Successfully implement and operationalize machine learning models to optimize and accelerate credit decisions



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01_Introduction

The pandemic has brought about significant economic disruption, thereby increasing the need for banks and financial institutions to be more agile. However, Covid-19 is not the only factor that drives automation and digitalization in the credit and lending process in credit institutions. Incumbent banks are increasingly facing pressure from neobanks, these having the strategic advantage of being "born digital". In addition, customers demand fully digitalized processes with regard to the ease of use and fast turnaround times.

Existing operations and legacy IT infrastructure may not be able to meet performance expectations related to quality, time to market, cost and innovation. If banks want to stay ahead of competitors, they need a more agile approach that capitalizes on advances in digitization, automation, and smart technology. From the way customers complete transactions, to how banks make decisions, digital tools are bringing greater speed, efficiency, and transparency to many aspects of the customer journeys.

One of the game changers is believed to be artificial intelligence (AI) and machine learning (ML). One of the game changers is believed to be artificial intelligence (AI) and machine learning (ML). While these topics were mainly hype trends until just a few years ago, related approaches and technologies have now become widely adopted in the financial sector at banks and insurance companies. It has been proven that the use of AI/ML has the potential to sustainably improve business processes from customer acquisition to loan approval decisions, and further, to monitoring and deepening existing customer relations.

The growth in the use of AI comes as no surprise. Back in 2017, Gartner's Top Ten Technology Trend Report identified AI and machine learning techniques as the No. 1 trend, particularly in financial services, where AI/ML tools are used both for prediction (e.g. fraud/default probabilities) and classification purposes. Recent surveys show that credit institutions are gradually adopting more AI/ML techniques in different areas, where hardly any financial institution who has not at the very least experimented with AI models.

Yet, many banks are still struggling to effectively operationalize machine learning into existing business processes and decision workflows. This is largely due to the fact that financial institutions need to be certain that the adopted solutions are aligned with all regulatory requirements and have a proof of compliance. Furthermore, and more importantly they fail to close the threshold between model development and integration into operational decision-making processes.



02 _Use cases of AI / ML across the lending life cycle

By injecting artificial intelligence and machine learning techniques, credit institutions can optimize workflows and business decisions across the lending life cycle. However, financial institutions need to prioritize where AI capabilities add the most value and should complement or replace static rule-based decisions. Many of the decisions best suited to AI/ML improvement are operational decisions: high volume, transactional decisions.

The following four areas are of main interest when leveraging AI/ML across the credit life cycle: customer acquisition, credit decisioning, monitoring and collections, and deepening of customer relationships (see Figure 1).

AI/ML OPTIMIZED WORKFLOWS AND BUSINESS DECISIONS ACROSS THE LENDING LIFE CYCLE



CUSTOMER ACQUISITON

- → Personalized offers
- → Customer retargeting

Customer acquisition rate

DEEPENING RELATIONSHIPS

- → Intelligent offers (e.g. next product to buy)
- \rightarrow Churn reduction

Products per customer; further credit application



CREDIT DECISIONING

- → Credit scoring & rating
- \rightarrow Limit assessment
- → Pricing determination
- → Fraud prevention

Credit-approval turnaround time; conversion rate

MONITORING AND COLLECTIONS

- → Early-warning signals
- → Probability of delay
- \rightarrow VAR-based
- \rightarrow Customer segmentation

Average days past due; nonperforming loans



Source: In accordance with McKinsey 2021



CUSTOMER ACQUISITION

The digital transformation has greatly changed communication between customers and companies. Instead of static mass communication, customers want timely updates, based on their specific needs and situation. Be it for product information or services, customers expect the digital channels to provide the same level of customization as is available with their trusted bank advisors. The combination of predictive analytics, big data and business rules enables intelligent product and service recommendations (personalized, relevant and needs-based) in real-time across multiple marketing channels.

CREDIT DECISIONING

In digital credit decision making, an applicant expects a credit decision while still on a banks' user touch point. This digital user experience is one of the drivers of future business and a software is needed that allows for fast, reliable, and secure decision making at the core.

By leveraging rule-based technology and ML, credit institutions can implement risk strategies and risk rating and scoring models. This allows to automate credit approvals thereby decreasing the turnaround time significantly.

How much should the maximum loan amount be? This is where AI/ML help with the evaluation of scanned documents as well as the analysis of multiple actions in the digital space (shopping activities, social media). Due to GDPR regulations, alternative data sources cannot be used everywhere. This is where credit institutions make use of PSD2 and/or Open Banking Data. By building datasets using both traditional and new data sources, banks can make a very accurate prediction of a customers ability to pay.

Credit institutions often use standardized interest rates for loans, which can only be adjusted by the credit departments with little leeway. But especially for borrowers with a higher risk, banks with machine learning approaches have various advantages. This is where dynamic risk-based pricing comes into play. Thanks to sophisticated ML models for risk assessment and interest rate setting, they can offer even such customers attractive interest rates at lower risk.

The possibilities of credit fraud are numerous, and therefore hardly completely detectable with regular rules-based models. It is here that ML algorithms can demonstrate their true strengths as they are much more efficient to evaluate various aspects and fraud indicator.

Especially with regard to credit decisioning it is of great importance to choose technologies that provide the right mix between bank-grade reliability, ease of use for integration and scalability, whilst at the same time allowing the integration of proprietary AI/ML driven components. This, however, must go hand in hand with auditability and compliance.



MONITORING AND COLLECTIONS

ML models come in handy when looking at nonperforming loans. More and more banks engage in a proactive manner with clients, thereby helping them to keep up with payments. Internal and external data sources allow credit institutions to build a 360-degree view of a client's financial situation. This enables them to spot early-warning signals that a borrower's financial situation might have changed, allowing for risk of default to be reassessed.

Examples are for instance the prediction of the probability of delay or the number of days delayed. This allows FIs to initiate different measures, e.g. sending an early payment reminder. Further, by having a 360-degree view on clients, portfolio quality assessments can be performed.

DEEPENING RELATIONSHIPS

The foundation of deeper relationships is a credit institution's precise understanding of the specific needs and expectations of each customer. Algorithms can be used to develop targeted strategies in order to meet an emerging need for credit (e.g. browsing history of financial products) and deliver them at the right time and through the right channel.

These are only selected use cases for AI / ML across the lending life cycle. By injecting AI / ML into these aspects, banks can improve customer acquisition and retention and make faster and more informed lending decisions.

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The initial outcomes of introducing AI result in high expectations by financial institutions

03 _Why do many AI/ML models never make it into production?

The initial approaches and results of introducing AI suggest that they provide a competitive edge, thereby resulting in high expectations by financial institutions for AI around risk management, fraud detection and prevention, and process automation. Even though the expectations are high, many firms are still in a stage of doing ad-hoc pilots or have just started to do more widely roll-out. According to a recent survey by Rackspace Technology, the great majority of companies (>80%) still find it challenging to implement AI initiatives.

When companies are asked what the biggest challenges are in putting the theoretical groundwork and models they have developed into practice, a study by Gartner identified a number of different barriers. In addition to the security and data protection concerns, data and model governance, it is the complexity of integrating the AI solution into the existing IT infrastructure appears to be a significant problem for many organizations (30% stated as one of the top 3 barriers).





BARRIERS TO AI IMPLEMENTATION

	Percentage of respondents	Sum of top th	ree 🗾 Firs	t choice
Security or priva	cy concerns	11%		30%
Complexity of AI	solution(s) integration with existing infrastructure	11%		30%
Data volume and	l/or complexity	8%	22%	
Potential risks or	r liabilities	7%	22%	
Data scope or qu	ality problems	6%	20%	
Lack of understa	nding AI benefits and uses	6%	20%	
Lack of technolog	gy knowledge	5%	19%	
Data accessibilit	y challenges	6%	19%	
Little improveme	nt over existing technologies	6%	18%	
Lack of skills of s	tuff	7%	18%	
Technology is too	o difficult to use or deploy	5%	17%	
Governance issue	es or concerns	5%	17%	
Lack of capabilit	y to leverage AI techniques	6%	16%	
Difficulty finding	use cases	5%	15%	
Unable/hard to n	neasure the value	3%	14%	
		0%	20%	
		070	2070	

gartner.com/SmarterWithGartner

n=601 all respondents, excluding "Not Sure" Q: What are the top three barriers to the implementation of AI techniques within your organization? Note: Numbers may not add to totals shown because of rounding. Source: Gartner 2019, AI in Organizations ©2021 Gartner, Inc. All rights reserved. CTMKT_1161674

Fig. 2

The complexity of integration thus plays a central role, especially when credit institutions try to implement AI/ML models in software themselves. This can only succeed, if they have previously purchased or built up the necessary know-how.

Rephrased, if financial institutions do not manage to close the gap between model development and integration into operational decision-making processes, AI experiments in many companies will remain just that: an experiment.

Hence, the crucial question is: How can a financial institution integrate and operationalize the developed (AI/ML) decision models - with as little effort as possible and in a short time - without failing due to the barriers described above and thus losing the investments already made?



04 _Digital Decisioning Platforms: The perfect combination of human and artificial intelligence

Experience shows that it takes more than just using the latest AI technologies and algorithms to successfully deliver AI in operational systems.

In order to remain competitive, financial institutions must modernize their legacy-based IT landscape by leveraging technology platforms that allow to build, deploy, run and monitor AI/ML at speed and scale. However, experience shows that it takes more than just using the latest AI/ML technologies and algorithms to successfully deliver AI in operational systems.

One of the most persistently adopted technologies for embedding AI into decisioning workflows are Digital Decisioning Platforms. These allow to automate high-volume, transactional, and operational business decisions. They execute the bank's business and policy rules, e.g. for credit approval and decisioning. Most Digital Decisioning Platforms also provide intuitive, low-code environments to flexibly adapt these decision strategies by business experts (rather than IT). By using a Digital Decisioning Platform, credit institutions are able to consistently digitize all decision-making processes on a central platform.

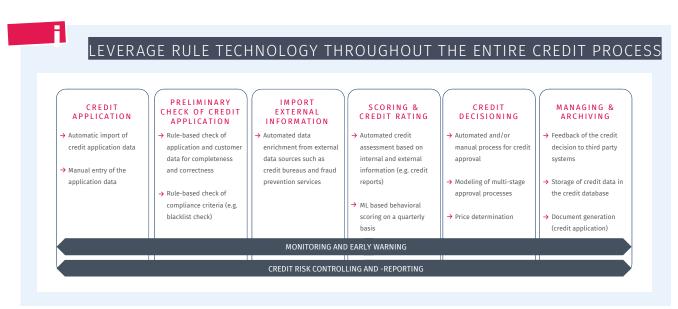


Fig. 3

Digital Decisioning Platforms also support bridging the gap between two sometimes 'incompatible' worlds: data scientists having developed (AI/ML) models with tools and languages such as Python, R, etc. on the one hand, whilst having core banking and workflow systems (e.g. in Java) on the other. Modern decisioning platforms enable the combination of AI/ML and deterministic rule-based models, thereby achieving better and explainable business decisions. Explanations of ML decisions to humans are also provided in understandable terms.



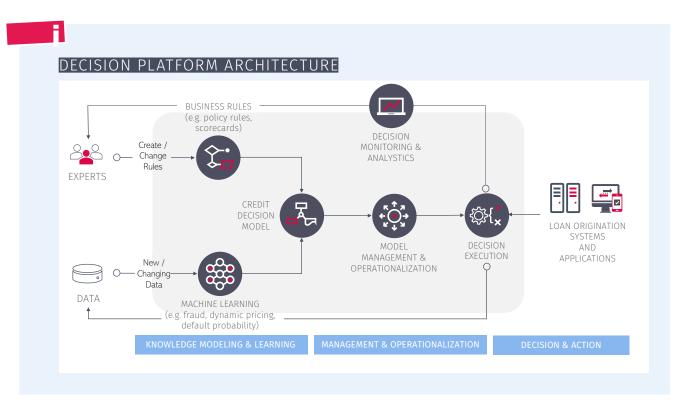
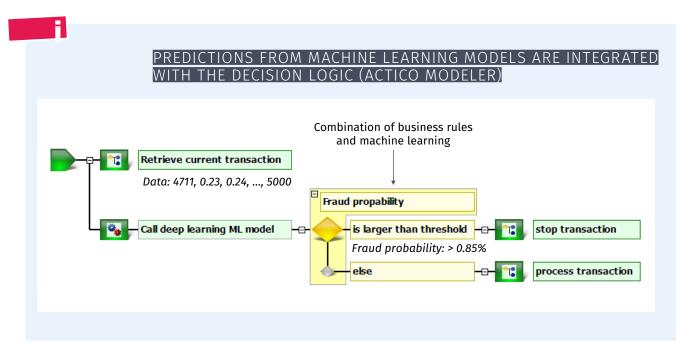


Fig. 4

As illustrated in Figure 4, a modern Decision Platform architecture must allow the integration between business rules and machine learning models. The resulting credit decision models thus reflect the bank's credit policy rules and decision strategies (implemented as business rules) and injected artificial intelligence (implemented as ML models). These decision models are controlled and governed by a model management lifecycle and then deployed for high performance, operational credit decisioning.

Figure 5 shows a screenshot of a rule flow implemented in the ACTICO Platform that executes an existing ML model to calculate a fraud probability from credit decisioning rules.





Digital Decision Platform enable credit institutions to exert control over every decision being made, conform with regulations, and implement ML and AI algorithms. The combination of business rules and ML models allow for more consistent, accurate decisions to be delivered across all channels. Any channel that needs the decision made invokes the decision service. This executes the business rules and ML models necessary to make the decision and logs how the decision was made. Thereby credit institutions adhere to regulatory compliance by making fully documented and traceable decisions.

Digital Decision Platform enable credit institutions to exert control over every decision being made, conform with regulations, and implement AI and ML algorithms. Centralized model repositories, automated storage and versioning of (ML) models (~life cycle management), and real-time monitoring allow to reduce the time it takes to build and deploy a model from a few months to a few weeks or even days.

05 _Conclusion

One of the game changers to stay ahead of competitors in the banking sector is believed to be artificial intelligence (AI) and machine learning (ML). By injecting artificial intelligence, credit institutions can optimize workflows and business decisions across the lending life cycle. Operational decisions (high volume, transactional decisions) within the credit life cycle offer the greatest potential when complementing or replacing rule-based decisions. Here, use cases within the areas of customer acquisition, credit decisioning, monitoring and collections, and deepening of customer relationships are of particular interest.

Yet, many credit institutions are not able to benefit from its full potential. Many institutions are still struggling in their adoption to operationalize AI/ML in automated business processes. This is largely attributed to the fact that institutions fail to close the gap between model development and integration into operational decision-making processes.

One of the most persistently adopted technologies for delivering scalable AI is achieved by introducing a platform that integrates decision logic (aka business rules platform) and AI-based insights, or so called Digital Decisioning Platforms. These Platforms enables credit institutions to exert control over every decision being made, conform with regulations, and integrate AI and ML algorithms.



06 _Solutions by Actico

Modern decisioning platforms enable the combination of AI/ ML and deterministic rule-based models

ACTICO's Credit Decision Platform is a robust and highly scalable platform for automated credit decisioning in retail lending. Through a powerful graphical rules engine, the platform enables the implementation, testing, simulation and optimization of a bank's risk models and decision strategies, including but not limited to risk scoring, pricing and credit decision strategies.

The following diagram (Figure 6) shows the main components of the Credit Decision Platform.

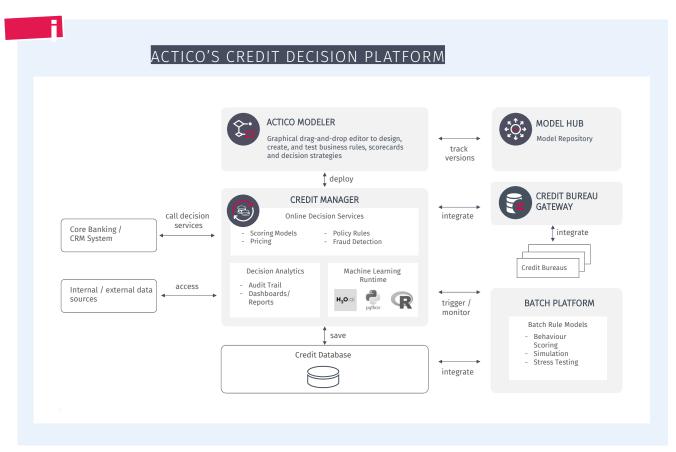


Fig. 6

For the integration of existing external models (e.g. ML models), the Platform is technology-agnostic and allows the seamless integration of most commonly used frameworks and technologies (e.g. Python, R, Java/H2O). This helps banks and financial service providers to leverage the benefits of artificial intelligence in a very short time and effectively embed them into the operational credit decisioning process.



07 _Sources

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ACTICO is a leading international provider of software for intelligent automation and digital decisioning. ACTICO solutions combine human knowledge and artificial intelligence with powerful automation technology. They are used to manage risks, fulfill regulatory compliance obligations, prevent fraud, enhance digital customer engagement and optimize operations.

With more than 20 years of experience in this field, ACTICO is the choice of small, mid-size and Fortune 500 companies around the globe who are seeking to digitize their decision-making processes. The company is headquartered in Germany and has offices in North America and Singapore.

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