Artificial Intelligence: Practical Superpowers

The Case for AI in Financial Services in Africa

BFA

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About FIBR

Launched in 2016, FIBR is an initiative of BFA in partnership with Mastercard Foundation to create new ways to connect low-income populations to financial services that meet their needs. Rapid uptake of smartphones in these markets means we can digitize data about how individuals otherwise informally, transact as employees, customers or suppliers in their communities and with local businesses. The digitization of these trusted business relationships allows for new data that a broader range of providers can use to offer tailored financial products and services to this demographic. FIBR focuses on how technology can enable the generation of data insights to empower employers, employees and customers in the MSME and PAYGO sectors with financial services to achieve their goals. For more information and to sign up for our newsletter, please visit: www.fibrproject.org. Follow on Twitter @FIBR_BFA #inclusivefintech.

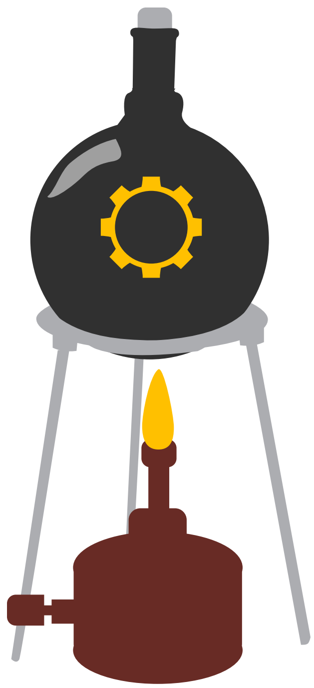
About Mastercard Foundation

The Mastercard Foundation works with visionary organizations to provide greater access to education, skills training and financial services for people living in poverty, primarily in Africa. As one of the largest private foundations, its work is guided by its mission to advance learning and promote financial inclusion to create an inclusive and equitable world. Based in Toronto, Canada, its independence was established by Mastercard International when the Foundation was created in 2006. For more information and to sign up for the Foundation's newsletter, please visit www.mastercardfdn.org. Follow the Foundation at @MastercardFdn on Twitter.

About BFA

BFA is a global consulting firm specializing in using finance to create solutions for low-income people. Our approach is to seek out, create and implement financial solutions to help people manage challenges and seize opportunities. We partner with cutting-edge organizations that touch the lives of low-income consumers such as financial institutions, fintech companies and information providers. In creating solutions, we integrate our deep expertise in customer insights, business strategy, new technology and growth-enabling policy and regulation. Founded in 2006, BFA's clients include financial institutions, technology companies, donors, investors and policymakers. BFA has offices in Nairobi, Delhi, Boston, Medellín and New York. For more information, please visit: www.bfaglobal.com and follow on Twitter @BFAglobal.

Innovating solutions for finance, for life.



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Executive Summary

While admittedly often overshadowed by hype, Artificial Intelligence (AI) today offers real opportunities for financial sector players to access new and augmented business abilities. Wielded well, AI can unlock data to reveal insights about customers, operations and businesses to inform key decisions. Sensors in smartphones also open up a whole new world of data as captured through images, text, sound and location, which AI can translate into information in real-time and with high fidelity. These kinds of advancements in the field are especially exciting for financial sector players in Africa, with real-use applications in the informal retail sector, and for businesses that rely on last-mile distribution networks, such as pay-as-you-go (PAYGo) providers,[1] to reach their customers. Grounded in creating a practical and compelling case for financial services providers (FSPs) in Africa, we present an overview of AI and its benefits to businesses -- lowering costs, increasing revenue and competing in a changing market -- that could ultimately enable a more customer-centric financial ecosystem.

FIBR, a program of BFA with the support of Mastercard Foundation, seeks to digitize the informal business relationships that individuals have in their communities and to use that data to make the case for FSPs, such as banks and fintech companies, to offer financial services to low-income customers in Africa. Given the FIBR lens, we interviewed firms that are based out of or operate in African markets to better understand the unique benefits and challenges of utilizing AI to extend financial services to African consumers. There are several fintech companies that already employ AI successfully to streamline customer service inquiries, extend digital credit and provide personalized financial advice or nudges directly to customers or in partnership with larger financial providers, such as banks or insurance companies. We have sought to lay out how these providers currently use AI and illustrate the four main use cases that are relevant for FSPs, which are:

- CREDIT RISK ASSESSMENTS
- CHATBOTS AND CONVERSATIONAL INTERFACES
- MACHINE VISION AND VOICE RECOGNITION
- PERSONAL FINANCIAL MANAGEMENT

To provide a glimpse of what is possible now and in the future in African markets, we have highlighted examples from our own work implementing applications of AI with African fintech companies, and from our experimental gallery of AI applications for the micro, small and medium enterprise (MSME) and PAYGo sectors that can be built with the technology available today.

Executives of institutions such as banks and PAYGo companies, learning about AI or seeking a starting point, should also consider several barriers to integrating AI into their businesses. These include:

1. The right question to ask
2. The right format, localization and quality of data
3. The right kind of talent and organizational capacity
4. The right infrastructure and regulatory environment
5. The right level of customer trust

With these challenges in mind, we outline how financial providers can approach AI for their organizations using an AI readiness framework. The framework establishes a hierarchy of needs to ensure that the right foundations -- data, insights and organization -- are in place for a successful AI strategy. We also consider AI post-implementation and the role that humans need to play in the oversight of a living model that learns over time.

While we came across only a handful of banks or insurance providers that are utilizing AI to disrupt services in African markets, we believe that the potential is clear and that there is ample room for more institutions to investigate and access these practical superpowers. From impacting internal processes to customer-facing ones, AI can help providers automate, derisk and extract deeper value from their massive datasets on customers. Above and beyond generating cost savings, in more advanced AI economies, such as the US, Canada and China, AI-first adopters consider the real benefit of AI to be increased market share and revenue.[2] In these markets, financial providers are among the first adopters, given their longer histories of digitization. Likewise, there are vast opportunities for African financial providers with their long customer histories to lead with AI towards the development of scalable and excitingly relevant customer-centered products and services.

1. Background

At **FIBR**, an initiative of **BFA** in partnership with **Mastercard Foundation**, we have been exploring how our partners might use artificial intelligence (AI) to augment their services and, ideally, ensure more relevant and compelling product offerings for their customers. FIBR creates partnerships between fintech firms and banks to tailor digital financial services to low-income customers in Africa and leverage networks of small businesses to reach customers. Though there is substantial hype around AI and many applications are not yet clear, the potential for AI to transform entire industries is very real. In the midst of these claims, in 2017 FIBR spoke with a number of financial providers to understand how AI can contribute to building a more customer-centric financial ecosystem.

This report is for executives of financial institutions and PAYGo companies that are familiar with AI and are considering it for their businesses. With these readers in mind, we gauge how financial providers are currently using AI, what challenges and barriers they are facing, and demonstrate current and future applications of AI. We interviewed firms that are based out of or operate in African markets to better understand the unique benefits and challenges of utilizing AI to extend financial services to African consumers, but these lessons should apply to financial innovators in other markets as well. We see that savvy players are adopting AI in core areas of the business, such as customer service and operations. These players are realizing real returns from greater accuracy in credit predictions, lower default rates and reduced costs of customer support.

AI adopters are looking to make inroads not only with artificial intelligence but specifically with machine learning (ML) to overcome the problem of irrelevant and inaccessible products for a larger swath of their customer base -- including the unbanked. If wielded well, there is a sense of liberation from a one-size-fits-all world of financial products. Imagine putting personalized services at the consumer's fingertips, anticipating needs or offering 24-hour customer service via multiple channels, whether through a chatbot application or entirely as a voice conversation (similar to Amazon's Alexa but for financial advice).

2. What Do We Mean by AI?

AI is typically defined as the capability of a machine to imitate intelligent human behavior, a definition which tends to evoke strong visions for the future in the form of either fix-all solutions or evil robot overlords. Here we intentionally take a more pragmatic approach, skirting the hype in favor of focusing on augmentation -- rather than imitation -- of human expertise, ingenuity, craftsmanship and intelligence.

In this sense, AI enables institutions to analyze large and increasingly complex datasets that would otherwise have been prohibitive or impossible for humans to do (for example, analyzing data from multiple, disparate data sources such as facial analysis, sentiments, etc.), or at least to do so more rapidly. In the case of financial services, this could mean, for example, recognizing customer payment patterns to identify payment profiles, which in turn permits the system to target individual customers with tailored offerings.

> "AI's don't get bored or distracted: a model can keep making decisions over different pieces of data, millions or billions of times in a row, and not get any worse (or better) at it."
>
> --Yonathan Zunger, Distinguished Engineer on the Privacy Team at Google

Defining AI is famously tricky -- so much so that the term "AI effect" refers to the nature of AI's definition as a constantly moving target. In this report we will seek to distinguish between automation and more sophisticated forms of artificial intelligence, as illustrated in Figure 1. Technically, AI includes manually crafted automation, such as macros, as well as statistics and traditional programming, such as manual regression (the first two columns). However, we will refer specifically to AI as applications that are already being automated, such as ML and Robotic Process Automation (RPA). On the far end of the spectrum, Artificial General Intelligence (AGI), or machine intelligence that would perform any intellectual task a human can, is still in its infancy and not covered here. Readers can refer to the Annex for in-depth explanations of the types of ML.

Automation

Automation refers to making automatic a set of tasks that humans might routinely perform. It allows computers or robots to perform tedious, repetitive functions for humans, freeing their time for more sophisticated work such as analyzing and decision-making versus cleaning and conditioning the data.

In the context of financial services, a basic chatbot for customer inquiries or customer onboarding might walk customers through a script programmed by basic if-then rules, or a software bot could save time for both customers and staff by automating the redundant process of filling in forms. Firms such as EY and AT&T in the US already employ back-end-facing software bots to automate repetitive and low-value tasks to help employees work more efficiently.[3] Basic biometric identification – the automated identification of individuals by querying a large database using anatomical and behavioral characteristics such as fingerprint, face, iris and voice -- is another example.[4]

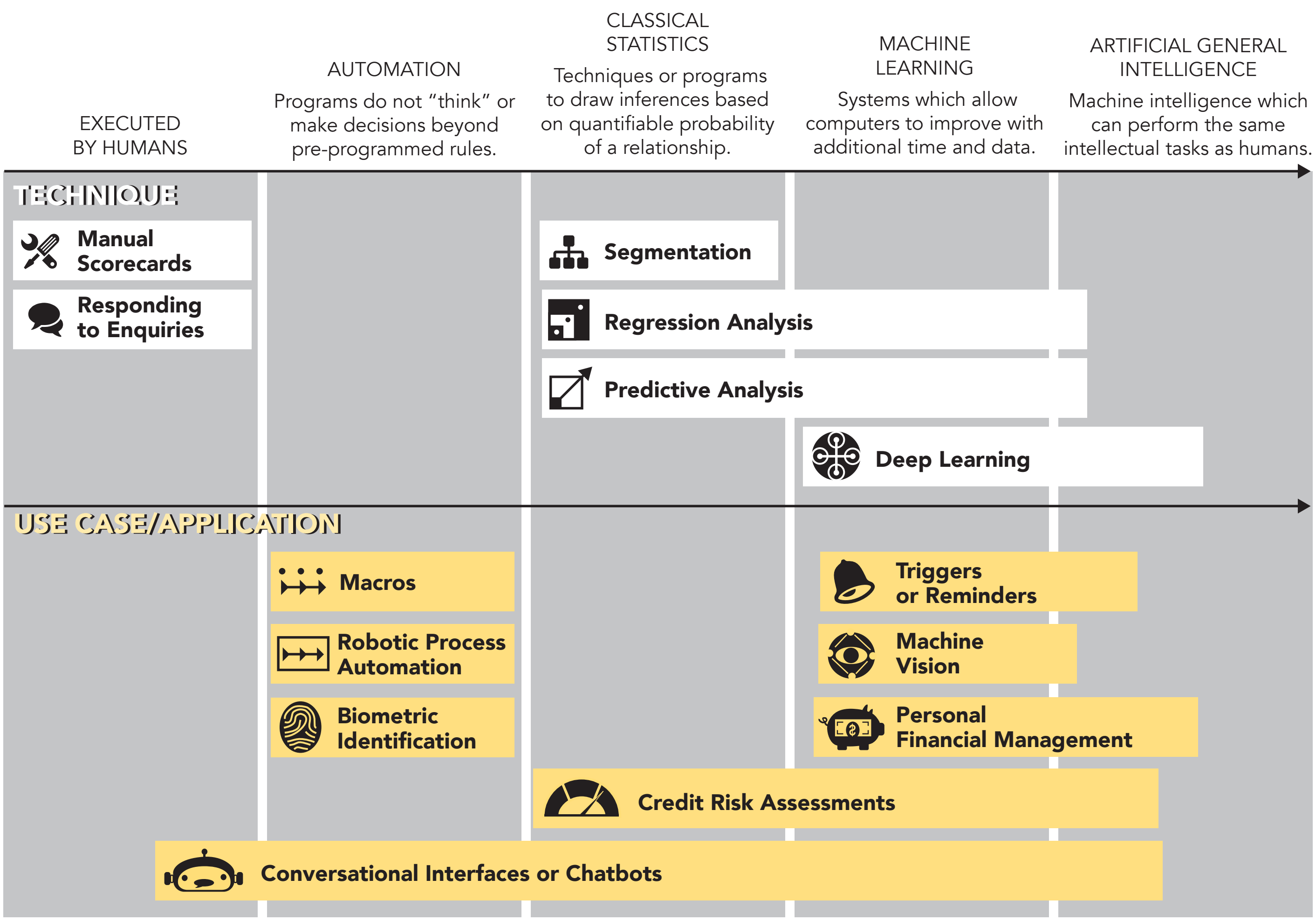
Statistics & Programming

One step beyond automation are classical statistical and programming techniques. These processes, typically undertaken by data analysts and data scientists, combine the use of tools such as probability distributions, summary statistics, software like Excel spreadsheets, statistics packages and numerical analysis libraries to come to a useful, often bespoke interpretation of the data.

An example of this category might include linear or logistic regression – a set of statistical processes for estimating the relationships among variables -- to determine whether the length of a chatbot request indicates anything about the urgency of the request. Another example might include customer segmentation, the practice of dividing a customer base into groups of individuals with similar characteristics that might be relevant to the marketing of the chatbot solution and underlying financial products.

Regression and classification analyses like these are interesting tools of statistics that also serve as a foundation for ML: systems that automatically and iteratively improve with the addition of relevant data. The term "relevant" here is key, and we argue below that solid business and customer insights foundations -- often built on traditional statistical techniques -- are core to the exploration of more sophisticated forms of AI.

Figure 1: The Spectrum of Artificial Intelligence



Machine Learning

This report focuses on the applications and benefits of ML, on which the vast majority of use cases currently in play are based. What is the distinction between regression analysis and ML? In the words of Mike Yeomans, a researcher of behavioral science and big data: "Think of [ML] simply as a branch of statistics, designed for a world of big data." Compared with regression analysis, ML is distinguished by the breadth and complexity of data that ML models can digest and learn from, combined with the fact that these algorithms can constantly refresh the results they produce in real-time, allowing institutions to act on these insights immediately. Therefore, the results can be used to provide analysis or responses tailored to the level of the individual.

Continuing with our exploration of Figure 1, chatbots can become highly sophisticated through a combination of natural language processing (NLP) and ML. Rather than preprogramming conversations based on fixed rules and a finite set of expected inputs, an ML algorithm can take the raw conversational data derived from users' responses and flow directly to optimize conversations, generate appropriate responses and improve over time as it gains more data points from customers interacting with the bot.

3. The ROI for AI

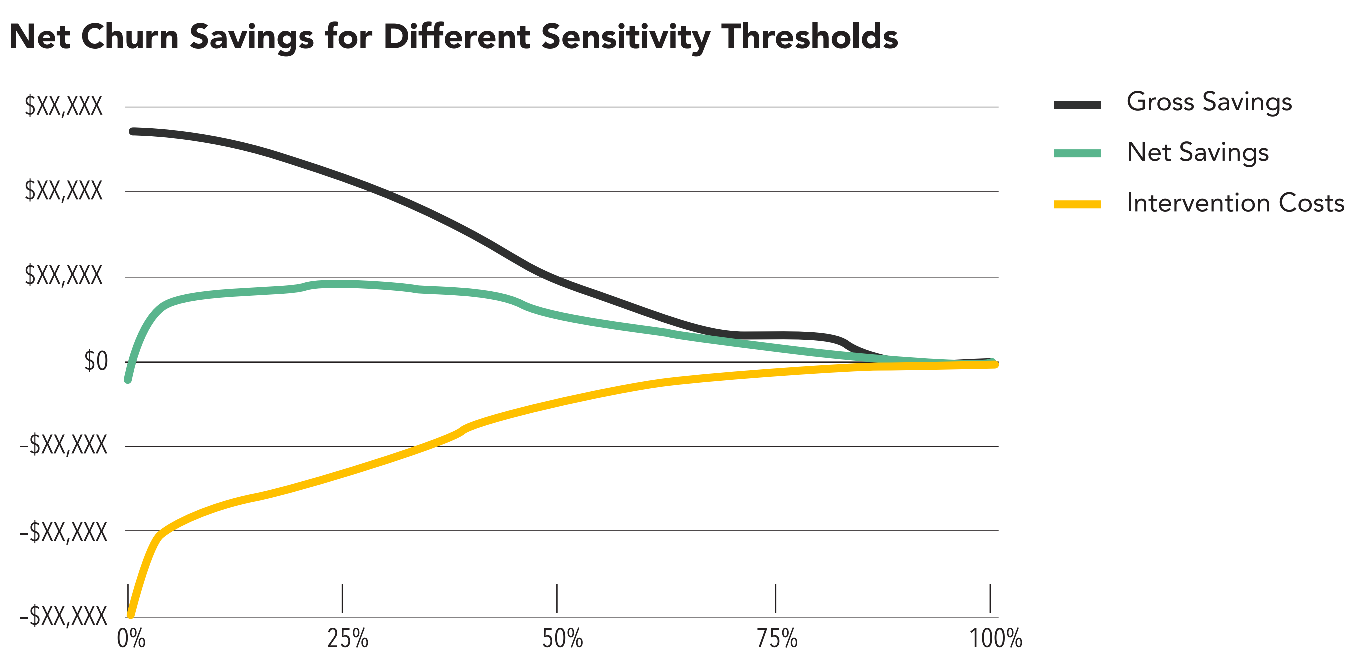
FSPs, in particular, can look to AI for a return on investment (ROI) in the form of reduced costs, increased revenue and differentiation in a changing marketplace. On the back-end, there are efficiency gains from automating processes and cost savings from managing risks, such as defaults or churn. On the front-end, personalized product offerings, deeper customer engagement, education over digital channels and seamless ID verification are some examples of reimagined customer experiences that give firms a competitive edge.

Cost Savings

Machine learning is bringing down the cost of predictions, allowing humans to make them in a cheaper, better and faster manner.[5] In this vein, BFA developed ***Chiron***, a business intelligence dashboard, to reveal insights that allow management, call centers and field and sales teams to make better decisions and take proactive approaches to improve customer health. Chiron offers a prediction model for customer churn (also referred to as rate of attrition or default) using ML techniques. The model allows the FSPs to categorize customers into archetypes based on historical payment data (i.e., no risk, low risk, medium risk, high risk) and calculate customer lifetime value.

Figure 2: ROI Calculator

Cost of Churn	Intervention Costs	Effectiveness of Intervention	Optimal Threshold	Number of Interventions	Cost of No Intervention	Minimal Cost	Clients Saved	Net Savings
$XXX	$XX	XX%	XX%	X,XXX	$XXX,XXX	$XX,XXX	XXX	$XX,XXX



We implemented predictive analytics models to determine likely future actions of each customer segment, including future payment behavior and churn risk. Also built into this analysis is a "ROI calculator" (Figure 2) demonstrating the effective savings from interventions that offset the cost of predicted churn, based on a conservative optimal threshold (25 percent). In one example, applying realistic company data, projected net annual savings amounted to almost $240,000, substantial for a mid-sized firm. We are now working with partners to plan testing with their current customers, including learning what interventions will be effective to reduce churn at an acceptable cost.

With **Destacame**,[6] an alternative credit scoring platform that uses data such as bill payment histories for basic services, to assess individual payment capacity and creditworthiness, we demonstrated that ML has the potential to substantially deliver better results in predicting good and bad payers while also saving firms time via automation.[7] But there is a second layer to the benefits of an ML-based approach for costing loans, and that is reducing the costs of delinquency. In our simulation of applying ML to credit scoring, the three cost levers -- deferred income, recovery costs and write-offs -- can impact cost in similar orders of magnitude.[8] ML, therefore, has the effect of impacting all three cost levers since there are overall fewer bad loans at acquisition.

Looking beyond AI based on purely financial data, alternative data is also helping reduce costs for lenders, resulting in unbanked individuals gaining better access to mainstream financial services. Data sources such as utility bills, automotive credit history, census data and airtime payments can serve not only as a proxy for the traditional credit scoring models but also to complement current credit scoring algorithms, and ultimately to reduce defaults and associated costs.

Increased Revenues

The ML insights can also lead to a more tailored product offering and to serving more customers. With **Nomanini**,[9] we analyzed transactional data to scope and assess the feasibility of predictive ML models, which confirmed that most airtime merchants had airtime stock outages during periods when they were otherwise predicted to have sales. Based on this predicted sales performance, merchants were offered short-term, non-collateralized loans. During the course of the initial pilot we saw two main effects. First, because of the access to funding, merchants had a seven percent higher rate of sales -- and therefore revenues -- on days when they had loans out. Second, through improvements to the user interface (UI) and customer education as well as ongoing data collection and retraining of the model the rate of default decreased progressively, from 14 percent in the first period of the pilot to 1.5 percent in the final phase.[10] Beyond these direct effects, the generated credit profiles are expected to inform and derisk the design of longer-term (1-3 months) loans, helping the merchants to climb the credit ladder.

> "When looking at artificial intelligence from the perspective of economics, we ask the same, single question that we ask with any technology: What does it reduce the cost of?"
>
> -- Ajay Agrawal quoted in an interview with McKinsey's Rik Kirklan

With the ability to cost-effectively segment and service customer groups further into the long tail, firms can look beyond the mass-market opportunity. For example, we are exploring smartphone financing models, whereby providers could offer more flexible, individualized terms that would allow some customers who would otherwise be considered delinquent by traditional standards to pay off their loans more quickly or benefit from periods of non-payment. Where the costs might once have been prohibitive, with ML providers can identify and serve micro-segmented customers with products that are better suited to how they manage their finances.

There is promise also for the business customer. Small businesses are notoriously difficult to lend to because lenders must estimate expected revenues, which requires some level of judgment. But data collected from the sensors in smartphones, whether voice, movement, temperature or light, open up possibilities that we have begun to explore in the FIBR AI Gallery (see below), such as assessing the number of people entering a store in a given time period or evaluating the shelves to assess the shopkeeper's creditworthiness.

Differentiation

How can providers rethink their product or service to turn them into a customer-centric offering? One key differentiator is bringing ease and convenience to the heart of the customer experience. Low-touch automated or personalized messaging can be used for financial and product education, a first start for engaging customers and prompting them to act. The promise of 24-hour customer care enabled by chatbots, proactive alerts, notifications and financial advice is already here with companies such as Arifu, Edume, Juntos, Teller and PesaKit. Through BFA's program RegTech for Regulators Accelerator (R^{2}A), chatbots are also being prototyped to address consumers' queries and complaints to financial authorities, whom can then leverage the resulting data and insights to inform oversight and policy development.

AI can also be used to take the headache out of cumbersome transactions, making the experience seamless, immediate and efficient. With BFA, **Smile Identity** (Smile ID)[11] developed a combination of open-source algorithms to authenticate identity based on facial recognition in response to a need for robust fraud detection in African markets. For many African consumers identity verification is a time-consuming process, requiring potential customers to deal with multiple forms and often travel great distances to physical banks to open a financial account. We worked with Smile ID to conduct user interviews and to test and improve their software development kit (SDK), which captures images on any smartphone and sends them for immediate processing using computer vision to match selfies with photo IDs and optical character recognition (OCR) to extract important personal details (name, date of birth, etc.), expediting processes for both institutions and customers. Singapore-based **LenddoEFL** is also combining computer vision with OCR and text extraction techniques to confirm the identity of new customers. A visit to the FIBR AI Gallery demonstrates applications of OCR to speech for dictating aloud terms of financial products for less literate populations, and for suggesting improvements to a store's layout using computer vision techniques such as image segmentation and classification. These are just some practical demonstrations of how AI today is significantly reducing the customer friction at points of interaction with the provider.

Over time, we expect to see additional innovations around financial offerings that are uniquely tailored to each customer's needs and behaviors, similar to the way Google and Facebook track a user's online activities and offer unique search responses, newsfeeds and ads.

4. AI Use Cases for FSPs in Africa

Today in Africa, we see financial providers and fintech companies implementing the following four broad categories of use cases (Figure 3). Again, many of these use cases build on the popularity of SMS messaging among broad segments of users, whether they use feature phones or smartphones. Messaging is also a natural starting point as most African consumers are not familiar with web browsers or applications beyond chat applications.

Credit Risk Assessments

Unsurprisingly, AI for credit risk assessments is among the most popular use cases currently employed in the African financial services market. A number of players we spoke with are investigating how to employ credit assessments to offer credit directly to individuals via mobile, such as Kenya's **Branch** and **Tala**, or to assess and lend to new segments, such as Nigeria's **Aella Credit** or South Africa's **Lulalend**, which focus on scoring small business borrowers.

Aella Credit, based in the US and Nigeria, provides ML-driven risk assessment in both a business to business (B2B) integration with employers or cooperatives and a business to customer (B2C) model using mobile. **Cignifi**, based in the US but with global operations, does the same but takes it two steps further by providing artificial-intelligence-as-a-service via a platform, Maxymus. With it, FSPs and mobile network operators (MNOs) can predict the creditworthiness of customers. Cignifi's platform employs neural networks to predict behavior and inform marketing decisions. As Qiuyan Xu, Chief Data Scientist at Cignifi, explained, Maxymus "allows users to drive without the burden of looking under the hood." Finally, LenddoEFL works with B2B clients to score potential customers based on a mix of traditional data, such as credit bureau, applicant or internal data, and non-traditional data, such as psychometric testing, mobile data, behavioral analytics and form-filling analytics. LenddoEFL utilizes a combination of AI techniques, such as random forest classification, long short-term memory (LSTM) and deep learning. It has found a lift in predictive power using AI techniques compared with traditional techniques.

Several institutions are also utilizing AI to lend to customers directly. Branch and Tala, for example, utilize behavioral data from phones, information on phone make and model, device details or call logs, demographics, social media information, airtime purchases and financial transactions, among others, to provide small credit directly to consumers. Both consider themselves ML-first in their approach.

> "It's important to focus on accessibility, trust, user experience, and the relationship. Without this, the AI won't work."
> -- Daniel Jung, COO, Branch

According to Branch's COO, Daniel Jung, one side of their business focuses on ML and big data, while the other side focuses on customer service. In his experience, "it's important to focus on accessibility, trust, user experience and the relationship. Without this, the AI won't work." In other words, the credit scoring algorithm alone is of no use if companies can't establish enough trust to collect data from customers consistently over time.

Lulalend started exploring predictive analytics for small-business lending three years ago. It utilizes ML models to assess business health and predict future income and combines this information with data from an online accounting platform, Zero, to determine a business's creditworthiness.

Lulalend obtains bank statements from clients to drive much of this analysis and lends directly to clients based on its assessments. Because Lulalend employs a fully online, fully automated model, it is able to provide lending decisions much faster than other FSPs in the market, and so far it claims to have one of the lowest default rates in the market. Its most popular product across industries are six-month, unsecured working capital loans to meet the needs of small businesses, but it refers clients to banks for secured lending if this option would better meet the needs of applicants. Eventually, Lulalend hopes to license its model to banks or partner with banks to explore other markets.

Personal Financial Management

NLP can be taken to the next level by exploring personal financial management tools for customers or to aid sales agents in guiding their customers to appropriate products for their financial needs.

We spoke with one company, **Abe AI**, which is doing just that. Based in the US, Abe AI is partnering with **Absa Bank**, a South African subsidiary of Barclays, to understand how to intervene early and often to guide customers towards their financial goals. The solution utilizes several ML financial algorithms to predict a customer's next purchase, promote or automate savings, provide overdraft protection and predict cash flows. Although based in the US, Abe AI found the opportunity to work with Absa compelling, given the prevalence of messaging among South African consumers.

Abe AI sees the real value of these algorithms in a combination of the various use cases and basing predictions on an individual's behaviors and habits. The algorithms are remodeled in real-time as new data is collected. Eventually, Absa hopes to provide customers with nudges towards healthier financial behavior. Absa sees this partnership as a way to remain competitive as digital-only "neobanks" (which are defined and explored in more depth in their own section below) enter the South African market and view their relationship with Abe AI and others as "more partnerships and less vendors," according to Tyron Reddy, product manager of Absa Bank's relationship with Abe AI and others. In 2017 Strands and Commercial Bank of Africa (CBA) partnered to bring a personalized digital banking experience to customers with Strands' white-label solution based on big data analytics and ML. The product incorporates insights with money management tools, personal financial education and community widgets.[12]

Conversational Interfaces

A recent Financial Times survey of 30 leading banks suggests there is a desire to use AI to reduce costs and boost returns through the use of chatbots and voice bots for first-order customer interaction and problem-solving.[13] The streamlining of operational processes through RPA, as mentioned earlier, could include advanced software bots built with machine learning algorithms. The growing field of conversational UI has the potential not only make the low-value task of filling out forms more efficient but also more engaging to users.[14]

Several fintech companies we interviewed are building ML models to augment conversations with their customers for a variety of purposes, including onboarding, customer service and inquiries, promoting greater usage of products and financial wellness. For the time being these chatbots focus on specific and narrow use cases, but the anticipated benefits are clear.

DataProphet, a South African AI-first company which provides B2B consulting and AI solutions to companies in multiple industries, is working with insurance companies to manage customer inquiries with chatbots. It has identified that customer support is the second-largest cost of servicing customers and that insurance companies must identify opportunities to reduce these costs in order to scale to larger volumes of clients.

DataProphet helps customers receive service with a lower-touch approach while realizing real savings for companies. It is deliberately developing a platform-agnostic solution that customers can access via text, web or their preferred channel.

FinChatBot, also out of South Africa, is developing similar chatbot algorithms but is focusing on onboarding of insurance customers. It cites US-based Lemonade as an inspiration, but its models will be B2B, capitalizing on the relationships and customer base of established South African insurance companies. Customers interacting with its chatbots will be able to provide introductory information and ask basic questions about the products and process before moving to call centers for more complicated inquiries. At the same time, it is also using ML to optimize the conversation flow in terms of order of questions and tone of conversation based on customer segment.

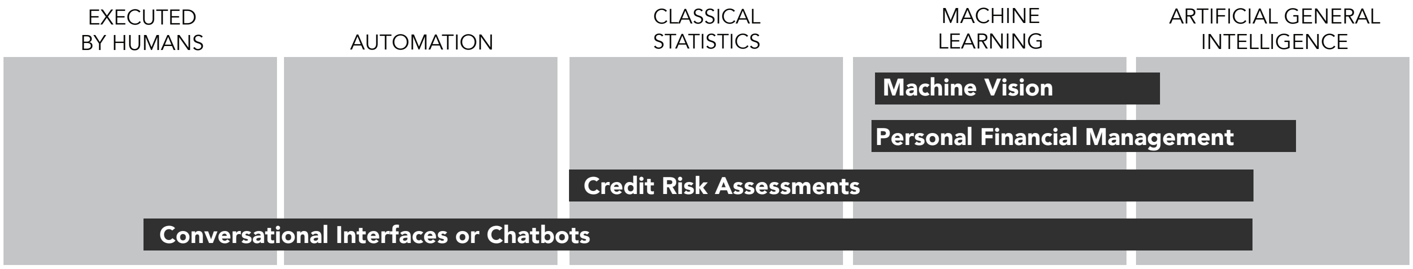
Figure 3: AI Use Cases for Financial Services

Credit Risk Assessments

APPLICATION	COMPANIES THAT CURRENTLY APPLY THIS TECHNOLOGY	● HOW BFA HAS APPLIED THIS TECHNOLOGY / ○ HOW THIS TECHNOLOGY COULD BE APPLIED TODAY	BFA
Using data generated via users' phones	AELLA CREDIT, TALA, LenddoEFL, branch	● Model to determine when airtime merchants had stock outages (BFA/FIBR and Nomanini):	fibr, nomanini
Based on small business transaction and accounting data	Lulalend, AELLA CREDIT, cignifi	● "Chiron" -- Churn Prediction Model (BFA/FIBR)	fibr
Mining existing and/or complementing with new or alternative data sources	LenddoEFL, cignifi	● Alternative Credit Scoring (BFA/Catalyst Fund and Destacame):	CATALYST FUND, DESTACAME.cl
Behavioral and psychometric testing	LenddoEFL		

Conversational Interfaces or Chatbots

APPLICATION	COMPANIES THAT CURRENTLY APPLY THIS TECHNOLOGY	● HOW BFA HAS APPLIED THIS TECHNOLOGY / ○ HOW THIS TECHNOLOGY COULD BE APPLIED TODAY	BFA
Customer service and general enquiries	Abe AI, JUNTOS, FinChatBot	● Address queries and complaints through the chatbot and use data and insights gathered through the chatbot for oversight and policy development purposes (BFA/R²A and Bank of the Philippines).	R²A
Customer onboarding and acqusition	Abe AI, TELLER, Kudi.ai, FinChatBot	○ Agent or user dictates contract	
Translation	Abe AI, TELLER	○ Predicting if a customer is confused about the terms of service	
Financial or product education	Abe AI, Arifu, edume, JUNTOS, TELLER	● Micro-training partner using automated low-touch engagement tools (BFA/FIBR) ○ Suggesting improvements to a duka's assortment/layout	fibr
Provide proactive alerts and notifications	JUNTOS, Abe AI, Kudi.ai		
Payments	JUNTOS, Abe AI, Kudi.ai		
Optimize conversation flow, language and tone	JUNTOS, FinChatBot, Kudi.ai		
Robo-adviser	PesaKit		



Personal Financial Management

APPLICATION	COMPANIES THAT CURRENTLY APPLY THIS TECHNOLOGY
Proactive alerts and notifications **Overdraft protection** **Next purchase predictions and advice** **Savings alerts or automation**	Abe AI

Machine Vision or Speech Recognition

● HOW BFA HAS APPLIED THIS TECHNOLOGY

○ HOW THIS TECHNOLOGY COULD BE APPLIED TODAY

APPLICATION	COMPANIES THAT CURRENTLY APPLY THIS TECHNOLOGY	BFA	
Identity verification for automation of KYC	LenddoEFL	● OCR and text extraction to match selfies with the pictures on official documents and to extract important bio details i.e., name, DOB, etc (BFA/Catalyst Fund and Smile ID)	CATALYST FUND SMILE IDENTITY
Validation/confirmation of inventory, farm status		● Historical weather data to compare conversion rates by village for predictive model of policies sold in communities (BFA/Catalyst Fund and World Cover)	CATALYST FUND WorldCover
		● Satellite imagery for agribusiness forecast (BFA/Catalyst Fund and Harvesting):	CATALYST FUND HARVESTING
		○ A PAYGo agent app evaluates the income level of a household by taking a picture	
		○ Finding off grid panels from the sky	

Above and beyond savings for customer support, a well-built chatbot can also provide additional benefits to the organization: analytics, multiple structured data points related to customers and transactions, 24-hour operations, insights into the sales funnel, and others benefits that may simply not have been captured before. Chatbots can allow for a more effective and streamlined data collection process, creating new pipelines and/or augmenting those currently plagued by inefficiencies, such as manual data collection, data entry and analysis.

Both FinChatBot and DataProphet are developing chatbot algorithms in-house, as is **Kudi**, a Nigerian payments company that utilizes chats to optimize payments for customers and for sales agents (for example, for sales of airtime). They have all found the off-the-shelf solutions to be insufficient to meet the needs of their respective markets. Given the fact that South Africa has 11 official languages and Nigeria has several languages and dialects, NLP models currently on the market are insufficient to meet their needs without significant feature engineering, so building from scratch has become the more attractive alternative. This also leads to competitive advantages, such as product differentiation. According to Antoine Paillusseau, CEO of FinChatBot, no other businesses are chatting about financial services in these languages at the moment.

Teller, another chatbot startup in this space, is piloting a mobile money assistant in partnership with Orange Money in Madagascar. This chatbot, named “MoMo”, was heavily tested with focus groups and has a friendly personality that invites users to learn more about the Orange Money service. One interesting aspect of this project is that Teller needed to build its own SMS-gateway from scratch to power the two-way messaging. Users without smartphones are now able to communicate with MoMo through SMS and even the ubiquitous Unstructured Supplementary Service Data (USSD) protocol.

Juntos partners with FSPs and MNOs to drive behavioral change in its customers entirely through mobile chat conversations. Behavioral experiments are tied to specific business goals, such as increasing savings deposits, engagement or reduced call center inquiries. Juntos’ carefully structured SMS conversations are analyzed on a daily basis with regression analysis and ML models to extract insights into what to say to which customers, and when to drive the desired behavior change.

The exploration of chatbots is a perfect opportunity for financial providers to partner with fintech companies that have invested in developing chat algorithms in local languages and dialects, are optimizing the tone and flow of the conversation, and have the teams in place to continue to refine and iterate based on an institution’s specific use cases.

Machine Vision or Voice Recognition

Banks might one day utilize photos of a prospective borrower’s shop or home to determine their creditworthiness based on information such as the size of the shop, the variety or density of goods stocked on shelves, the material used for the floor or roof -- the list could go on. Other sensors in a merchant’s smartphone might track the number of customers that pass through his or her shop on a daily or weekly basis, providing valuable information on sales traffic and potential for growth. This is the type of data that ML can sort through and make sense of in a way that humans simply could not process -- and it could continually update with new data over time. Many of the tools to perform these functions are already available for use and would not require an institution to build a model from scratch, but rather adapt it to local context and conditions.

There is also potential to offer new modes of interaction for those more likely to be excluded (less literate clients, the elderly, the blind, etc.). In a world with around one billion functionally illiterate individuals,[15] voice recognition offers one such possibility. At its recent 2018 I/O developer conference, Google showcased Google Duplex, a new technology for conducting natural conversations to carry out “real world” tasks over the phone such as making an appointment. The sentiment was bewilderment at the AI’s ability to carry out the task without being detected by the human at the other end of the line.[16] While we have not come across such examples in African markets just yet, we are starting to see examples in other markets, such as in South Asia. For instance, in India 28 percent of Google searches are now conducted by voice,[17] demonstrating promise for the development of NLP technologies in other markets. At BFA, we have developed a simple application to convert printed text into speech using just a basic smartphone, which would allow less literate populations to navigate the terms of financial products more easily. This app also has the potential to translate the digitized text into other languages before reading it aloud, offering the possibility of translating from English into local languages not only for customers but also for agents or the support staff of financial providers.

Low-income clients often have a hard time placing trust in complicated contract terms, partly due to lower literacy levels but partly also because many are encountering formal financial terminology for the first time. Customers will frequently consult trusted sales agents, family or friends to help them navigate contract terms, but this is by no means ideal. BFA's research with PAYGo customers found that understanding contract terms, such as the length of a loan, the consequences of late or non-payment and incentives, can greatly affect this customer trust.[18] Based on qualitative interviews with customers, we know that when these customers feel that they have been misled, they may be less likely to repay. Providing this information to clients through text-to-speech applications can increase trust and transparency and ensure that clients can refer to their loan terms as and when needed -- not just when an agent or family member is available to assist them.

5. The FIBR AI Gallery: Supersensory powers

Beyond the examples mentioned above, we also aim to push the boundaries of what is typically seen as feasible in low-income, low-connectivity environments. Over the past few years we have witnessed significant advancements in machine perception in both academia and industry, for instance, the ability of a computer to "sense" the world as we humans do.[19] However, many of these technologies are not yet available in the kind of practical form that would meet the needs of the lower-income populations we work with, or our partners who serve them.

For this reason, we at BFA have created the initial version of the **FIBR AI Gallery** (www.fibr.ai), which serves the goal of accelerating the introduction, adaptation and "productization" of these AI elements. More specifically, as a starting point we are actively exploring scenarios in which computer vision, predictive analytics and NLP can be used to produce gains and alleviate pains for MSMEs and in the PAYGo solar, water and smartphones space.[20]

Ultimately our goal for the AI Gallery is to bridge the gap between the real needs of our partners and the cutting-edge AI developments that have the potential to address these needs. We are accomplishing this by first demonstrating to these partners some of these technologies in their raw, non-productized form and openly discussing whether and how they see these technologies being useful in their day-to-day life. Starting from this first-hand expression of potential value, we then work to build proofs of concept either directly, e.g., using tools such as **Google's Tensorflow "TFLite" for Android**,[21] or by working to adapt existing products of technical partners who have a similar offering that needs to be tailored to the local context.

The sections below explore our initial cohort of concepts, which we will continue to adapt and expand on in the coming months. In describing these select cases we follow the aforementioned process: starting with a perceived need being addressed, mapping the technology/technologies that can help to address that need, assessing the validations and gaps that exist and exploring potential partnership opportunities.

Use Cases: AI for MSMEs

USE CASE 1: PRODUCT COUNTER FOR ESTIMATING SALES TO ASSESS CREDITWORTHINESS

Needs Identified. For MSMEs looking to purchase from wholesalers to restock their inventory, access to credit is critical but can be limited by the lack of a digitized sales ledger. To compound this pain, smaller merchants see digital point-of-sale systems either as overkill for their shop or as requiring too much training or effort to operate. Additionally, shop owners with multiple shops have issues with employees miscounting inventory, in some cases defrauding the shop and stealing goods.

Technology. By positioning an Android device with a camera such that it has a view of the counter, we can utilize Tensorflow's computer vision libraries to perform object detection and tracking, counting and tracking the number of items that pass over the counter in a given

day. As the variance in pricing is typically quite tight, an average or median price in the shop can be used to estimate the gross revenue of products sold. Reporting interfaces can be exposed to both the shop's owner for the sake of reconciliation, and to potential lenders for the sake of providing data to be used in an assessment of creditworthiness.

Validation. After visiting dukas (small shops) in the Kibera district of Nairobi, Kenya to demonstrate a proof of concept for the object tracking feature, we had strong validation of the hypothesized value propositions. While access to credit seemed valuable to each shop owner, the owners of multiple shops saw the reconciliation and monitoring of theft as the technology's primary potential value.

Gap. The main gaps identified concerned localized product data and quality of hardware. While the proof of concept generally worked to identify products even in low-light conditions, to detect only products in the inventory that are passing across the counter, the model should ideally be trained on labeled images of the local products being sold. As far as hardware is concerned, while shops often do have smartphones, they are sometimes damaged and frequently several generations old.[22] To conduct our testing, we purchased a range of common smartphones with integral cameras, which would likely need to be offered to merchants on a payment plan.

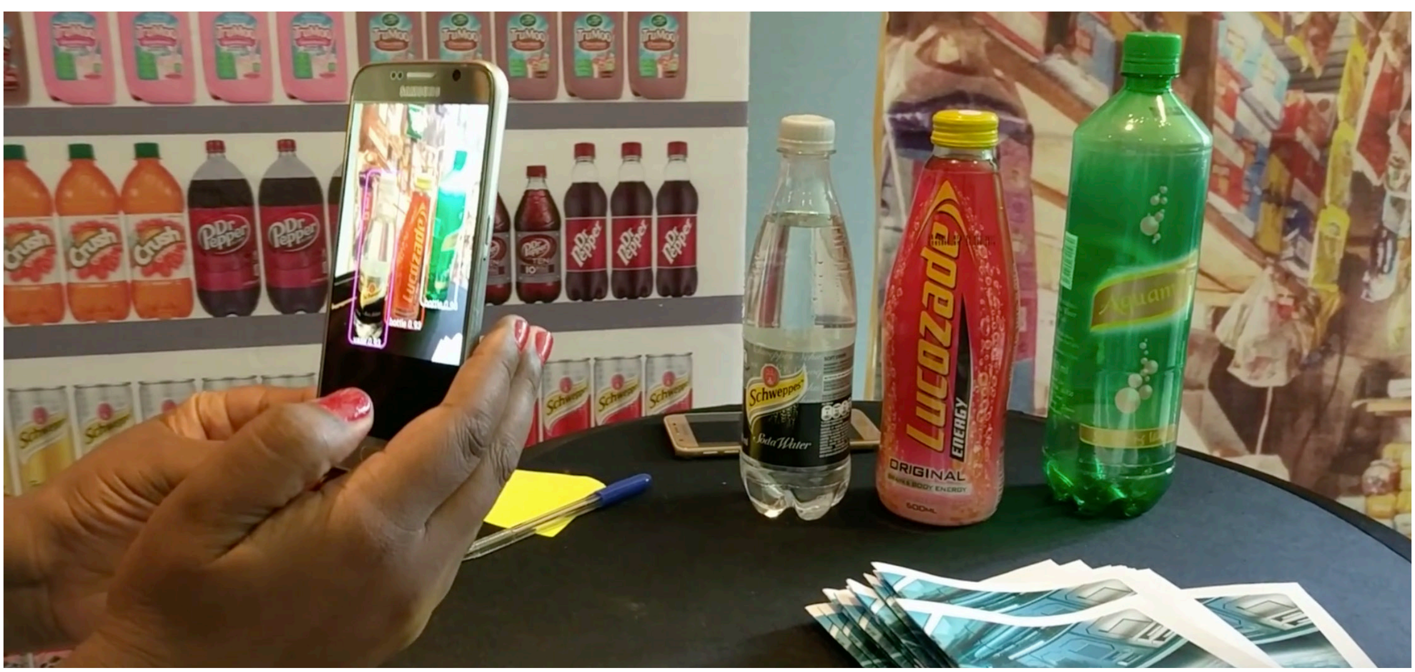
Potential partners. Until now we have built the demo apps in-house, but we are working to organize discussions with the team behind the TensorFlow Android libraries to see what support may be available to including this work as a demonstration in their core libraries. We have also engaged with local developers who have been experimenting in this area to explore whether they would be interested in taking this product forward. Community banks have also expressed interest in creating credit models based exclusively on the average quantity of items being sold daily.

USE CASE 2: PRODUCT RECOGNITION FOR QUANTITY AND PRICING SUGGESTIONS

Needs Addressed. MSMEs need to be able to track products sold to determine which and how many products to reorder when replenishing their inventory. The ability to simply point a camera at a product and be provided with pricing and ordering quantity suggestions would free up merchants from the tedious process of mental or manual calculations based on a historical paper ledger and tracking down stock-keeping units (SKUs) for ordering.

Technology. Using computer vision and object classification, we can train a model to translate key features of a live camera image into a product identifier, then look up information on pricing and availability. One example of this type of technology already in use is the image-based search technology in Amazon's mobile application, which is what we used for demonstration purposes.

Validation. While visiting dukas in the Kibera district of Nairobi to demonstrate proof of concept of the product recognition using Amazon's app, we received generally positive feedback. While the initial reaction was that "this looks like an app for the younger generation," after a minute of playing with the app the merchant explained that he'd love to have such an app for ordering -- without having to wait for the wholesaler to come around.



Gap. The main gaps here once again were around localized product data and the quality of the hardware, as described in Use Case 1 above. The prescriptive pricing algorithms would also benefit from network effects in data provided by a critical mass of merchants in sufficiently close proximity and may be limited in their effectiveness in their initial rollout.

Potential partners. In terms of access to product data, **Jumia** is the closest to an Amazon equivalent in the region we explored. **Frogtek**, a company working with small merchants globally, has developed tools for prescribing pricing and quantity. **Sokowatch** is a FIBR partner specializing in last-mile distribution and the digitization of sales records.

Use Cases: AI for PAYGo Providers

USE CASE 1: PROJECTED ROI FOR COLLECTION INTERVENTIONS

Needs Addressed. Like any business reliant on recurring payments, PAYGo providers experience churn, otherwise known as attrition, in their customers' repayment plans. Predicting when and where churn will occur, how effective a targeted intervention might be, and the ROI for a set of interventions can help to prioritize such interventions, reducing costs and increasing overall revenue.

Technology. By feeding into a machine learning model features engineered from data on products, transactions, demographics, income and more, predictions can be made as to where churn is likely to occur in the next 30 days. An ROI calculator (Figure 2) can then take this model's predictions along with other metrics (e.g., cost of intervention, likelihood of success, unit cost of churn) and turn them into a prescribed set of interventions to maximize ROI.

Validation. A majority of the PAYGo providers to whom we gave the demo expressed a strong interest in adopting such a tool.

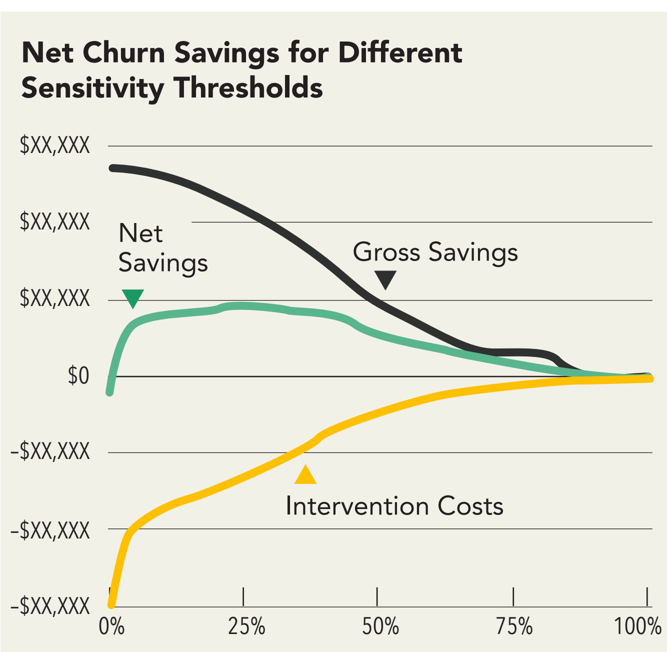
Gap. While the approach and model are both portable to other providers, the lack of standardization in the data portfolio and payments could present some hurdles in adapting the technology to a new partner.

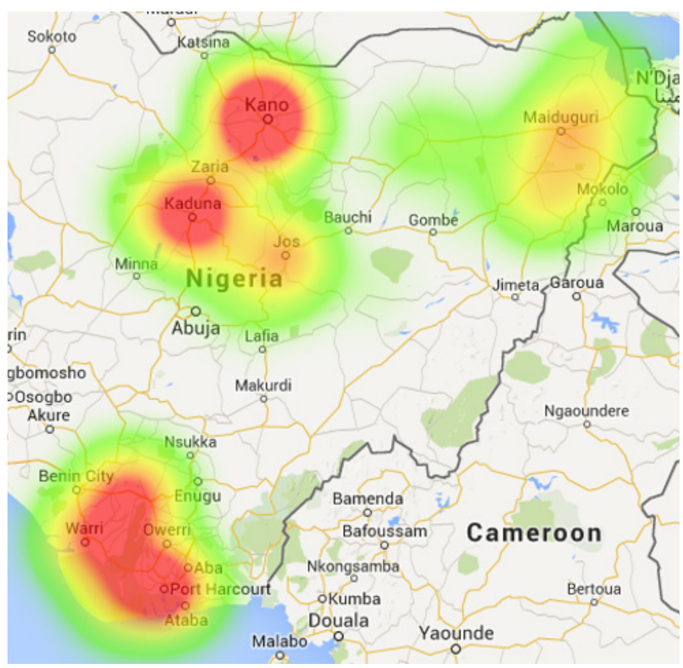
Partners. We are currently working with a PAYGo provider in partnership with **BigML**, a cloud-based machine-learning-as-a-service provider, to pilot this model and measure its effectiveness in the medium term.

USE CASE 2: PREDICTIVE LEAD FUNNEL FOR NEW GEOGRAPHIES

Needs Addressed. PAYGo providers looking to enter a new geography must currently conduct bespoke sets of analyses to determine which specific households or communities to target. The cost of failure here can be substantial, and this risk could be mitigated by a tool that helps predict the likelihood of success.

Technology. By combining the provider's product, pricing and payments data with contextual data for a given geography, a heat map could be produced that highlights predictions for the most promising regions to enter next. Contextual data might include distance from the energy grid, access to mobile money agents and usage of these services, cellular signal, population density, photovoltaic





potential and weather, among other factors.

Validation. A majority of the PAYGo providers to whom we gave the demo expressed a strong interest in adopting such a tool.

Gap. While the partners and the technology are already tentatively in place, we have only begun discussion of a pilot of this technology. The predictive power of such a model will be dependent on the precise modeling technique and the accessibility and quality of both the contextual and the provider data on which to train the model.

Partners. BFA, along with the Bill & Melinda Gates Foundation, is currently working with financial authorities globally on the implementation of a Data Stack program to gather this contextual data. Part of the program is to explore the value that can be provided back to the private sector players, such as banks and PAYGo providers, which can help to foster financial inclusion initiatives and general economic health.

6. Why AI now?

Cost: Using These Tools Has Become Considerably Cheaper

The cost of implementing AI has gone down considerably, making these tools more accessible thanks to advances in data storage and computer processing power. The barriers to entry are lower than ever before. The introduction of the cloud allows companies access to powerful computing at a fraction of the cost of what was previously a massive upfront capital investment. And over the last five years these tools have also become easier to access and use.

Many algorithms are now open-source, allowing institutions to adopt and engineer them according to their needs. These include **PyTorch** and Google's TensorFlow, two open-source machine learning frameworks, the **Microsoft Cognitive Toolkit** for deep learning algorithms, and **Acumos**, an AT&T and Tech Mahindra project that seeks to make AI accessible to a wider audience. Platforms such as BigML seek to democratize ML with a machine-learning-as-a-service model, which BFA has leveraged as a partner in several ML-intensive engagements. Each of these tools, as well as a plethora of other open-source tools and communities not listed here, can prove to be critical cost-savers for startups and other providers developing in-house algorithms to serve products more deeply tailored to their respective verticals.

Finally, although talent in AI and ML are expensive to acquire in African markets, we anticipate that the situation will improve with the growth of local innovation ecosystems combined with distributed online education platforms such as Coursera, deeplearning.ai or fast.ai.

Performance: AI Will Allow Institutions to Improve Over Traditional Systems

The benefit of AI is the sheer complexity of data that can be processed at scale and in real-time. Institutions we interviewed highlighted the value of being able to use a larger variety of data formats and structures to include information from PDFs, images, emails, sensors, SMS conversations and other data points that simply could not have been processed meaningfully by humans.

Institutions that can wield algorithms will be able to lower the cost of operations, improve their service and accelerate time to market. Eventually, these cost savings should lead to lower cost of services for customers. Interviewees spoke of getting improved performance from the increased precision of predictions compared with regression modeling, thus allowing them to apply insights to their business with greater accuracy. Further, ML models can be updated or refreshed on a regular basis -- say, monthly or weekly -- to inform business operations, while rerunning regression analysis or retraining can be unwieldy and time-consuming with limited resources.

For one partner, ML models of over 150 variables resulted in improved predictions that were 1.5 times stronger than those with regression analysis. Aella Credit, which builds credit-scoring technology for individuals and small and medium enterprises to obtain unsecured credit in Nigeria, described that "the level of accuracy and reduction in human error has been a game changer" compared with manual methods. And compared with regression analysis, Aella Credit's CTO, Wale Akanbi, described AI as producing returns amounting to three times the initial investment, while Cignifi's Chief Data Scientist, Qiuyan Xu, reported: "For our major deployment in South America, we have achieved 50 percent increase in acquisition and 60 percent decrease on risk."

Data: Financial Services Providers Have the Necessary Data and Relationships in Place

Plentiful, high-quality data is key to ML.[23] Without this fuel, the ML engine cannot run.[24] Yet among fintech companies that we interviewed limited data rose to the top as the primary barrier to AI development in African markets.

Financial institutions tend to have plentiful data related to customer transactions, demographics and payment history

– as do utilities companies, MNOs, government agencies and firms that transact with SMEs. This does not mean that just because FSPs have the data, adopting AI will be easy. As we will discuss below, having data is a necessary requirement but not enough in itself. FSPs must also put time into determining whether this data is sufficient; they must prepare and structure this data for use; and they may have to investigate new systems for collecting, housing and organizing data.

Competition: Institutions Must Face Off with Neobanks and Superplatforms

New, digital-only "neobanks" are starting to enter markets with entirely mobile-first offerings. Distinct from traditional banks that utilize digital channels or even from mobile money offerings, neobanks are digital-first both on the front-end and the back-end (i.e., overcoming legacy IT systems) with a razor-sharp focus on customer experience. Although neobanks are most prevalent in developed markets, they are starting to make their presence felt around the globe.[25]

In South Africa, for example, provisional banking licenses were granted in 2017 and 2018 to Discovery Bank, Bank Zero, Post Bank and TymeDigital, which specifically seek to challenge incumbents to reach new customer segments with purely digital offerings.[26, 27] These neobanks will be equipped to apply advanced technologies, such as AI and ML, to banking services to differentiate themselves from traditional incumbents.

Neobanks are set up to act in an agile, swift manner. They are built from the ground up with entirely modern core banking systems and with the intention of disrupting with branchless offerings. Many incumbents will see these neobanks as threats. But experience in the US and UK, where neobanks have gotten a head start, suggests that these neobanks may shake up business models but likely will not knock incumbents out of place and will instead find ways to partner with banks to offer customers both the flexibility and the tailored services of neobanks along with the financial strength and product depth of existing FSPs.[28] Recently, UK challenger bank CivilisedBank turned in its banking license to focus on its fintech offering amidst a very competitive market.[29]

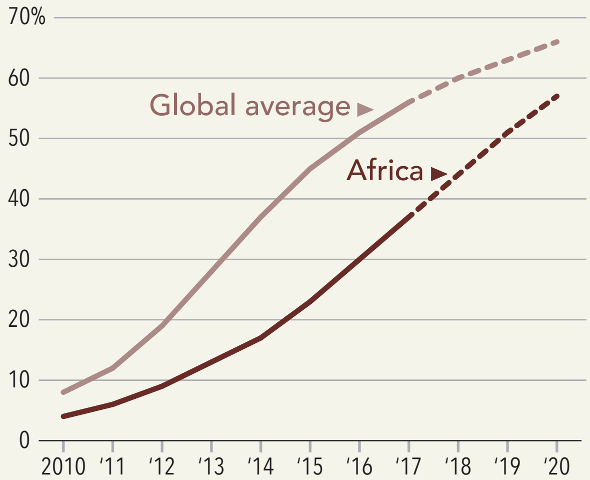
More concerning than neobanks or other digital-first competitors are superplatforms, such as **Amazon**, **Alibaba**, **Facebook**, **Google**, **PayPal** or **Tencent**, which are also at the door.[30] These superplatforms are defined by a two-way exchange of physical and digital assets and a masterful use of technology and data. Many of these superplatforms are leading the development of AI, having attracted formative researchers to lead their AI initiatives or by aggressively acquiring promising AI startups.[31] It is no secret that these players are expanding to new markets, ambitiously. In 2017 **Alipay** expanded to South Africa, and **PayTM**, an Alibaba-backed payment bank and gateway in India, is on a major expansion drive.[32] In 2017 Jack Ma of Alibaba visited Kenya and Rwanda seeking strategic investment opportunities.[33]

Financial providers, on the other hand, are more likely to have a customer base with associated transactional histories. They have established and often trusted brands and they have a physical footprint that can be leveraged even with a digital-first outlook. We know that customers in FIBR markets who are new to financial services may feel the need for some physical interaction before they fully trust digital channels.[34] Branch mentioned that one current limitation of AI technology in African markets is skepticism from its customer base. Even in Kenya, which is further ahead in terms of digitization and mobile adoption, its customers express varying levels of doubt about the value of AI-powered features and tools. But with the advent of neobanks and superplatforms, financial providers with stronger assets in technology, data and customer bases will have greater leverage.[35, 36]

Financial providers must continue to move in the direction of overhauling their technology systems and operations to remain competitive in the face of these new entrants, and only those that can leverage data insights as part of their core culture will truly continue to stand apart as leaders in the financial services space. As described above, AI is one particularly effective tool to maintain and should be seen as a key part of financial institutions' long-term strategy.

Figure 4

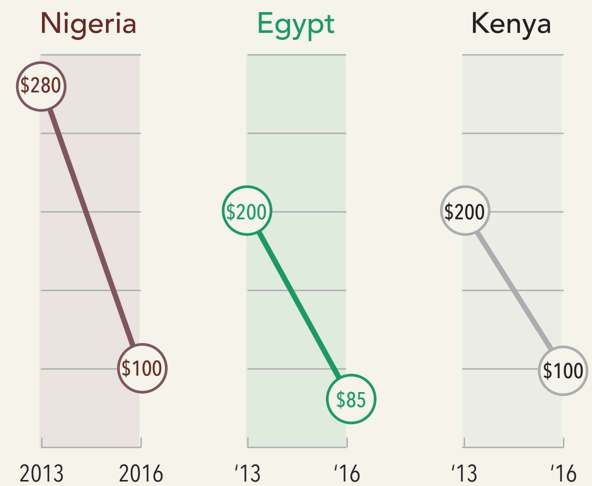
Smartphone adoption is growing in Africa, percentage of connections



Source: GSMA Intelligence

Figure 5

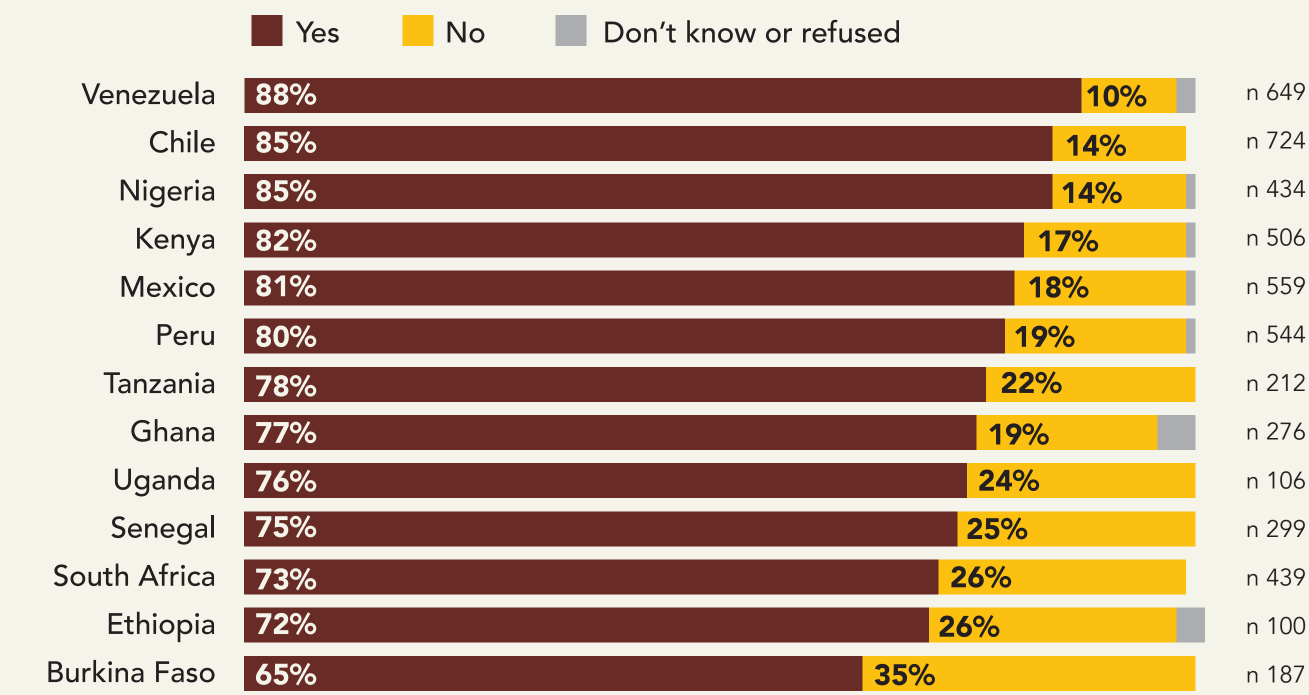
Average price of a smartphone



Source: Jumia

Figure 6

Social networking among internet users or smartphone owners



Note: Percentages may not add up to 100% due to rounding.

Source: Pew Research Center, Smartphone Ownership and Internet Usage Continues to Climb in Emerging Economies," 2016. Page 44

Consumers Are Increasingly Ready for Tailored, Real-Time Servicing and Feedback

Feature phones are still prevalent in most African markets, but this is changing fast. Between 2014 and 2016 smartphone connections in Africa nearly doubled (Figure 4). And Jumia, Africa's largest online commerce platform, reports that the average cost of smartphones in its three main markets, Nigeria, Egypt and Kenya, dropped precipitously on its platform between 2013 and 2016 (Figure 5). Budget-friendly smartphones in Africa are priced at around $40, while South African manufacturer Onyx Connect last year announced the launch of a $30 smartphone.[37] Growing connectivity -- in terms of mobile subscriptions, the transition to mobile broadband and the use of social networking and other digital apps -- means that more African consumers have digital footprints, generating data that can feed into algorithms to provide financial services (Figure 6). In particular, the accelerating adoption of smartphones allows the collection of richer and more abundant data in real-time compared with feature phones.

Connected African consumers are likely accessing the internet via their smartphones, for which mobile-first strategies of neobanks are not unrealistic. In Latin American markets such as Brazil, where consumers are mobile-first, neobanks are starting to gain in popularity, especially among the unbanked.

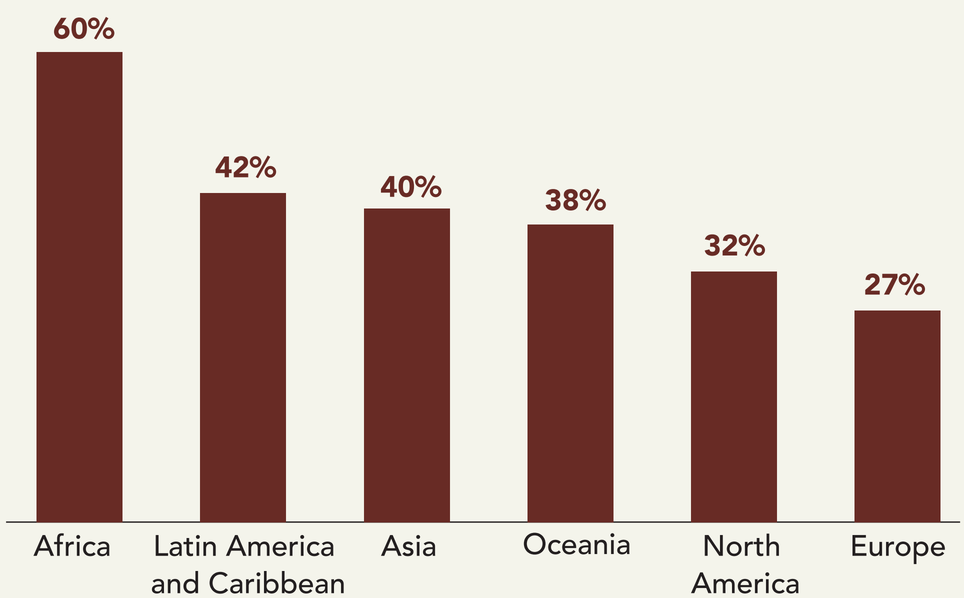
Although we know from partners that digitization still has limitations in many African markets -- for example, consumers may own smartphones but may not necessarily utilize applications comfortably, and many consumers ration their use of data to times when they have a network connection at a coffee shop or restaurant -- it does not mean that institutions should wait to explore superior digital offerings to which AI can contribute.

Africa has the youngest population in the world (Figure 7), and the number of young people in Africa is expected to double by 2045, according to the World Bank.[38] These youths are first adopters of new technologies and are more literate and savvy with digital tools and will expect products and services with superior user experience. Falling smartphone prices, expanded broadband networks and the youth bulge mean that the majority of African consumers will be online soon and ready for rich mobile offerings.

Many of the fintech companies we interviewed are taking advantage of the enormous popularity and comfort with social messaging apps and SMS to pursue two-way communications with customers, which generate data in and of themselves and allow them to utilize AI for use cases such as customer support, onboarding, customer education -- and of course, digital lending. But as more digital data is generated and consumers become adept with digital tools, we expect the applications of AI for consumers to broaden and become more sophisticated, including new modes of interaction for those most likely to be excluded, such as illiterate, elderly or blind clients, augmenting their ability to navigate information-dense product offerings.

Figure 7

Percentage of the population under 25 years of age



Source: United Nations, "World Population Prospects: Key Findings and Advanced Tables." 2017 Revision.

7. Challenges and Barriers for Fintech Players Implementing AI in Africa

The stage is now set for fintech companies and banks to begin to incorporate AI to augment their effectiveness, but this process is not completely without its hurdles. As part of kicking off the process of adopting AI tools, a team should begin to consider these challenges at the outset and work to create strategies to address each of them. Here, we provide common challenges and some suggestions for how to approach them; then in the next section we provide a framework for assessing and working towards AI readiness in a methodical manner.

The Right Question to Ask

To begin exploring AI and data without a question in mind is akin to acquiring a room full of power tools and various materials without knowing what you are going to build. To be effective, the design of an AI implementation must focus first on the action it should have on an aspect of the business.[39] Two key questions to ask are:

In what environment, will this AI act, and for whom? It is critical to define the persona having their abilities augmented by AI – is it around retention of a specific segment of the customer base, efficiency gains for a role on the operations staff, better insights and reports for the executive team, or something else?

What problem would the persona like to use AI to solve? This is best expressed in the simplest terms possible, for example as a use case: "As a [persona], I would like [description of proposed gain creator/pain reliever] so that [description of desired effect]."

The Right Format, Localization and Quality of Data

With the question at hand, a model's predictions will be directly tied to the data that is used to train it, meaning that a model can only be as good as that incoming data. Data can be incomplete, and even when sufficient, it requires extensive cleaning, analysis and feature engineering before it can be fed into an algorithm.

Further, the importance of feature engineering is more pronounced as AI is developed for markets in Sub-Saharan Africa. Algorithms that were developed in Western markets will, of course, contain quirks which may not apply in these markets, and even the context in Tanzania will be very different from the context in Kenya, despite both countries being in East Africa. In the case of Branch, while much of its tech team is based in San Francisco, teams in each market provide essential context into local culture, language and trends that guide product and algorithm development.

As part of preparing for the adoption and/or creation of AI tools, an organization must take an inventory of the data that is available to assess at least the following aspects as part of their strategy:

- Existence + Relevance: In considering the use cases to be addressed, what data can you think of that may be relevant as part of any analysis or machine learning training? Which of these data are already being systematically gathered and stored? For the data that are not currently being gathered, what new product instrumentation or Application Programming Interfaces (APIs) might need to be put in place?
- Location + Ownership: For the data that exists, where is it stored? Does access to the data require additional partnerships or other access controls? Are there data protection and/or privacy regulations that must be respected?
- Quality: Are the data located in databases normalized to reduce redundancy and increase speed of access? Are the data stored in a tidy[40] format to reduce friction in analysis?

The Right Kind of Talent and Organizational Capacity

Preparing for sophisticated AI use cases takes time, investment of resources, and in many instances a reorganization of an institution. Several fintech companies we interviewed felt that unrealistic promises related to the potential of AI can derail efforts before any real traction can be made with African financial providers.

To mitigate this risk, DataProphet, demonstrates the value of AI by developing early demos to help clients understand the benefits of AI. Such tools can provide a point of comparison with existing analysis or tools that is more powerful than words alone. Tyron Reddy, at Absa Bank, described the process of moving teams gradually towards considering AI tools by using workshops and roadshow techniques internally to demonstrate the wide range of potential applications of AI, from medical applications to agri-business platforms.

In general, to avoid overpromising or overwhelming the targets of AI features, fintech firms and banks must establish clear, short-term wins while simultaneously pursuing a longer-term AI vision and related strategies. During the preparation phase they should start with activities with clear potential of lowering operational expenses (such as reducing the time devoted to call center inquiries) as a means of gradually building the case for the continued investment of time and resources into more sophisticated solutions.

The Right Enabling Environment

Even with all the key pieces in place to address a real-world application using an AI solution, a non-enabling fintech environment may prevent such a solution from being deployed or limit its impact. In a recently published report,[41] BFA offered ten recommendations for creating an enabling environment for fintech innovation:

GOVERNMENT SUPPORT FOR FINTECH STARTUPS

1. Provide direct support (e.g., accelerators, incubators)
2. Serve as early adopters of fintech solutions
3. Adopt favorable fiscal policies (e.g., taxation and investor incentives)

DIGITAL AND FINANCIAL INFRASTRUCTURE

4. Foster strong digital connectivity and data affordability
5. Promote broad access to digital financial services
6. Ensure fair and open access to data, payment channels and APIs

LEGAL FRAMEWORK

7. Develop enabling regulation that creates space for fintech firms to offer financial services
8. Create an enabling environment for doing business
9. Establish transparent rules that facilitate safe and responsible processing of personal data
10. Ensure fair competition to create a level playing field for all

In a non-enabling environment, fintech companies may struggle to innovate. For example, incumbents may block access to existing customer data and payments infrastructure or may refuse access to key telecommunications infrastructure. In addition, unduly burdensome restrictions on data processing (e.g., strict data localization requirements, prohibitions on sharing/selling data) may raise computing costs (by as much as 30-60 percent)[42] or prevent fintech companies from processing customer data even with customer consent.[43]

BALANCING OPENNESS AND CUSTOMER PROTECTION

While an enabling environment is critical for fintech innovation, many fintech companies operate in countries where data protection laws are limited or non-existent. Even in environments where certain data protection requirements exist, abuses are commonplace in the absence of proper policies governing the processing of customer data.

While the world is currently focused on revelations of the illegal sale of Facebook customer data to Cambridge Analytica, a firm hired by Donald Trump's 2016 election campaign, there have been many previous examples of illegal or unethical use or sharing of Facebook data. For example, researchers (both internal and external) have used Facebook data to manipulate emotions and to identify emotional vulnerability in children and young adults.[44] Furthermore, recognizing the power of default settings to shape decision-making,[45] Facebook has developed default settings for both Facebook[46] and its subsidiary WhatsApp[47] that authorize broad sharing of customers' personal information.

Many fintech companies operate in markets that lack comprehensive data protection regulation, effective enforcement of existing requirements, or both.[48] Even in the absence of specific data protection requirements, fintech companies should observe the following principles when processing (including collecting and sharing) customers' personal data:[49]

1. **Legitimate processing criteria:** Fintech companies should rely on a legitimate criterion for processing customer data. Ideally, customer consent should be obtained, although some countries permit companies to process personal data without explicit consent if the processing promotes the "legitimate interests" pursued by the company and does not affect the customer's fundamental rights and freedoms.
2. **Purpose and relevance of collection and processing:** In countries that lack a strong data protection legal framework, some providers may collect and store data without a clear idea of how the data will be used. As data breaches are common, more personal data stored in more places increases the risk of harm to consumers. Therefore, personal data should be collected for specified, explicit and legitimate purposes. In addition, the data collected must be adequate, relevant and not excessive in relation to the purposes for which it is collected and/or processed further. Moreover, any additional processing of the data should be compatible with the specific purposes for which the data were collected.
3. **Quality and accuracy:** Fintech companies should ensure that processed personal data are accurate and that inaccurate or incomplete data are corrected or deleted.
4. **Security:** Fintech companies should comply with all relevant laws and regulations governing data security.

Providers operating in jurisdictions lacking specific data security requirements should adopt industry-standard data security policies and should refer to international standards, such as the ISO 27,000 series of information-security-related standards.

5. **Sensitive or special personal data:** Most countries with comprehensive data protection legislation place specific restrictions on the processing of "sensitive" or "special" personal data, which may include personal data relating to attributes such as race, ethnicity, political or religious or philosophical beliefs, trade union membership, sex life and health. Fintech companies should be particularly cautious about the processing and use of such data. They should strive to obtain informed customer consent before processing such data, protect such data against disclosure (whether accidental or malicious), and ensure that such data are not used for discriminatory purposes (see below "A Word on Discrimination and Bias").

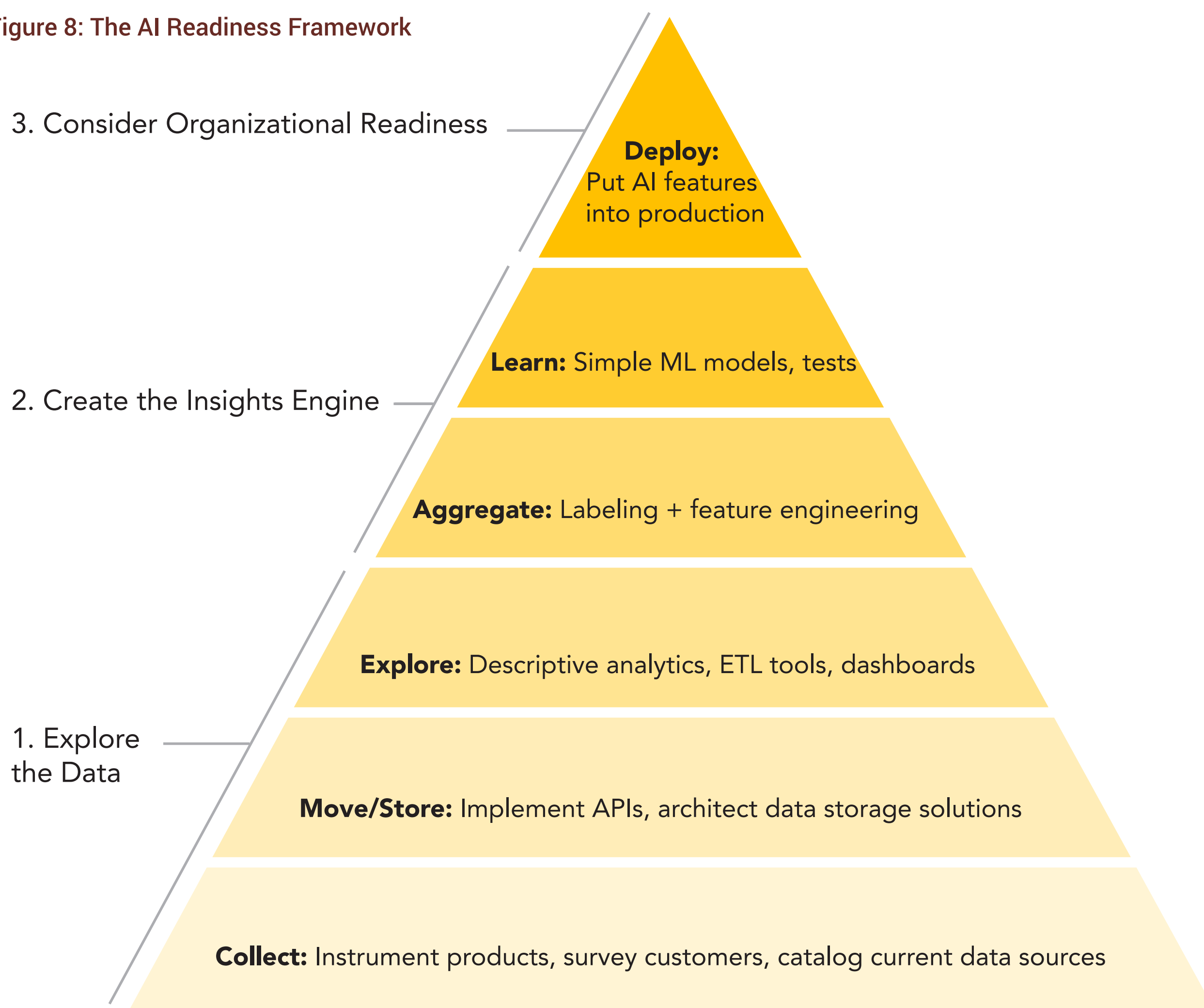
The Right Level of Customer Trust

Customer distrust grows when providers are not transparent, do not consistently deliver on their promises and compromise customers' experience with the product. When trust is breached, it is very difficult to rebuild. Lack of trust adds significantly to costs, time and stress that affect the company's bottom line.

Organizations that know how to design to enhance and maintain trust with customers gain a major competitive advantage with suppliers, clients, investors and employees. Juntos, for example, considers its data analytics and chat automation as a vehicle to create trust first and foremost. Companies employing AI strategies might do so in ways that protect customer trust, especially in mostly digital transactions. Platform-based players require trust between the two sides of the markets for the digital marketplace to work and grow.

There are five elemental drivers of trust in digital financial services: competency, appearance, control, transparency and commitment & benevolence. By taking specific actions or building in features along the stages of acquisition,

Figure 8: The AI Readiness Framework



activation, retention and referral, firms can increase customer perception of trust along their journey with the product or service.[50] Developed through BFA, organizations offering digital financial services can refer to the Catalyst Fund Trust Toolkit to assess customer trust and to apply the practical principles of trust creation.

8. AI Readiness: Actionable Steps for Service Providers

Once a provider has understood what AI is, the potential ROI, how it can be used, and has explored some of the risks and strategies for mitigations, there are additional preconditions that must be satisfied to effectively incorporate this technology as a core tool in their day-to-day operations. In 2017 data scientist and venture capitalist Monica Rogati famously connected some of these requirements in a Maslow-inspired hierarchy of AI needs,[51] which we have adapted and extended here in Figure 8.

1. Explore the Data

The foundation for all AI is based in the underlying data, which is the focus of the first three layers of the hierarchy. Fintech startups, financial institutions and financial authorities all sit along a spectrum of quality and quantity of data, positioning them at various levels of "data readiness." Regardless of this status, however, there are some concrete steps an organization can take to prepare its data for AI.

First and foremost, whether a solution is to be developed in-house or brought in as a plug-and-play solution, providers eager to employ AL/ML must base their approach on a good understanding of their customers, which is a perspective that only analyzed data can provide.

To build this foundation, providers first need to assess the existence of and access to data that is relevant to the use case being addressed. This starts with conducting an inventory of relevant data, including format, location, ownership, access restrictions and legal protection of the data. Any relevant data that has not been collected already will need to be generated through surveys, focus groups and the instrumentation of products.

From here, data can be moved into optimal storage mechanisms and locations using tools such as APIs.[52] Finally, an exploratory analysis should be conducted to extract meaningful insights from the data and understand the relationship to these processes that will be used to train the AI feature.

A WORD ON DISCRIMINATION AND BIAS

One of the biggest risks in assessing data is that institutions may become overly trusting of their AI models, with insufficient checks in place to understand how these models might be biased. As algorithms become more complex and incorporate more data, new biases can be added, and understanding and explaining how these algorithms work can be challenging even for the most advanced companies.

There is a real likelihood for models to reinforce existing biases against disadvantaged groups if checks are not put into place to evaluate the decisions of models with respect to their impact on these groups. Models are only as accurate as the data that goes into them, and often our data sources may reflect societal biases -- which the algorithm will learn. Growing evidence has found this to be the case with models for lending decisions in the US, for example, or for predicting prison recidivism rates.

Preventing or protecting against bias requires proactive work. Removing variables such as gender, income, race or ethnicity from a model is not sufficient to prevent it; many models will make decisions based on variables such as formal employment that are highly correlated with variables such as gender or income. And models trained on datasets that have less data on particular sub-populations will be more prone to bias.[63] This is a potential concern for institutions looking to expand financial access to historically underserved groups. Juntos, for example, mentioned that while they tend to work with partners that are driving financial inclusion, dormant populations are difficult to analyze due to lack or limited availability of data.

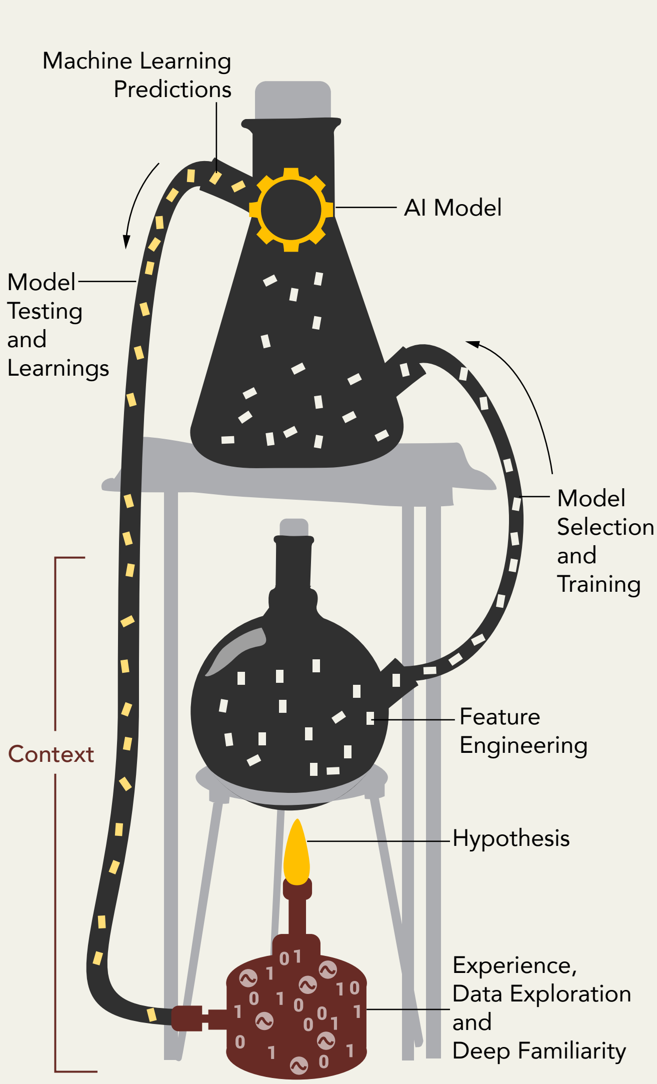
One way to reduce the potential of discrimination and bias in models is to ensure diversity in the teams developing models and interpreting their results. More diverse individuals -- including women, for example, or individuals from under-represented groups -- may identify sources of bias inherent in the data and processes that might have been missed otherwise. And with the right reinforcement training in place, paired with supervision, algorithms do have the potential to overcome societal biases.

2. Create the Insights Engine

In the next two layers (Aggregate + Learn), the data must be brought together with the context of the problem to be solved. This is accomplished through a process of data transformation, labeling, feature engineering and iterative modeling. This process of determining the most relevant factors for predictions, generating ML models and testing hypotheses can be unpacked into an "Insights Engine" framework that meaningfully and appropriately informs the ML model, as BFA formalized and explored in more detail with WorldCover,[53] an AI-first insurer for smallholder farmers' crops.

This process, illustrated in Figure 9, consists of data generation and predictive machine learning modeling ("model-building") iteratively driven by new insights ("learnings"). A data-driven organization makes its way up the "stack," building on context and experience to produce data-driven hypotheses that inform quantitative features and ML models.

Figure 9: The Insights Engine



Insights produced by the model must then be captured, feeding these learnings back into a new, deeper understanding of the context to inform the next iteration. Optimization requires not only a foundational understanding of the real-world context but also a feedback mechanism to inform the next iteration.[54]

BUT DON'T CREATE A BLACK BOX

"Black box" refers to the opaque nature of many ML algorithms, especially as they become more complex and include additional parameters. Even the data scientists who developed the model may have no deep knowledge of the human behavior or financial sector insights necessary to interpret the results -- again highlighting the importance of teams with deep sector and market experience to provide context.

Often, this opacity extends to customers, particularly for decisions based on proprietary algorithms. Numerous digital lenders provide clients with few explanations as to why they were denied or granted credit, and these reasons or requirements evolve over time as algorithms are refined.[55] Many markets now have multiple competing digital lenders, each with distinctly different algorithms. As of March 2017, for example, 19 digital credit providers were active in Kenya.[56] For consumers, navigating this landscape is confusing and opaque and provides little guidance on reasons for denial. In many jurisdictions, financial providers are required by law to provide a basis for credit denials. For example, the South African National Credit Regulator requires companies to provide reasons for credit denials or limits. It is not enough to say that clients are declined because a score is too low, but clients must be provided with a composition for disclosure. South Africa also prevents companies from using discriminatory criteria in their credit evaluation process, including "colour, race, age [except for minors], political affiliation, sexual orientation, religious belief, or affiliation to any particular trade union." Similarly, many markets with data protection regulation place certain restrictions on the use of fully automated decision-making processes in the financial inclusion context.[57] Providing an explanation that can be understood by humans is important not only to comply with local jurisprudence, but from a business standpoint it is key to establishing trust with customers.

3. Consider Organizational Readiness

Once the data is in a good place and the ML model has been developed and thoroughly tested, there is one set of considerations left to reach the top of the AI hierarchy: technology, team and operations. BFA has been actively exploring these topics and is in the process of producing a data readiness self-assessment toolkit on the subject.

However, we have found that at a minimum the following considerations must be addressed.

TECHNOLOGY

Integration. Will the institution just add an AI/ML layer on top of existing systems, will it gut part of the management information system (MIS) and integrate it closer to the source of data, or will it revamp how the institution does business completely and build everything from the ground up?

Most institutions will choose the first option to start with as it is the least risky, potentially moving to a greater integration of systems later as AI becomes more embedded in their operations. While this strategy does indeed reduce the risks inherent in the adoption of new technology, it also involves a tradeoff in the form of a longer runway to the cost-saving effects of full AI adoption. Whenever a provider's decision places them along this spectrum, this position should not be considered final and should be regularly reviewed, as it depends greatly on an organization's risk appetite, willingness to invest in new technology and emphasis placed on cost savings at any given time.

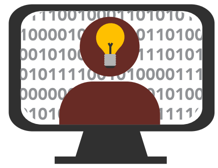
TEAM

Champion. Who will own the roll-out of the product? Success requires enthusiastic support from a C-level stakeholder and additional support from other roles directly affected by the adoption of AI.

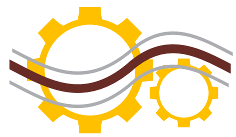
Specialists. Who will lead the implementation? An organization needs access to serious data chops to lead the AI/ML department. Options include:

- Building everything in -- house by hiring experts or acquiring a firm of experts[58]
- Partnering with tech -- why reinvent the wheel when the goods are already for sale?[59]

OPERATIONS



Fear Management. How will the FSP prepare for cultural change? Letting computers assist or even make decisions can get mixed responses, all the way from "it took my job!" to a lackadaisical work ethic based on a false sense of "AI's got my back." Creating a plan around this change is a critical driver of success.



Process Management. Accelerating existing workflows towards real-time can put pressure on existing processes that are more serial and time-consuming in nature -- a provider must have a strategy in place to address this prior to launching any AI-powered product.

Skills Management. Relevant staff have to start thinking in an evidence-based way. There is little point in doing all this if the "learning" part of ML is lost, so investing in training and professional development is typically a wise decision.

Product Management. What parts of the firm will AI/ML touch? Products? Ecosystems? Processes? Staffing? The answer is "probably all of the above." the question is "how."

4. Deployment & Considerations

Finally, now that these three dimensions of AI readiness have been addressed, we have reached the top of the hierarchy. The product can now be deployed and some of the initial theories of change can be tested. However, ongoing monitoring and evaluation of the product are critical to minimize the likelihood and impact of the risks.

The true value of AI, especially in the context of emerging markets, is its ability to augment the expertise of humans in their existing context. This ability relies on feature engineering, the craft of leveraging existing insights to create and test the data's quantitative features, which act as inputs to machine learning algorithms. This in turn requires the domain knowledge, intuition and expertise of humans that can make sense of large datasets and ask pointed questions related to the decisions taken by algorithms. AI can provide valuable feedback to institutions, but it should never operate without oversight. People with insights into customers and market context should be involved at the point of building algorithms to identify which features are appropriate to include in a model, but they should interpret and make sense of a model's feedback before making decisions about how to act on these insights.

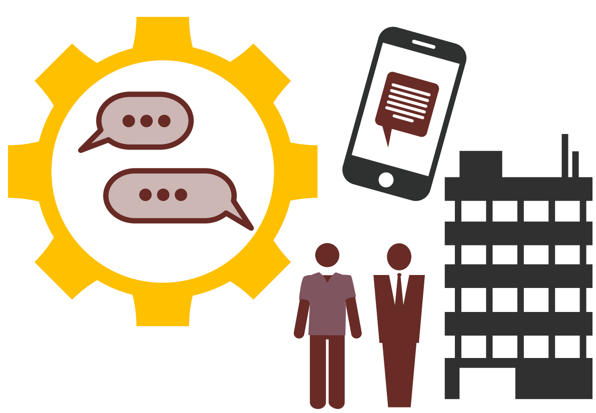
Institutions exploring AI should first ensure that they have defined the use case they are addressing, the success metrics for the predictive model, and the expected business outcomes of operationalizing the model. For example:

- Use case: "As a loan originator, I want to offer loans with a minimal chance of default, so that my portfolio-level ROI is sufficient to run a sustainable, profitable business."
- Success metrics: The model to predict non-defaulting borrowers, based on labeled, historical test data, should maintain 95 percent precision (ratio of non-defaulters to all borrowers), and 78 percent recall (ratio of non-defaulters approved by the model to the number of all non-defaulters in the historical data).[60]
- Expected outcomes: Reduce default rate by X percent, reduce costs in handling bad debt by $X.

These definitions are necessary but not sufficient in deploying an effective system. Providers must then put in place adequate controls to monitor on an ongoing basis and measure outcomes to manage these risks. The outcomes to be measured should not only cover the success metrics but unintended outcomes as well, to ensure the best possible experience for those working with the system.

9. Final Thoughts

Through FIBR we continue to actively encourage financial services providers to develop their thinking around the adoption of data and AI best practices as part of their core culture. We look forward seeing the evolution of financial services as they increasingly incorporate AI and also work to ensure the proper measures are in place to foster the inclusiveness and equitability of these services. As providers begin to incorporate into their cultures a continual assessment of AI readiness, and actively monitoring against risks and biases, we hope to see the monetary and competitive gains from AI to take financial services to the next level.



Annex A: List of Financial Services AI Companies in Africa Interviewed for Report

- Abe AI - Rob Guilfoyle, CEO
- Absa Bank - Tyron Reddy, Product Manager
- Aella Credit - Wale Akanbi, CTO
- BigML - Francisco Martin, Co-founder and CEO
- Branch - Daniel Jung, COO
- Cignifi - Qiuyan Xu, Chief Data Scientist
- DataProphet - Frans Cronje, Managing Director and Co-Founder
- LenddoEFL - Javier Frassetto, Chief Risk & Analytics Officer; Amie Vacarro, Director of Marketing
- FinChatBot - Antoine Paillusseau, CEO and Co-Founder
- Juntos - MacGregor Lennarz, Head of Business Development; Katie Macc, Chief Commercial Officer; Chris Walker, Principal Data Scientist
- Kudi - Pelumi Aboluwarin, CTO
- Lulalend - Neil Welman, CTO
- Smile Identity - Mark Straub, CEO
- Tala - Shivani Siroya, CEO; Lauren Moores, Director of Data Analytics (formerly employed by Tala); Ian Parish, Senior Data Scientist & Manager
- Teller - Sidharth Garg, CEO

Annex B: The Types of Machine Learning

ML includes supervised learning, unsupervised learning and reinforcement learning.[61] With supervised learning labels are added to training data to guide the algorithm until it reaches a point of predetermined accuracy. Unsupervised learning occurs when training data is not classified (or "labeled") beforehand; instead, the algorithm is meant to present insights based on the structure of the data. Many real-world examples fall in between these extremes -- some of the data might be labeled while others are not. This is referred to as semi-supervised learning. Finally, reinforcement learning allows an algorithm to process unlabeled data and receive feedback or reinforcement from humans who help the model to learn. It is important to note that whether an algorithm utilizes supervised or unsupervised learning does not determine its sophistication -- many supervised algorithms address complex problems, while unsupervised algorithms may address simpler problems.

ML Task	Example Application[62]	Inputs	Outputs
Supervised learning	"I need to predict when a user will default"	User features	Likely to default or not (labeled)
Unsupervised learning	"I need to understand the types of users in my system"	User features	Unlabeled groupings (these can be labeled manually or with another supervised learning problem, e.g., urban vs. rural)
Reinforcement learning	"I want my support chatbot to learn from past interactions in order to maximize customer retention"	User features	Optimized behavior of chatbot

In the case of semi-supervised learning, datasets are only partially labeled, so the algorithm "learns" with limited supervision from humans. Finally, in unsupervised learning the algorithm detects correlations or patterns in behavior from large, unlabeled datasets.

Endnotes

1 Kaddaras, Jim, "The Rise of a New Asset Class: Can 'PAYGo Finance' Connect Investors to Low-Income Customers?", NextBillion, July 2017. Available at: https://nextbillion.net/the-rise-of-a-new-asset-class-can-paygo-finance-connect-investors-to-low-income-customers/

2 McKinsey Global Institute. Artificial Intelligence: The Next Digital Frontier. June 2017.

3 The Wall Street Journal, "Machine Learning at Scale Remains Elusive for Many Firms", 27 April 2018. Available at: https://blogs.wsj.com/cio/2018/04/27/machine-learning-at-scale-remains-elusive-for-many-firms/

4 Biometrics Research Group, "What is Biometrics?", Department of Computer Science and Engineering, Michigan State University. Available at: http://biometrics.cse.msu.edu/info/index.html

5 Agrawal, Ajay, "The economics of artificial intelligence", McKinsey Quarterly, April 2018. Available at: https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/the-economics-of-artificial-intelligence

6 Destacame is a portfolio company of the Catalyst Fund, a program of BFA to accelerate early-stage fintech innovation.

7 Grasser, Matt, "Racing into Machine Learning: Data Readiness and the Developing World", Catalyst Fund Blog, 1 August 2017. Available at: https://blog.catalyst-fund.org/racing-into-machine-learning-data-readiness-and-the-developing-world-3aac261a2237

8 Amin, Ashirul, "Machine Learning Meets Credit Scoring: How it Can Help Reduce Loan Delinquency Costs", Catalyst Fund Blog, 8 June 2017. Available at: https://blog.catalyst-fund.org/machine-learning-meets-credit-scoring-how-it-can-help-reduce-loan-delinquency-costs-bf6eb6b28aea

9 Nomanini is a partner of FIBR, a BFA program to create new ways to connect low-income populations to financial services by partnering with financial and nonfinancial providers.

10 Monadjem, Vahid, "How data-driven short-term loans to informal merchants can drive financial inclusion," Nomanini, 3 April 2018. Available at: https://www.nomanini.com/single-post/How-data-driven-short-term-loans-to-informal-merchants-can-drive-financial-inclusion

11 Smile ID is a portfolio company of the Catalyst Fund, a program of BFA to accelerate early-stage fintech innovation.

12 Strands News, "Banking from an African Angle", 14 March 2017. Available at: https://finance.strands.com/strands-brings-pfm-to-commercial-bank-of-africa/

13 Financial Times, "AI in banking: the reality behind the hype", 11 April 2018. Available at: https://www.ft.com/content/b497a134-2d21-11e8-a34a-7e7563b0b0f4

14 Mitual Makadia, "7 Ways AI Conversational Interfaces Will Replace Web Forms", DZone, 14 March 2018. Available at: https://dzone.com/articles/7-way-conversational-interfaces-will-replace-web-f

15 UNESCO Literacy Statistics, 2017. Available at: https://en.unesco.org/themes/literacy

16 Leviathan, Yaniv Leviathan and Yossi Matias, "Google Duplex: An AI System for Accomplishing Real-World Tasks Over the Phone", Google, 8 May 2018. Available at: https://ai.googleblog.com/2018/05/duplex-ai-system-for-natural-conversation.html

17 Goel, Vindu, "Google Missed Out on China. Can It Flourish in India?" New York Times, 5 December 2017. Available at: https://www.nytimes.com/2017/12/05/technology/google-india.html?_r=0

18 Zollmann, Julie et al, Escaping Darkness: Understanding Consumer Value in PAYGo Solar. CGAP, December 2017. Available at: http://bfa.works/paygvalue

19 Database for publications on research in machine perception is available at: https://research.google.com/pubs/MachinePerception.html

20 NextBillion, "The Rise of a New Asset Class: Can 'PAYGo Finance' Connect Investors to Low-Income Customers?", July 2017. Available at: https://nextbillion.net/the-rise-of-a-new-asset-class-can-paygo-finance-connect-investors-to-low-income-customers/

21 TensorFlow, Android Demo App, 30 March 2018. Available at: https://www.tensorflow.org/mobile/tflite/demo_android

22 Meka, Sushmita and Linares, Javier, "Three Barriers to Smartphone Readiness in Emerging Markets", FIBR Blog, 9 May 2018. Available at: https://blog.fibrproject.org/three-barriers-to-smartphone-readiness-in-emerging-markets-3da5608184d0

23 Although new approaches for "small data" are being applied to AI, these efforts are nascent. See Ben Bowles, "How Quid uses deep learning with small data", Engineering Blog, 17 November 2017. Available at: https://quid.com/feed/how-quid-uses-deep-learning-with-small-data

24 Grasser, Matt, "Racing Into Machine Learning: Data Readiness & the Developing World", Catalyst Fund Blog, 1 August 2017. Available at: https://blog.catalyst-fund.org/racing-into-machine-learning-data-readiness-and-the-developing-world-3aac261a2237

25 Parbhoo, Amee, "7 Fintech Trends to Watch in 2018", Accion Blog, 17 January 2018. Available at: http://blogs.accion.org/features/7-fintech-trends-to-watch-in-2018/

26 Naidoo, Prinesha, "Inside Michael Jordaan's New Digital Bank Venture", Tech Central, 19 January 2018. Available at: https://techcentral.co.za/inside-michael-jordaans-new-digital-bank-venture/79085/

27 Parry, Calum, "Prime Tyme for South Africa's Newest Bank", Fintech Futures, 29 September 2017. Available at: http://www.bankingtech.com/2017/09/prime-tyme-for-south-africas-newest-bank/

28 Panno, Kellsy, Neo-Banks Pivot from Bank Disruptor to Partner, S&P Global Market Intelligence, 21 July 2016.

29 Flinders, Karl, "UK challenger bank gives up banking licence to focus on fintech", ComputerWeekly.com, 6 April 2018. Available at: https://www.computerweekly.com/news/252438486/UK-challenger-bank-gives-up-banking-licence-to-focus-on-fintech

30 Porteous, David and Olga Morawczynski, "Superplatforms are Coming and they Will Transform Financial inclusion", NextBillion, 22 January 2018. Available at: https://nextbillion.net/the-superplatforms-are-coming-and-they-will-transform-financial-inclusion/

31 CB Insights, "The Race For AI: Google, Intel, Apple In A Rush To Grab Artificial Intelligence Startups", 27 February 2018. Available at: https://www.cbinsights.com/research/top-acquirers-ai-startups-ma-timeline/

32 Rai, Saritha, "Alibaba-Backed Paytm Aims to Become World's Largest Digital Bank", Bloomberg, 28 November 2017. Available at: https://www.bloomberg.com/news/articles/2017-11-28/paytm-aims-to-become-world-s-largest-full-service-digital-bank

33 Kuo, Lily, "Ali Baba's Jack Ma is Visiting Kenya and Rwanda to Look for Deals and Inspired Entrepreneurs", Quartz, 20 July 2017. Available at: https://qz.com/1034377/alibabas-jack-ma-is-visiting-kenya-and-rwanda-to-look-for-deals-and-inspire-entrepreneurs/

34 Lamont, Paul. "Does human touch have a place in the age of financial services?" Accion Ventures Blog. https://medium.com/accion/does-human-touch-have-a-place-in-the-age-of-digital-financial-services-fed27c63f8c9

35 Porteous, David and Olga Morawczynski, "Superplatforms are Coming and they Will Transform Financial inclusion", NextBillion, 22 January 2018. Available at: https://nextbillion.net/the-superplatforms-are-coming-and-they-will-transform-financial-inclusion/

36 Djelassi, Bilal, "Full-stack neobanks are taking the retail banking market to the next level", Medium, 12 July 2017. Available at: https://medium.com/@bilal.djelassi/full-stack-neobanks-are-taking-the-retail-banking-market-to-the-next-level-cc0f3d2692dd

37 Scott, Katy, “Is Africa’s $30 smartphone a game changer?”, CNN, 5 May 2017. Available at: https://www.cnn.com/2017/05/05/tech/africa-30-smartphone/

38 African Development Bank Group, African Economic Outlook 2012: Promoting Youth Employment, 2012.

39 Zunger, Yonatan, “Asking the Right Questions About AI”, Medium, 12 October 2017. Available at: https://medium.com/@yonatanzunger/asking-the-right-questions-about-ai-7ed2d9820c48

40 Wickham, Hadley, “Tidy Data”, Journal of Statistical Software, Volume 59, Issue 10, August 2014.

41 di Castri, Simone and Plaitakis, Ariadne, “Going Beyond Regulatory Sandboxes to Enable FinTech Innovation in Emerging Markets”, SSRN, 23 January 2018. Available at: https://ssrn.com/abstract=3059309 or http://dx.doi.org/10.2139/ssrn.3059309

42 O’Connor, Brendan, Quantifying the Cost of Forced Localization, Leviathan Security Group, 24 June 2015. Available at: https://www.leviathansecurity.com/blog/quantifying-the-cost-of-forced-localization

43 For example, Ghana’s Data Protection Act prohibits the purchase and sale of customers’ personal data, even with customer consent.

44 Leetaru, Kalev, “The Problem Isn’t Cambridge Analytica: It’s Facebook”, Forbes, 19 March 2018. Available at: https://www.forbes.com/sites/kalevleetaru/2018/03/19/the-problem-isnt-cambridge-analytica-its-facebook/#52db2eba58a5

45 Ruth Pogacar et al, “The Subtle Power of Default Choices”, FastComany, 9 April 2018. Available at: https://www.fastcompany.com/40403706/the-subtle-power-of-default-choices

46 Constine, Josh, “Facebook and the Endless String of Worst-Case Scenarios”, TechCrunch, 19 March 2018. Available at: https://techcrunch.com/2018/03/18/move-fast-and-fake-things/

47 Taylor, Martin, “How to Stop WhatsApp from Sharing your Information with Facebook”, cnet.com, 16 August 2016. Available at: https://www.cnet.com/how-to/how-to-stop-whatsapp-from-sharing-your-information-with-facebook/

48 For a map showing which countries had adopted or were considering comprehensive data protection legislation as of January 2018, see David Banisar, National Comprehensive Data Protection/Privacy Laws and Bills 2018.

49 Data protection regulation typically focuses on the protection of personal data. While definitions vary, generally speaking “personal data” refers to information relating to an identified or identifiable natural person.

50 Catalyst Fund, “Toolkit: Design for Trust”. Available at: https://www.cftoolkit.org/design-for-trust-index

51 Rogati, Monica, “The AI Hierarchy of Needs”, Hacker Noon, 1 August 2017. Available at: https://hackernoon.com/the-ai-hierarchy-of-needs-18f111fcc007

52 For more information on APIs, see BFA’s “Implications, insights and guidance on use of Open Application Programming Interfaces (APIs) by financial services providers in emerging economies”. Available at: http://fsdkenya.org/publication/implications-insights-and-guidance-on-use-of-open-application-programming-interfaces-apis-by-financial-services-providers-in-emerging-economies/

53 WorldCover is a portfolio company of the Catalyst Fund, a program of BFA to accelerate early-stage fintech innovation.

54 We have expanded on this interplay between data analysis and real-world context in a FIBR Briefing Note entitled “The Lean Product Waltz: Data-Driven User Research & Research-Driven Data Analysis”. Available at: http://www.bfa.works/fibrBN2

55 Cook, Tamara and Claudia McKay, “How M-Shwari Works: The Story So Far”, CGAP and FSD Kenya Forum Note, 2015.

56 Mustafa, Zeituna et al, “Where Credit Is Due: Customer Experience of Digital Credit in Kenya”, MicroSave, March 2017. Available at: http://www.microsave.net/resource/where_credit_is_due_customer_experience_of_digital_credit_in_kenya

57 South Africa’s Protection of Personal Information Act, for example, provides some protection to individuals and legal entities (referred to as “data subjects”) with respect to decisions based solely on automated processing of personal information that have legal consequences or affect data subjects “to a substantial degree”. Similar restrictions are included in data protection regulation in other African jurisdictions, including Ghana, ECOWAS, SADC and the African Union Convention on Cyber Security and Personal Data Protection.

58 IFC and Mastercard Foundation, “DATA ANALYTICS AND DIGITAL FINANCIAL SERVICES”, 2017. Available at: https://www.ifc.org/wps/wcm/connect/22ca3a7a-4ee6-444a-858e-374d88354d97/IFC+Data+Analytics+and+Digital+Financial+Services+Handbook.pdf?MOD=AJPERES

59 Kelly, Sonja et al, “How Financial Institutions and Fintechs Are Partnering for Inclusion: Lessons from the Frontlines”, Center for Financial Inclusion at Accion and the Institute of International Finance, July 2017. Available at: http://www.centerforfinancialinclusion.org/storage/CFI_IIF_FI_Fintech_Partnerships_Report_2017.07.pdf

60 Optimizing around precision and recall necessarily requires a tradeoff. An optimistic model -- one that gives loans to all applicants -- will end up with low precision and high recall. On the other hand, a pessimistic model -- one that treats all applicants as defaulters -- will end up with high precision but low recall.

61 McKinsey & Company, An Executive’s Guide to AI. Available at: https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/an-executives-guide-to-ai

62 Machado, Gustavo, “ML Basics: supervised, unsupervised and reinforcement learning”, Medium blog, October 6 2016. Available at: https://medium.com/@machadogj/ml-basics-supervised-unsupervised-and-reinforcement-learning-b18108487c5a

63 Osoba, Osonde and William Wesler IV. An Intelligence in Our Image: The Risks of Bias and Errors in Artificial Intelligence. RAND Corporation, 2017. Available at: https://www.rand.org/content/dam/rand/pubs/research_reports/RR1700/RR1744/RAND_RR1744.pdf

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