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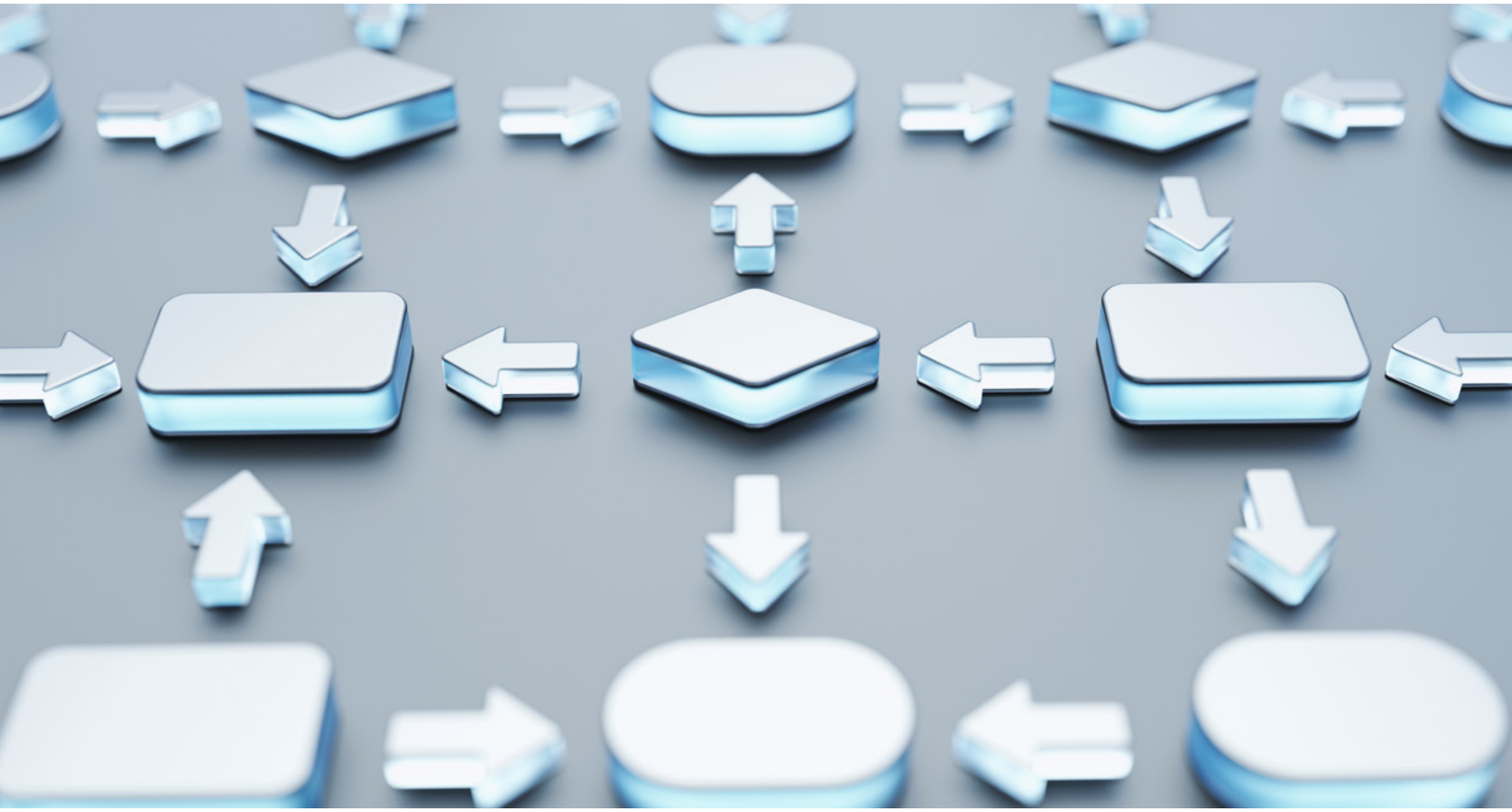
Global Banking & Securities

AI-powered decision making for the bank of the future

Banks are already strengthening customer relationships and lowering costs by using artificial intelligence to guide customer engagement. Success requires that capability stacks include the right decisioning elements.

by Akshat Agarwal, Charu Singhal, and Renny Thomas



March 2021

The ongoing transition to digital channels creates an opportunity for banks to serve more customers, expand market share, and increase revenue at lower cost. Crucially, banks that pursue this opportunity also can access the bigger, richer data sets required to fuel advanced-analytics (AA) and machine-learning (ML) decision engines. Deployed at scale, these decision-making capabilities powered by artificial intelligence (AI) can give the bank a decisive competitive edge by generating significant incremental value for customers, partners, and the bank. Banks that aim to compete in global and regional markets increasingly influenced by digital ecosystems will need a well-rounded AI-and-analytics capability stack comprising four main layers: reimagined engagement, AI-powered decision making, core technology and data infrastructure, and leading-edge operating model.

The layers of the AI-bank capability stack are interdependent and must work in unison to deliver value, as discussed in the first article in our series on the AI bank of the future.[1] In our second article, we examined how AI-first banks are reimagining customer engagement to provide superior experiences across diverse bank platforms and partner ecosystems.[2] In the current article, we focus on the AA/ML decisioning capabilities required to understand and respond to customers' fast-evolving needs with precision, speed, and efficiency. Banks that leverage machine-learning models to determine in (near) real time the best way to engage with each customer have potential to increase value in four ways:

— *Stronger customer acquisition.* Banks gain an edge by creating superior customer experiences with end-to-end automation and using advanced analytics to craft highly personalized messages at each step of the customer-acquisition journey.

— *Higher customer lifetime value.* Banks can increase the lifetime value of customers by engaging with them continuously and intelligently to strengthen each relationship across diverse products and services.

— *Lower operating costs.* Banks can lower costs by automating as fully as possible document processing, review, and decision making, particularly in acquisition and servicing.

— *Lower credit risk.* To lower credit risks, banks can adopt more sophisticated screening of prospective customers and early detection of behaviors that signal higher risk of default and fraud.

As banks think about how to design and build a highly flexible and fully automated decisioning layer of the AI-bank capability stack, they can benefit from organizing their efforts around four interdependent elements: (1) leveraging AA/ML models for automated, personalized decisions across the customer life cycle; (2) building and deploying AA/ML models at scale; (3) augmenting AA/ML models with what we call "edge" capabilities[3] to reduce costs, streamline customer journeys, and enhance the overall experience; and (4) building an enterprise-wide digital-marketing engine to translate insights generated in the decision-making layer into a set of coordinated messages delivered through the bank's engagement layer.

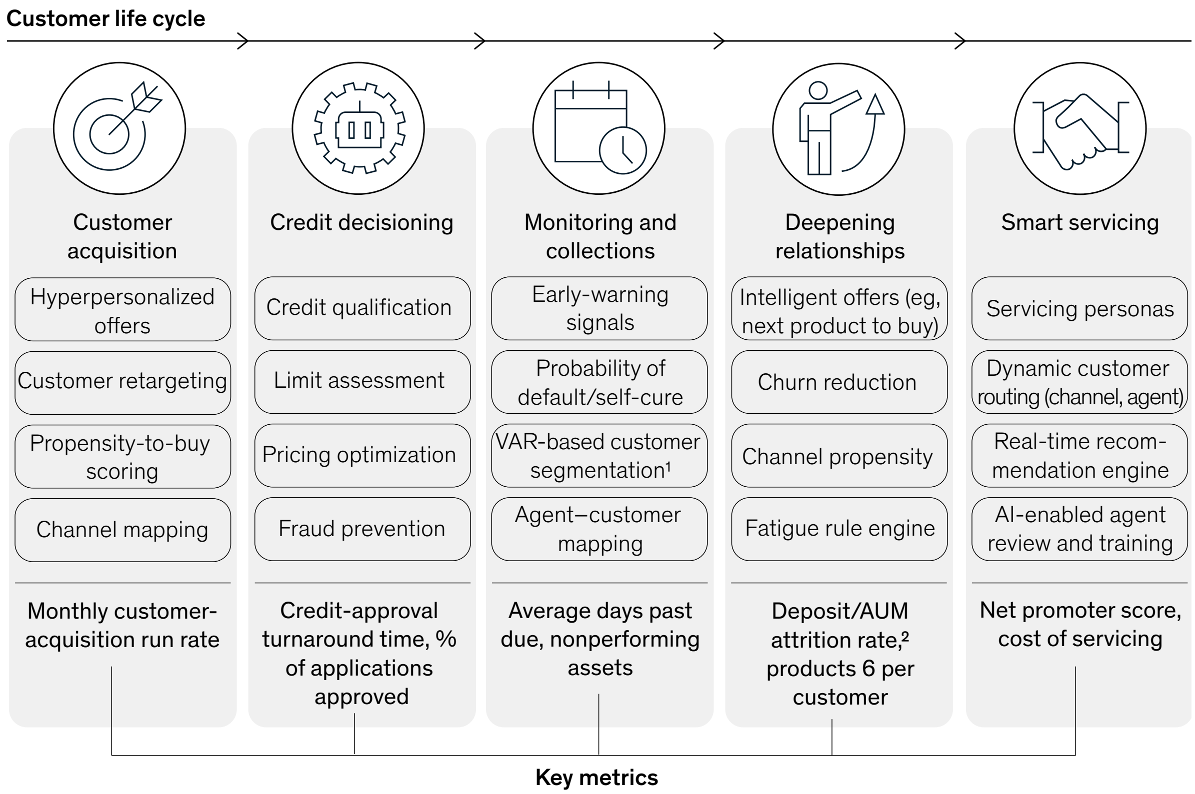
Automated, personalized decisions across the customer life cycle

If financial institutions begin by prioritizing the use cases where AA/ML models can add the most value, they can automate more than 20 decisions in diverse customer journeys. Within the lending life cycle, for example, leading banks are relying increasingly on AI and analytics capabilities to add value in five main areas: customer acquisition, credit decisioning, monitoring and collections, deepening relationships, and smart servicing (Exhibit 1, next page).

[1] Suparna Biswas, Brant Carson, Violet Chung, Shwaitang Singh, and Renny Thomas, "AI-bank of the future: Can banks meet the AI challenge?" September 2020, McKinsey.com.
[2] Violet Chung, Malcolm Gomes, Sailee Rane, Shwaitang Singh, and Renny Thomas, "Reimagining customer engagement for the AI bank of the future," October 2020, McKinsey.com.
[3] Edge capabilities refer to next-generation AI-powered technologies that can provide financial institutions an edge over the competition. Natural language processing (NLP), voice-script analysis, virtual agents, computer vision, facial recognition, blockchain, robotics, and behavioral analytics are some of the technologies that we classify as "edge capabilities." These capabilities can be instrumental in improving customer experience and loyalty across multiple dimensions (engagement channels, intelligent advisory, faster processing), personalizing offers with highly accurate underwriting, and improving operational efficiency across the value chain (from customer servicing to monitoring, record management, and more.).

Exhibit 1

Banks should prioritize using advanced analytics (AA) and machine learning (ML) in decisions across the customer life cycle.



[1]VAR is value at risk.
[2]AUM is assets under management.

Customer acquisition

The use of advanced analytics is crucial to the design of journeys for new customers, who may follow a variety of paths to open a new card account, apply for a mortgage, or research new investment opportunities. Some may head directly to the bank's website, mobile app, branch kiosk, or ATM. Others may arrive indirectly through a partner's website or by clicking on an ad. Many banks already use analytical tools to understand each new customer's path to the bank, so they get an accurate view of the customer's context and direction of movement, which enables them to deliver highly personalized offers directly on the landing page. Following local regulations governing the use and protection of customer data, banks can understand individuals' needs more precisely by analyzing how customers enter the website (search, keywords, advertisements), their browsing history (cookies, site history), and social-media data to form an initial profile of each customer, including financial position and provisional credit scoring. Based on real-time analysis of a customer's digital footprint, banks can display a landing page tailored to their profile and preferences.

These tools can also help banks tailor follow-up messages and offers for each customer. Replacing much of the mass messaging that used to flow to thousands or tens of thousands of customers in a subsegment, advanced analytics can help prioritize customers for continued engagement. The bank can select customers according to their responsiveness to prior messaging—also known as their "propensity to buy"—and can identify the best channel for each type of message, according to the time of day. And for the "last mile" of the customer journey, AI-first institutions are using advanced analytics to generate intelligent, highly relevant messages and provide smart servicing via assisted channels to create a superior experience, which has been shown to contribute to higher rates of conversion.[4]

Credit decisioning

Setting themselves apart from traditional banks, whose customers may wait anywhere from a day to a week for credit approval, AI-first banks have designed streamlined lending journeys, using extensive automation and near-real-time analysis of customer data to generate prompt credit decisions for retailers, small and medium-size enterprises (SMEs), and corporate clients. They do this by sifting through a variety of structured and unstructured data collected from conventional sources (such as bank transaction history, credit reports, and tax returns) and new ones (including location data, telecom usage data, utility bills, and more). Access to these nontraditional data sources depends on open banking and other data sharing guidelines as well the availability of officially approved APIs and data aggregators in the local market. Further, while accessing and leveraging personal data of customers, banks must secure data and protect customer privacy in accordance with local regulations (e.g., the General Data Protection Regulation in the EU and the California Consumer Privacy Act in the US).

By using powerful AA/ML models to analyze these broad and diverse data sets in near real time, banks can qualify new customers for credit services, determine loan limits and pricing, and reduce the risk of fraud.

— *Credit qualification.* Lenders seeking to determine if a customer qualifies for a particular type of loan have for many years used rule-based or logistic-regression models to analyze credit bureau reports. This approach, which relies on a narrow set of criteria, fails to serve a large segment of consumers and SMEs lacking a formal credit history, so these potential customers turn to nonbank sources of credit. In recent years, however, leading banks and fintech lenders have developed complex models for analyzing structured and unstructured data, examining hundreds of data points collected from social media, browsing history, telecommunications usage data, and more. This decisioning process is automated from end to end, so it can be completed nearly instantaneously, enabling the bank to predict the likelihood of default for individuals in a vast and potentially profitable segment of unbanked and underbanked consumers and SMEs. As banks build and refine their qualification model, they can proceed gradually, testing and improving the model—for example, by using auto-approvals for customers up to a certain threshold with significantly lower default risk and using manual verification to review those estimated to have a higher default risk and then gradually shifting more cases to automated decisioning.

— *Limit assessment.* Leading banks are also using AA/ML models to automate the process for determining the maximum amount a customer may borrow. These loan-approval systems, by leveraging optical character recognition (OCR) to extract data from conventional data sources such as bank statements, tax returns, and utilities invoices, can quickly assess a customer's disposable income and capacity to make regular loan payments. The proliferation of digital interactions also provides vast and diverse data sets to fuel complex machine-learning models. By building data sets that draw upon both conventional and new sources of data, banks can generate a highly accurate prediction of a customer's capacity to pay. Just a few data sources that may be available for analysis (with the customer's permission) are emails, SMS, and e-commerce expenditures.

— *Pricing.* Banks generally have offered highly standardized rates on loans, with sales representatives and relationship managers having some discretion to adjust rates within certain thresholds. However, fierce competition on loan pricing, particularly for borrowers with a strong risk score, places banks using traditional approaches at a considerable disadvantage against AI-and-analytics leaders. Fortified with highly accurate machine-learning models for risk scoring and loan pricing, AI-first banks have been able to offer competitive rates while keeping their

[4] Erik Lindecrantz, Madeleine Tjon Pian Gi, and Stefano Zerbi, "Personalizing the customer experience: Driving differentiation in retail," April 2020, McKinsey.com.

risk costs low. Some are also using their decisioning capabilities to quantify the customer's propensity to buy according to the customer's use of different types of financial products. Some even leverage natural-language processing (NLP) to analyze unstructured transcripts of interactions with sales and service representatives and, in some cases, collections personnel. By basing the offered rate on both creditworthiness and propensity to buy, the bank can optimize the balance of total asset volume, risk, and interest income within a lending portfolio.

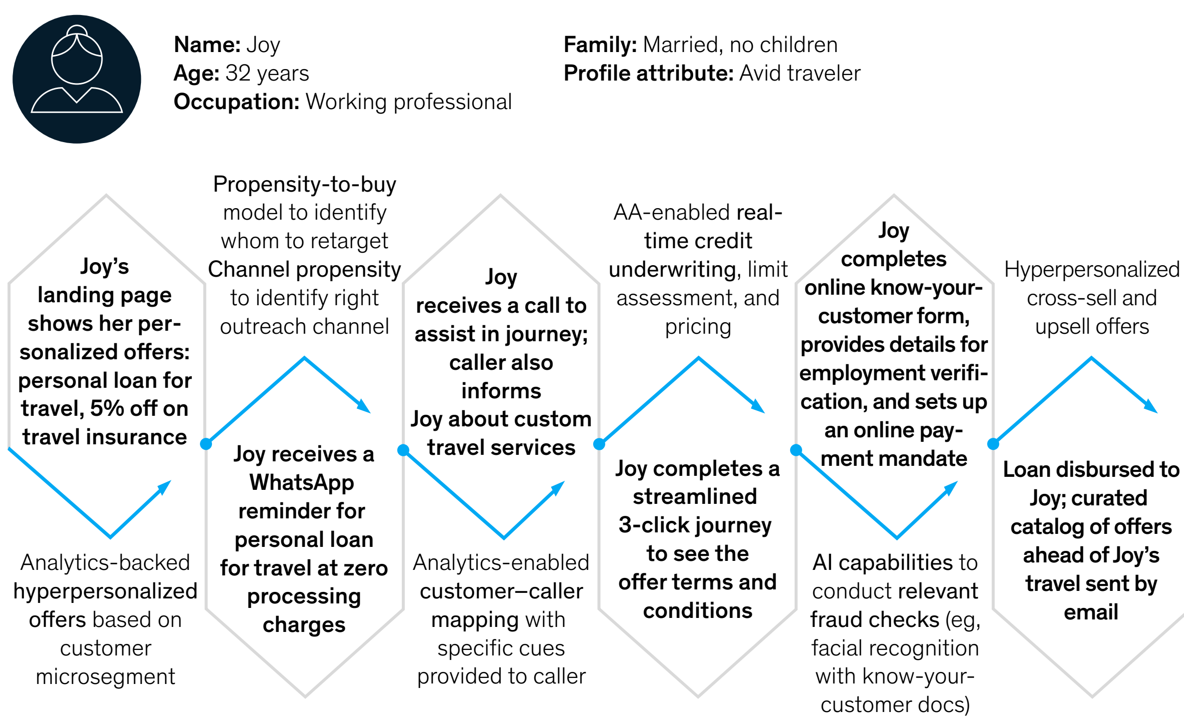
— *Fraud management*. As competition for credit relationships becomes concentrated in digital channels, the automated processing of loan applications and use of AA/ML models to expedite credit approval and disbursement of funds not only positions the bank to acquire new customers and increase market share, but also opens new opportunities for fraud. The costliest instances of fraud typically fall into one of five categories: identity theft, employee fraud, third-party or partner fraud (e.g., fraud by sales agents), customer fraud, and payment fraud (including money laundering and sanctions violations). Banks should continuously update their fraud detection and prevention models, as we discuss later with regard to edge capabilities. Ping An, for example, uses an image-analytics model to recognize 54 involuntary micro-expressions that occur before the brain has a chance to control facial movements.[5]

AI-driven credit decisioning can build the business while lowering costs. Sharper identification of risky customers enables banks to increase approval rates without increasing credit risk. What is more, by automating as much of the lending journey as possible, banks can reduce the costs of support functions and strengthen each customer's experience with faster loan approval and disbursement of funds, fewer requests for documentation, and credit offers precisely tailored to meet customer needs. Exhibit 2 illustrates how AI-enabled decisioning capabilities underpin a customer's onboarding journey.

[5] "Chinese banks start scanning borrowers' facial movements," Financial Times, October 28, 2018, ft.com.

Exhibit 2

The combination of AI and analytics enhances the onboarding journey for each new customer.



Monitoring and collections

Once a bank has employed AA/ML models to automate loan underwriting and pricing, it can also deploy AI and advanced analytics to reduce the burden of nonperforming loans. Increasingly, banks are engaging with clients proactively to help them keep up with payments and work more closely with clients who encounter difficulties. By drawing upon internal and external data sources to build a 360-degree view of a customer's financial position, banks can recognize early-warning signals that a borrower's risk profile may have changed and that the risk of default should be reassessed.

Beyond conventional data sources like repayment data and credit bureau reports, banks can digitize and leverage other interaction data from campaigns, field visits, and collection agents' comments to draw insights for collections strategy. Further, a variety of external data partnerships for location data and transaction history can help the bank understand both the customer's position and the most effective approach, or contact strategy, for averting default (Exhibit 3).

Contact strategy. To determine an appropriate contact strategy for customers at risk of default, banks can segment accounts according to value at risk (VAR), which is the loan balance times the probability of default. This allows banks to focus high-touch interactions on borrowers that account for the highest VAR; banks can then use low-cost channels like telephoning and texting for borrowers posing less risk. Banks have used this approach to reduce both the cost of collections and the volume of loans to be resolved through restructuring, sale, or write-off.[6]

[6] Ignacio Crespo and Arvind Govindarajan, "The analytics-enabled collections model," April 2018, McKinsey.com.

Exhibit 3

Advanced analytics and machine learning can classify customers into microsegments for targeted interventions.

Customer type

	True low-risk	Absentminded	Dialer-based	True high-touch	Unable to cure
Targeted intervention	Use least experienced agents provided with set scripts	Ignore or use interactive voice message (segment will probably self-cure)	Match agents to customers; send live prompts to agents to modify scripts	Focus on customers able to pay and at high risk of not paying	Offer debt-restructuring settlements early for those truly underwater
Impact	Onscreen prompts guide agent–client conversation based on probability of breaking promises	10% of time saved, allowing for reassignment of agents to more difficult customers and specific campaigns	Matching and prompts can increase sense of connection and likelihood of paying	Added focus addresses higher probability of default rates in this segment	Significant increase in restructuring and settlements increases chance of collecting at least part of debt

Source: Ignacio Crespo and Arvind Govindarajan, "The analytics-enabled collections model," McKinsey on Payments, August 2018, McKinsey.com

Treatment strategy. If contact strategies through various channels are inadequate to help the customer resume timely payment, banks must pursue stronger measures, according to the customer's ability and willingness to pay. Customers with high willingness but limited ability to pay in the short term may require restructuring of the loan through partial-payment plans or loan extensions. In cases where the customer exhibits both low willingness and limited ability to pay, banks should focus on early settlement and asset recovery. Advanced analytics, enabled by unstructured internal data sources such as call transcripts from collections contact centers and external data sources such as spending behavior on other digital channels, can improve the accuracy of determinations of ability and willingness to pay.

Deepening relationships

Strong customer engagement is the foundation for maximizing customer value, and leaders are using advanced analytics to identify less engaged customers at risk of attrition and to craft messages for timely nudges. As with any customer communication in a smart omnichannel service environment, each personalized offer is delivered through the right channel according to the time of day. Rich internal data for existing customers can enable financial institutions to create a finely tuned outreach strategy for each individual customer, guided by risk considerations.

Deeper relationships are predicated on a bank's precise understanding of a customer's unique needs and expectations. A bank can craft offers to meet emerging needs and deliver them at the right time and through the right channel. By doing so, the bank demonstrates that it understands customers' current position and aspirations and can help them get from the former to the latter. For example, by analyzing browsing history and spending patterns, a bank might recognize a consumer's need for credit to finance an upcoming purchase of a household appliance. Analysis of internal data on product usage can also reveal areas where the bank can make its offering more relevant to a customer's current needs. Ping An, for example, has developed a prediction algorithm to estimate the ideal product-per-customer (PPC) ratio for each user, based on individual needs. If analysis of a customer's needs produces an anticipated product usage ratio of eight but the customer uses only two products, the relationship manager receives a prompt to reach out to the customer and cross-sell or up-sell relevant ecosystem products.[7]

Servicing and engagement

AI-powered decisioning can enable banks to create a smart, highly personalized servicing experience based on customer microsegments, thereby enabling different channels to deliver superior service and a compelling experience with interactions that are fast, simple, and intuitive.[8] Banks can support their relationship managers with timely customer insights and tailor-made offers for each customer. They can also significantly improve agents' productivity with streamlined preapproved products crafted to meet each customer's distinct needs. Models that analyze voice and speech characteristics can match agents with customers based on behavioral and psychological mapping. Similarly, transcript analysis can enable prediction of customer distress and suggest resolution to the agent.

Deployment of AA/ML models at scale

Leveraging AI to automate decision making in near real time is a complex and costly endeavor. If banks are to earn the required return on their technology investments, they must begin with a strategy and road map to capture maximal scale benefits in the design, building, and deployment of AA/ML models.

As banks embark on this journey, leaders must encourage all stakeholders to break out of siloed mindsets and think broadly about how models can be designed for uses in diverse contexts across the enterprise. AI-first organizations have succeeded by organizing the effort around four

[7] "Ping An Bank: Change everything," Asiamoney, September 26, 2019, asiamoney.com.
[8] Violet Chung, Malcolm Gomes, Sailee Rane, Shwaitang Singh, Renny Thomas, "Reimagining customer engagement for the AI bank of the future," McKinsey.com, October 2020.

main elements: First, they prioritize the analytics use cases with the biggest impact on customer experience and the most value for the bank. Second, they ensure that the data architecture, data pipelines, application programming interfaces (APIs), and other essential components are available for building and deploying models at scale through standardized, repeatable processes.[9] Third, they establish a semiautonomous lab for experimentation and prototype development and set up a factory for industrial-scale production of the solution. Fourth, they assemble the right mix of talent for agile, cross-functional teams and empower them to maximize value in close alignment with enterprise strategy.

Several leading banks have established semi-autonomous labs offering a test-and-learn environment where cross-functional teams can experiment with different approaches to achieving the value-generating goals of a particular use case, moving from minimal viable product to scalable solution in a matter of weeks. Building AA/ML models at scale and deploying them across the enterprise depend on matching the right talent and skills with each of the roles required for a successful analytics lab and factory (Exhibit 4).[10]

The lab combines talent from business, analytics, technology, operations, and more. There are two main technical roles. One is the data scientist, who is responsible for identifying the analytics techniques required to meet the business goal and for programming advanced analytics algorithms. The other is the data engineer, who scopes the data

[9]Tara Balakrishnan, Michael Chui, Bryce Hall, and Nicolaus Henke, "The state of AI in 2020," November 2020, McKinsey.com.
[10]Nayur Khan, Brian McCarthy, and Adi Pradhan, "Executive's guide to developing AI at scale," October 2020, McKinsey.com.

Exhibit 4

Diverse roles are necessary for building and deploying AA/ML models at scale.

Lab environment

Product owner
Leads the squad; typically a business owner who provides voice of the customer

Data scientist
Frames the business problem and develops advanced analytics algorithms

Data engineer
Scopes the data available; builds data architecture and data pipelines

Translator
Interfaces between business and technical stakeholders

Designer
Focuses on interaction between end users and the analytics solution output

Delivery manager
Responsible for all aspects of delivery of the analytics solution to meet squad goal

Factory environment

Product owner
First point of contact for external stake-holders; defines the solution criteria

ML engineer
Optimizes ML models for performance and scalability; deploys the models into production

DevOps engineer
Develops CI/CD[1] pipelines to automate parts of the software-deployment pipeline

Infrastructure architect
Designs infrastructure components for the analytics use case

Full-stack developer
Develops software components for the back and front ends of AI solutions

[1]Continuous integration and continuous deployment.

available, identifies major sources of data to be consolidated for analytics, develops data pipelines to simplify and automate data movement, and sets up data architecture for storage and layering. In addition, the role of translator is crucial to ensure consistent communication and smooth collaboration between business leaders and analytics specialists.

On factory teams, one of the primary technical roles is the DevOps engineer, who is responsible for developing continuous integration (CI) and continuous deployment (CD) pipelines for deploying software. In addition, the full-stack developer is responsible for developing software components for other layers of the stack. The machine-learning engineer prepares models for deployment at scale, and the infrastructure architect ensures that the analytics solution is compatible with the architecture of the core tech and data layer of the capability stack.

The lab-and-factory setup requires flexible and scalable technologies to handle the changing requirements of analytics engines. It is also important to give analytics teams access to the centralized data lake, and these teams must be able to draw upon raw data from diverse sources to generate data sets to be used in building models. The technology supporting the solution must be modular to allow the transfer of developed solutions to factory production using DevOps tools. Finally, it is crucial to embed performance management and risk controls within models to avoid adverse impacts on operations.

Once the lab has developed a model, the factory takes over, running 24/7 to put the model into production and deploying it at scale in diverse use cases across the enterprise.

Augmented AA/ML models with edge capabilities

The rapid improvement of AI-powered technologies spurs competition on speed, cost, experience, and intelligent propositions. To maintain its market leadership, an AI-first institution must develop models capable of meeting the processing requirements of edge capabilities, including natural-language processing (NLP), computer vision, facial recognition, and more.

Some edge technologies already afford banks the opportunity to strengthen existing models with expanded data sets. For example, many interactions with customers—via telephone, mobile app, website, or increasingly, in a branch—begin with a conversational interface to establish the purpose of the interaction and collect the information required to resolve the query or transfer it to an agent. A routing engine can use voice and image analysis to understand a customer's current sentiment and match the customer with a suitable agent. The models underpinning virtual assistants and chatbots employ NLP and voice-script analysis to increase their predictive accuracy as they churn through vast unstructured data generated during customer-service and sales interactions.

While each customer-service journey presents an opportunity to deepen the relationship with the help of next-product-to-buy recommendations, banks should constantly seek to improve their recommendation engines and messaging campaigns. Feedback loops, for example, can help marketing teams and frontline officers gauge the effectiveness of an offer by analyzing customers' ongoing browsing and transaction activity within the bank's digital ecosystem and beyond (Exhibit 5, next page).

As edge capabilities become more powerful, leaders are developing new, increasingly complex analytics solutions to create a superior experience and introduce distinctive innovations. Use of computer vision and voice-to-script conversion can speed the completion of forms—for instance, enabling a customer to respond orally to questions and upload documents from which relevant data can be extracted automatically using optical character recognition (OCR). Facial and sentiment analysis during an in-person consultation or videoconference can support frontline representatives with messages and offers finely tuned to the customer's needs and aspirations.

Several banks use voice recognition to verify customer identity for certain low-value, high-volume transactions. Some are using facial

Exhibit 5

Edge capabilities enhance customer-service journeys.

Digital self-cure channels for customers (eg, WhatsApp, mobile app, website)	**Voice-recognition-enabled IVR,**[1] **frontline bots** handling 30–50% of queries	**AI-enabled customer profiling, customer–agent matching**	**Voice-analytics- and NLP**-enabled[2] customer-sentiment analysis	AI-enabled **service-to-sales engine**	**Feedback loop** via engagement channels
Customer may seek immediate resolution of queries through digital self-service channels	If query is not resolved through automated channels, customer may contact bank via chat or request call with live agent	Customer connected to the appropriate agent (chat or call) based on type of query and customer profiling	Contact-center agents supported by live feedback and prompts to sustain superior customer experience	Customers are prompted for any specific offers preapproved for them	Postcall feedback and automated follow-up occur via digital channels

[1]Interactive voice response.
[2]Natural-language-processing-enabled.

recognition to authenticate customers' identity as soon as they enter a branch, approach an ATM, or open the banking app on a mobile device. As noted earlier, facial analysis is also useful in identifying potential fraud.

Leading banks are using blockchain to create smart contracts, secure trade documents and automate the release of funds upon delivery of goods, and establish shared utilities to reduce the burden of know-your-customer (KYC) and anti-money-laundering (AML) compliance for banks and customers. Edge capabilities deployed as part of an enterprise strategy to enhance the AI bank's value proposition have the potential not only to improve credit underwriting and fraud prevention but also to reduce the costs of document handling and regulatory compliance.

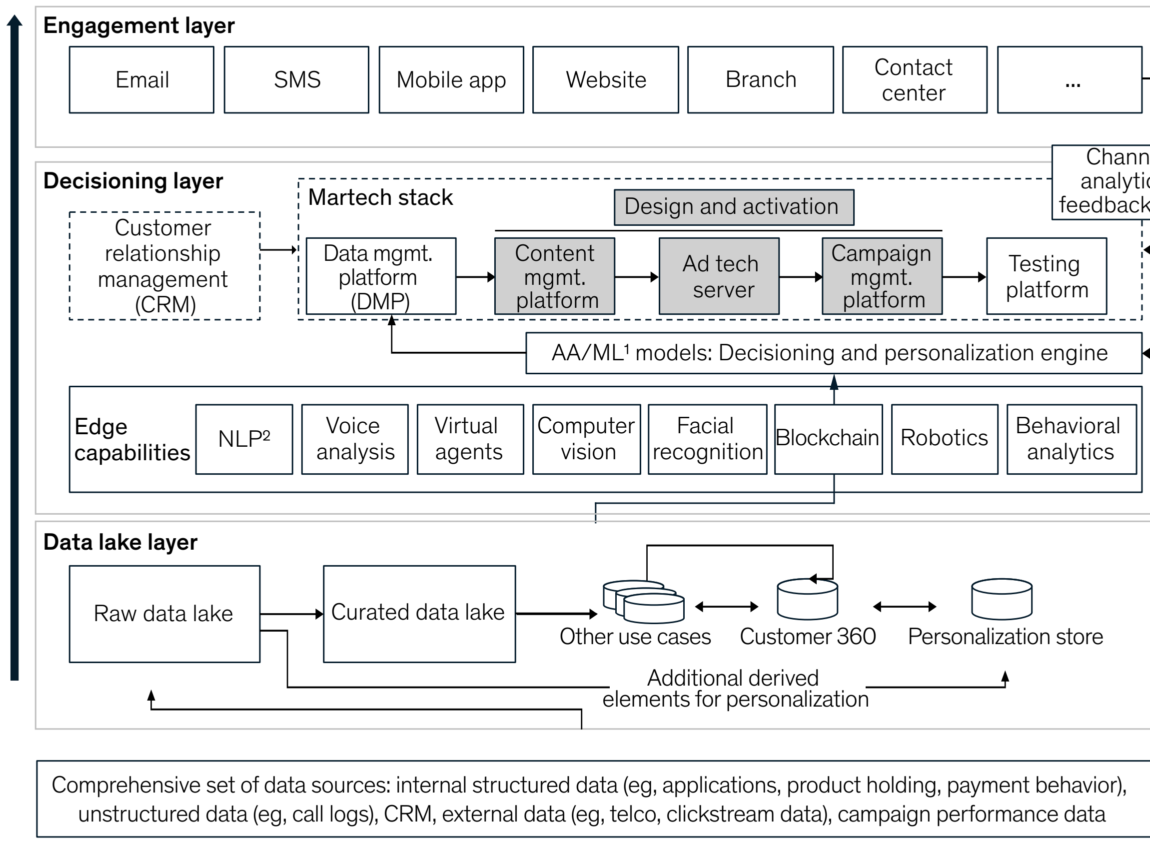
Enterprise-wide digital marketing engine

While the automated decisions generated by AA/ML models provide highly accurate, real-time predictions of customer behaviors, banks must go the last mile to ensure that these analytical insights have an impact on customer behavior, such as purchasing a product, making a loan payment, or exploring new service offers. In other words, an organization must establish a mechanism to "translate" analytical outcomes into compelling messages to communicate to the customer at the right time, through the preferred channel—be it email, SMS, mobile app, website, branch staff, or a relationship manager—according to the time of day.

This last mile from decisioning to messaging is the domain of the digital marketing engine. Seamlessly integrated with applications across the full AI-and-analytics capability stack with the help of APIs, from data infrastructure to engagement channels, this engine supports the nearly instantaneous processing of raw data to produce tailored messages communicated via engagement channels. Exhibit 6, on the next page, illustrates the position of the digital

Exhibit 6

The digital marketing engine requires full stack capabilities.



[1]Advanced-analytics and machine-learning.
[2]Natural-language processing.

marketing engine (or martech stack) within the decisioning layer of the AI-bank capability stack.

The digital marketing engine comprises platforms and applications fulfilling four main functions: data management, design and activation, measurement and testing, and channel analytics. The data management platform, which forms part of the core tech and data infrastructure layer of the AI-bank capability stack, supplies the data used to create and manage target customer segments. The design and activation function has three elements: (1) the content management platform, where messages, offers, advertisements, and other interventions are created, managed, and modified; (2) the ad tech server, which automates advertisements based on data analysis; and (3) the campaign management platform, which supports the creation and management of marketing campaigns, which are conducted automatically according to the microsegmentation generated by the data management platform.

Just as the AI-and-analytics capability stack entails fundamental changes in the organization's talent, culture, and ways of working, the success of digital marketing capabilities depends on an agile operating model. This model consists of autonomous cross-functional teams (or pods) drawing upon the talent of different parts of the enterprise, such as business units, marketing, analytics, channels, operations, and technology. Each pod should also include representatives from partner organizations crucial to the digital marketing effort—for example, user-interface and user-experience designers, who lay out the campaign's look and feel and its flow, and copywriters, who finalize the language of any intervention. The members of each pod collaborate on developing, managing, and improving engagement campaigns, and each member is accountable for campaigns' impact according to clearly defined key performance indicators (KPIs).

To achieve the desired outcome, an AI-first bank launching daily personalized communications to millions of customers must build tools for continual testing and learning. The measurement and testing platform flags potential aspects of content or distribution to improve, thereby enabling teams to evaluate in real time the effectiveness of campaigns.

Another source of continual feedback is channel analytics, which includes tools and dashboards for real-time tracking of engagement across each target segment. Every day, each pod leverages the channel analytics and measurement and testing platforms to closely track various indicators, including delivery rates, email open rates, click-through rates by channel for customers seeking more information (the first call to action), conversion rates, and more. These diagnostics help members of the pod experiment with potential enhancements to messages, advertisements, and campaign design. As an example, Commonwealth Bank of Australia (CBA) leverages its mobile app to test messages and learn within hours what works and what must be changed. This cadence enables rapid scaling of campaigns to similar customer segments.[11]

In measurement of campaigns' impact, scientific rigor is crucial. To allow for precise measurement of the incremental value of the campaign, each target segment should include a control group of customers excluded from the campaign. The tools and capabilities for evaluating the effectiveness of customer-engagement campaigns help employees across the organization understand how they can enhance their impact on individual customers and add value to an AI-oriented culture.

The rapid improvement of AI-powered technologies spurs competition on speed, cost, experience, and intelligent propositions. To remain competitive, banks must engage customers with highly personalized and timely content to build loyalty. Personalized offers with tailored communication delivered at the right time through the customer's preferred channel can help banks maximize the lifetime value of each customer relationship and reinforce the organization's market leadership. To achieve these benefits, banks must build AI-powered decisioning capabilities fueled by a rich mixture of internal and external data and augmented by edge technologies. The core technology and data infrastructure required to collect and curate increasingly diverse and voluminous data sets is the topic of the next article in our series on the AI-bank capability stack.

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[11] Paul McIntyre, "CommBank's analytics chief on how its AI-powered 'Customer Engagement Engine' is changing everything," Mi3, September 21, 2020, mi-3.com.au.