions by deploying cutting edge machine learning models, and improve flexibility, scalability, transparency, and customer experience by leveraging the power of cloud.

The credit decisioning platforms at numerous banks today are not scalable and dare we say cannot be upgraded due the legacy technology that is incompatible with modern tools at hand. So, these legacy platforms can only ingest limited datasets, leaving a broken, siloed customer view, thereby impacting customer experience. This inability of credit decision platform to look at the bigger picture of customer 360 view, hampers bank's competitive positioning, and regulatory compliance. Also, the agility that these platforms offer is limited, thereby significantly compromising the banks velocity to respond to changes like BNPL lending.

Although updating credit infrastructure is a long and laborious task, there is a compelling case for banks and other financial institutions with legacy credit risk and decisioning systems to transform their credit decisioning infrastructure. Financial institutions need to adopt a strategic approach to overhaul their legacy credit decision platforms. It starts with a Build vs Buy decision. Accordingly, the future state architecture has to be designed and built,followed by delineating the strategy to migrate legacy data to the new platform. There are clear and tangible benefits that banks can reap from migrating to new age decisioning platforms. Moving towards a nimbler and data driven modern architecture is sure to tip the scales of success decidedly in favor of the banks which undertake this journey.

Customer story: Credit decisioning platform for a global banking major

Our client, a global banking major with operations spanning 50+ countries, undertook migration of its enterprise credit decision platform from a soon-to-be-discontinued product to a new-age intelligent decisioning product. The client then wanted to deploy the credit decisioning platform to the cloud to augment its availability and flexibility. Zensar investigated and extracted the banking product-related strategy from the mainframe-based product along with business rules, switches, policies and exclusions, decision trees, scorecards, etc., with customizations applied across the business portfolio. Zensar worked closely with the client for the E2E migration to the cloud-based to be system across select geographies.

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