



July 1, 2021

By electronic submission to 2021-RFI-AI@cfpb.gov

Comment Intake
Bureau of Consumer Financial Protection
1700 G Street, NW
Washington, DC 20552

Re: Request for Information and Comment on Financial Institutions' Use of Artificial Intelligence, including Machine Learning: Docket CFPB-2021-0004

Dear Sirs and Madams:

The Online Lenders Alliance (OLA) welcomes the opportunity to respond to the request for information regarding the use of artificial intelligence (AI), including machine learning (ML) by financial institutions.

OLA represents the growing industry of innovative companies that develop and deploy pioneering financial technology, including proprietary underwriting methods, sophisticated data analytics and non-traditional delivery channels, to offer online consumer loans and related products and services. OLA's members include online lenders, vendors and service providers to lenders, consumer reporting agencies, payment processors and online marketing firms.

Fintech companies are at the vanguard of innovative online tools that reach new customers, prevent and mitigate fraud, manage credit risk, and service loans. Online lenders provide benefits to consumers, particularly those in underserved communities, with fast, safe, and convenient choices that simply are not available through traditional lending markets.

OLA advocates that regulators give strong consideration to a flexible policy framework that encourages collaboration and capacity building. Such an approach will foster an environment that gives consumers the ability to find the products and services that best fit their needs.

Much of the innovation undertaken by OLA members through the application of AI/ML has given consumers greater control over their financial future. This is especially the case when it comes to access to capital. Whether purchasing a home, starting a business, financing an education, or even paying for auto repairs, the ability to find and secure credit is often a determining factor in a consumer's financial wellbeing. While AI/ML have played a major role in these endeavors, they

should not be viewed solely in their own silo. Instead, they are one of a set of tools that, along with new data sources and the advent of innovative bank-fintech third party service relationships, have helped create a new financial service landscape.

Role of Data in AI/ML

This paradigm shift is due in large part to changes in today's credit markets, as consumers seek new products or look for different ways to improve their credit. While new to portions of the financial services sector, much of the underlying statistical methods on which AI/ML are predicated have existed for years. These methods access, analyze and draw conclusions about enormous amounts of data far faster and more efficiently than ever before. As a result, consumers are now able to tailor the process to meet their needs in ways that were not possible a decade ago, unlocking the doors to credit for millions of Americans.

One unique aspect of these tools is that the value of data does not diminish when used and, in some cases, the value increases as more data is accumulated. The expanded availability of different types of data, including cell phone payments, checking account activity, utility payments, rent and other everyday transactions, is fueling phenomenal growth and creating new products and services that are revolutionizing the marketplace. While relatively new to the consumer credit markets, these types of data have been a staple of business reporting credit agencies like Dun & Bradstreet. When teamed with compliant AI/ML modeling techniques, these data sources create a more inclusive credit system. Research by LexisNexis found that when alternative data is factored into borrowers' existing credit history, twenty percent (20%) of those borrowers qualify for a loan with better terms and conditions.¹

This is especially important for individuals with low scores due to late payments, high debt, a lack of credit history and other negative factors, who often end up paying more in the form of higher rates or are locked out from mainstream credit altogether. For decades, much of the lenders' credit decision-making process was predicated on a consumer's credit score from one of the big three national credit bureaus. However, many traditional credit scores do not provide the full picture of a consumer's credit history, which has prevented millions of Americans from accessing the credit they sorely need. AI/ML, when teamed with expanded data options, plays a significant role in connecting these consumers with new products and services.

Impact of Bank-Third Party Vendor Agreements on the Growth of AI/ML

The growth and widespread use of AI/ML in the credit market would not have been possible without the formation of new working relationships between banks and fintech companies. This has led to innovative offerings that provide more choices to consumers with a wide range of credit profiles and histories.

¹ Alternative data uncovers new opportunities in a changing environment; <https://risk.lexisnexis.com/insights-resources/white-paper/loan-growth-in-a-new-economy>

For financial institutions that aim to serve consumers who lack access to formal financial services, these new tools offer an unprecedented opportunity. AI/ML provide the ability to capture and analyze vast amounts of information in real-time, use in-depth analytics to improve credit models, identify new customers, evaluate the products they need at the right time, and create seamless customer experiences.

The dynamic growth in AI/ML holds the potential to improve efficiencies in banking procedures, allowing financial institutions to better understand customer needs, transform credit options and help the underbanked gain more access to traditional financial services. Historically, banks have routinely relied on relationships with third parties to deliver financial services more broadly and efficiently, and with less risk to consumers and the banks themselves. Today, working with a fintech company that employs AI/ML services can bridge many of the challenges banks face in supporting today's consumers. Many of these fintech firms have spent years developing innovative and proprietary technologies and analytics. Using fintech company expertise enhances banks' ability to serve more nonprime consumers. These connections allow the bank to deploy its own capital to make new loans, thereby providing broader access to credit for consumers and small businesses.

Much of this growth has taken place due to the Office of the Comptroller of the Currency's (OCC) efforts to encourage greater bank use of third-party service providers as a way to foster innovation in the banking system and promote inclusivity for underserved consumers and communities. OLA applauds the OCC's work on several policy initiatives that encourage banks to utilize the resources that non-banks can offer.

The Center for Financial Services Innovation, in a comment letter to the FDIC, characterized bank third party fintech agreements as a "win-win-win" for all involved, including consumers. Banks win because they can serve a broader and deeper segment of the consumer market than they otherwise could; third-party fintech providers win by creating an opportunity to offer products and services to consumers that they could not otherwise reach; consumers win because they "get access to high-quality credit that they otherwise would not." This can also allow "smaller and more rural banks to broaden the portfolio of products and services they can offer to consumers and small businesses in their communities."²

The Federal Deposit Insurance Corporation (FDIC), in proposed examination guidance for third-party lending programs, echoes these sentiments: "Third-party lending arrangements may provide institutions with the ability to supplement, enhance, or expedite lending services for their customers. Engaging in third-party lending arrangements may also enable institutions to lower costs of delivering credit products and to achieve strategic or profitability goals."³

With banks of all sizes routinely relying on third parties to provide critical services, a robust regime of third-party supervision has been established by the federal banking agencies. Importantly, this ensures that activities occurring outside of the bank are examined and supervised to the same extent as if they were being conducted by the bank itself. This

² CFSI Comment Letter on Proposed Guidance for Third-Party Lending (Oct. 27, 2016), <https://cfsinnovation.org/research/cfsi-comment-letter-on-proposed-guidance-for-third-party-lending/>.

³ FDIC, Proposed Guidance: Examination Guidance for Third-Party Lending (July 29, 2016), <https://www.fdic.gov/news/news/financial/2016/fil16050a.pdf>.

supervision protects consumers and the financial system. Bank-sponsored lending programs with fintech firms are no exception, and both the OCC and FDIC have published detailed guidance as to how these relationships should be managed and supervised. These guidelines clearly state that any loans issued by a bank—including those that benefit from the technology of a fintech partner—are subject to the same high level of scrutiny and regulation as any other loan issued by the bank. This ensures borrowers are protected and that the level of supervision is appropriately applied. It also enables consumers to choose to work with a federally licensed lender, providing greater confidence and security.

Use of AI by Small and Community Banks

Consumers' use of the internet for financial services and products has accelerated during the pandemic, requiring banks to have the capacity to leverage evolving technologies. For small and community banks, utilizing a third-party vendor provides enormous opportunities to reach new customers and obtain greater portfolio risk diversification, particularly in the areas of process automation and fraud detection.

Non-bank fintech providers offer small and community banks expertise in AI/ML, as well as in innovative underwriting and credit risk assessment techniques, that such banks may not possess. This enables smaller banks to make greater use of the internet to originate loans. It can also open opportunities for these banks to move beyond consumer loans to small business lending and other new borrowers outside their traditional footprint. Borrowers of lesser credit quality, whether they are thin-file or no-file consumers, can benefit from the algorithms and greater use of non-traditional analytics employed by fintech firms. These new technologies can allow a bank to better target and more accurately customize product offerings, increasing overall efficiencies. All of this translates into greater competition among providers, a lowered cost of credit, and more options and credit access for consumers.

For the bank, due diligence is critical when selecting a third-party vendor to learn how AI/ML models are generated, operated, and monitored. Ongoing vendor oversight to “check the work” and ask the right questions is equally important. This underscores the reality that today, all companies are data companies, especially financial service organizations. Accordingly, it is not only prudent but necessary from a competitive standpoint to have a lead executive overseeing data science and predictive modelling. Many community banks may not have the requisite expertise in house. If they lack such expertise, they should look to use the resources of a board member or hire an external entity to hold the third-party company accountable to best practices. This can also be a challenge for larger institutions that can carry risks due to the use of multiple models that makes oversight difficult without decentralization.

Organization size is a factor when choosing the right AI/ML models to meet their needs. Smaller institutions many encounter data size issues, making certain model techniques a poor fit due to the limited scope of their data pool. This only reinforces the need to have access to a trained professional who understands data science and predictive modelling to gauge risks associated with each modelling technique.

Explainability and AI

With the increased application of AI/ML and its growing complexity, questions have been raised over the scalability of AI/ML systems. AI/ML models are often viewed as extremely opaque, with questions over algorithms and an inability to provide rationales for outcomes. This has, in turn, increased calls for transparency and understandability of the systems.

This is particularly a challenge when using AI for a “true credit score,” where it is important to know the most influential variables that contributed to a score. While this can be more difficult, specific model methodology used is key. Several highly advanced modelling techniques are still relatively easy to explain, like tree-based models.⁴ Conversely, others like neural network⁵ and similar models are “harder” to explain due to their complexity. Furthermore, the ability to show the influence of a particular variable on a decision is difficult without significant scenario analysis that controls for fluctuations in all other variables.

Still, it is not impossible for financial institutions looking to evaluate models to do so. There are several options available, including conducting random sample testing, out-of-sample/holdout testing and out-of-time testing, as well as monitoring for stability over time during product development to ensure the continued predictive quality of the models. These methodologies are quite common for any model development, and it benefits the end user to utilize these options.

Taking these steps will ensure the stability and viability of the model. It is important to monitor models for input variable(s) degradation or changes in distribution. If these do occur, a redevelopment or update may be required. One way to guard against this from happening is to use variables with a certain confidence and predictive threshold, thus guarding against the volatility and over-fitting associated with uncontrolled and automated AI models.

A significant limitation to the validity of post-model development testing and evaluation methods is the sample size used as a holdout. It is essential during development to ensure that holdouts are representative of the current environment or other similar environmental factors. Issues with data drift (i.e., distribution swings between development and production populations) can be monitored and, should they occur, addressed by model re-development at elevated levels.

A major concern regarding transparency is to guard against overfitting.⁶ This can be addressed by using out-of-sample testing, random sample testing, and altering the sensitivity of the model by forcing “broader binning.” Again, oversight is key. If performance that is not warranted does occur, it can be corrected as more data becomes available, allowing the model to adjust without overfitting.

⁴ Tree-based models use a decision tree to represent how different input variables can be used to predict a target value. <https://c3.ai/glossary/data-science/tree-based-models/>

⁵ Neural network models are forecasting methods that are based on simple mathematical models of the brain. They allow complex nonlinear relationships between the response variable and its predictors. <https://otexts.com/fpp2/nnetar.html>

⁶ Overfitting is a modeling error in statistics that occurs when a function is too closely aligned to a limited set of data points. <https://www.unite.ai/what-is-overfitting/>

Some best practices for institutions are to monitor inputs and not allow them to occur unsupervised. All systems need management and oversight on an ongoing basis by a knowledgeable data scientist. The biggest risk to the quality of the output is introducing unstructured data or data that could be misconstrued. That is why it is vital to feed the model only variables and data that are acceptable to use and review. It is important to make sure that any and all data the system utilizes is predictive enough for use before the addition of new variables. Models should not add new variables without advance knowledge of their impact.

This monitoring is especially important for “dynamic updating.” Institutions cannot let systems evolve “un-supervised,” which is why as a part of monitoring and management, institutions should be involved in the approval of any major changes (model method, inputs, etc.) before deployment. It is also essential to have model and input variable stability scorecards/tracking in place to ensure that, should “drift” occur, the institution is aware and can evaluate the new data. Using multiple explanatory techniques and stress testing models can more rigorously validate a model’s decision-making, leading to greater trust and reception of AI/ML models.

Cyber Security and Fraud

Shopping for financial products online has been on the rise over the past decade and has accelerated during the COVID-19 pandemic as virtual experiences have replaced many traditional face-to-face interactions. Gone are the days when perspective borrowers only go to their bank for a loan. Such interactions served many purposes, including allowing the institution to determine some level of proof that the individual was who they said they were.

While the increase in digital transactions has given consumers greater flexibility, it has also created an element of uncertainty for the lender. AI/ML helps determine the validity of potential borrowers through modeling that compares ID elements used across applications; examines transaction details, such as the type of device used and time of day; and checks Social Security numbers against birth dates, addresses and death records.

Security concerns and potential liability exposure often are cited as a concern by financial institutions that are hesitant to work with fintech providers. This can often result in limiting the use of AI/ML models. It also can result in the institution putting in place processes and protocols that hamper banks’ ability to take full advantage of the benefits that AI/ML offer.

OLA and its members take data security very seriously, which is why it has established Best Practices that include consumer data protections⁷. In addition, the very technology that has allowed fintech firms to develop new products has also been central to the development of strong security protocols. Along with these guidelines many fintech firms must also comply with provisions of the Gramm-Leach-Bliley Act to the extent that they obtain personally identifiable financial information from banks. Lenders, fintech’s, and other providers similarly need to comply with industry standards such as PCI-DSS (if they accept card transactions or support a card-based product). These are on top of state data breach notifications, and other state laws (i.e., California’s CCPA) and the soon-to-be effective CPRA, that put in place consumer-focused data privacy protections that has led to other

⁷ OLA Best Practices <https://onlendlendersalliance.org/best-practices/>

states considering the implementation of their own standards. Additionally, these companies may be subject to supervision by financial regulators such as FFIEC members.

Cyber security/fraud prevention tactics used by the fintech industry are as varied as the companies themselves. AI-based tools for cybersecurity have emerged to help information security teams reduce breach risk and improve their security posture efficiently and effectively. AI/ML have become critical technologies in information security, able to quickly analyze millions of events and identify many different types of threats, from malware exploiting zero-day vulnerabilities to identifying risky behavior that might lead to a phishing attack or the download of malicious code. These technologies learn over time, drawing from past actions to identify new types of attacks. Behavior histories build profiles on users, assets, and networks, allowing AI to detect and respond to deviations from established norms.

There simply is no “one size fits all” solution that works in all instances. This has required fintech companies and their partners to tailor tactics and strategies, developing protocols based on specific and unique security challenges. While necessary, this presents additional barriers to product development and access to new customers, particularly for niche products or companies looking to enter smaller markets.

Fair Lending

As financial institutions increasingly deploy artificial intelligence tools to make loans, it is important that lenders guard against the same biases that have plagued credit decision making in the past. AI/ML can help financial institutions reverse past discrimination and foster a more inclusive economy. The key lies in building AI-driven systems that are predicated less on historic trends and more focused on providing greater equity. That requires training and testing regimens that are cognizant of past biases and prioritize fair lending principles.

Fintech companies routinely take steps to test their underwriting models for compliance with fair lending laws, including the use of CFPB’s report on fair lending analysis to test for potential discriminatory impacts. In addition, companies regularly make use of model risk management guidance from federal banking regulators to review their models for unintended bias, and many companies employ third parties, including consulting and law firms specializing in fair lending, to test their systems for compliance with fair lending laws. These proactive steps have helped mitigate any potential for unintentional biases creeping into the modeling.

To successfully guard against bias, the use of FCRA compliant inputs for credit decisions ensures that that systems are making sound credit decisions. This also ensures that, even with more advanced modelling techniques, the variables used will allow for the explanation of their directionality and weight. Additionally, fintech companies can utilize credit decision models predicated on more explainable techniques such as binned trees and linear or logistic regression and utilize other model types in non-credit related decisions like fraud detection.

Critical to protecting against unintended bias is to guard against employing inputs that could be directly or indirectly discriminatory. AI/ML models are inherently free of bias and only show the predicted value (score or prediction) based on what the inputted data reports. Data cannot see color, gender, or race; any remaining potential for a higher weighted average risk score (or

lower credit score) is the result of the inputs it was given to use. For example, if men have lower average credit scores than women, this does not indicate that the score is biased against men; rather, it means that in the data set, men exhibited statistically more “risky” behaviors (late payments, defaults, etc.) than women. It is the valid input data that made the determination, based on the actual observed performance of the group.

Successful AI/ML model management should utilize oversight practices and risk management principles that apply variable choice, model selection, and stability monitoring to ensure that fair lending laws are observed. One particular challenge for online lending is the fact that the financial institution does not know the gender, race, or other demographic factors of a prospective borrowers, making bias testing difficult. Still, lenders that employ strong fair lending compliance oversight that utilizes FCRA-compliant data and employs explainable modelling methodologies offer important safeguards to ensure fair and equitable lending.

Challenges and Barriers to AI/ML

Despite its substantial promise, AI/ML faces potential obstacles that could limit its adoption. Regulators have at times been overly cautious about innovation, and in the case of AI/ML have communicated the rules of engagement inconsistently. This has led to uncertainty that discourages traditional financial institutions from engaging in new and creative uses for these techniques that could end up limiting availability of credit to consumers.

These challenges are exacerbated by an antiquated regulatory patchwork structure that is ill-suited to adapt to today’s rapidly changing digital landscape. The rules are better suited to an age when information was mainly on paper or floppy disk and stored on servers down the hall. Such rules are obsolete in today’s environment, where massive amounts of information are moved seamlessly and instantaneously around the globe.

The regulatory framework has a sizable influence over innovations that will be critical to the success of fintech, such as machine learning, digital ID, artificial intelligence and cloud-based systems. Policymakers need to make sure the rules are technology-neutral to prevent impeding innovations that otherwise could meet the financial needs of consumers.

To maximize the potential of fintech, regulators should keep in mind that AI/ML-driven technologies are exponentially more powerful and effective when they have access to larger pools of information. The harmonization of definitions, requirements, and expectations for data protection through a national standard would provide a level of legal certainty that would facilitate the continued growth of these new technologies, while protecting consumers from unwanted access and use of their data.

Standards should recognize today’s technology needs by offering the flexibility and space to innovate. This will give companies of all sizes the ability to take a risk-based approach to innovation, tailoring what best works for their own business models, practices and customer needs. This is particularly critical for startup companies, enabling them to devote limited resources to expanding their products and services instead of towards complying with prescriptive rules unfit for their risk profiles. This also makes it easier for firms to operate securely across various jurisdictions and enter new markets.

As with any new product or service, important questions remain around appropriate uses and oversight. It will be important to monitor the application of AI/ML models to track adherence with safety and soundness protocols, particularly in the areas of cyber security and data privacy. It is also incumbent upon the industry to provide proper training and transparent testing of its models and algorithms to guard against unintended bias creeping into its products and services. However, these concerns should not be used as an excuse to block the smart use of AI/ML in the financial system.

AI/ML has revolutionized the financial services sector, altering business models, risk mitigation strategies and systems performance. As this technology continues to evolve, consumers increasingly will come to expect more accessible products and services in real time, which will change the way both individuals and companies engage in financial activities. That is the ultimate promise of fintech: delivering safer, more transparent, lower cost, and more convenient financial products and services to consumers.

OLA appreciates this opportunity to offer input on these key issues. If you have questions or need additional information, please feel free to contact me at mday@OLADC.org.

Respectfully submitted,

A handwritten signature in cursive script that reads "Michael Day".

Michael Day
Policy Director
Online Lenders Alliance