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Submitted via regulations.gov

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RE: COMMENT REQUEST FOR INFORMATION AND COMMENT ON FINANCIAL INSTITUTIONS' USE OF ARTIFICIAL INTELLIGENCE, INCLUDING MACHINE LEARNING (MARCH 31, 2021) (OCC DOCKET ID OCC-2020-0049, FRB DOCKET No. OP-1743, FDIC RIN 3064-ZA24, CFPB DOCKET NP. CFPB-2021-0004, NCUA DOCKET No. NCUA-2021-0023)

The Independent Community Bankers of America (ICBA)¹ appreciates this opportunity to comment in response to the Office of the Comptroller of the Currency, Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation, Bureau of Consumer Financial Protection and National Credit Union Administration (collectively the "Agencies") request for information (the "RFI") on financial institutions' use of artificial intelligence ("AI"), including machine learning ("ML").²

Like many technological innovations, AI and ML present a mixture of risks and opportunities for the community banking industry. Though not widely implemented by community banks, AI can

¹ The Independent Community Bankers of America creates and promotes an environment where community banks flourish. ICBA is dedicated exclusively to representing the interests of the community banking industry and its membership through effective advocacy, best-in-class education, and high-quality products and services. With nearly 50,000 locations nationwide, community banks constitute 99 percent of all banks, employ more than 700,000 Americans and are the only physical banking presence in one in three U.S. counties.

² 86 Fed. Reg. 16837.

be used to automate back-office and compliance functions such as the notice requirements of the Equal Credit Opportunity Act (ECOA) and fraud detection. As the technology becomes more accessible, automating these compliance functions may become a viable option for community banks which are seeking tools to combat an ever-increasing regulatory burden.

AI can also be used in some customer-facing roles, like 24/7 chatbots that enable customers to access support when staff is not available. Finally, AI/ML can be used to automate underwriting, though this use-case requires model risk management to prevent inadvertent fair lending violations. While cybersecurity and data privacy risks are not unique to AI, they are worthy of consideration because AI/ML algorithms cannot function without access to sensitive customer personally identifiable information (“PII”).

While AI/ML is an emerging technology, it seems likely that, in the longer run, it will play an increasingly larger role in the banking industry. For this reason, ICBA believes that regulators should not act prematurely to promulgate rules and regulations that inadvertently stifle innovations that could lower costs and benefit the industry and consumers alike.

Furthermore, from a banker’s perspective, it is less important whether a technology product is branded as AI, ML, or something else – what matters are the outcomes it delivers. Indeed, it can sometimes be difficult to determine whether technologies billed as AI are truly innovative and add value or merely a marketing gimmick. In this same vein we believe that existing, outcome-based regulations are often sufficiently flexible to regulate AI models and that AI-specific regulation is not usually required.

Explainability

The potential usefulness of AI in underwriting is that it can analyze vastly more data than a human underwriter and identify non-obvious, non-intuitive relationships. This creates the potential for AI to identify creditworthy borrowers that traditional underwriting methods might have missed. Given the importance of reaching historically underserved populations, this potential benefit of AI underwriting cannot be ignored.

According to the CFPB, 26 million consumers—about one in 10 adults in America—could be considered credit invisible because they do not have any credit record at the nationwide credit bureaus. Another 19 million consumers have too little information to be evaluated by a widely used credit scoring model. AI has the potential to expand credit access by enabling lenders to evaluate the creditworthiness of some of the millions of consumers who are unscorable using traditional underwriting techniques.³

³ CFPB, “CFPB Report Finds 26 Million Consumers Are Credit Invisible” (May 5, 2015), available at: <https://www.consumerfinance.gov/about-us/newsroom/cfpb-report-finds-26-million-consumers-are-credit-invisible/>.

In addition to credit scores, AI models can review alternative data that is cost prohibitive to analyze using traditional underwriting models, including cash flow, rent history, utility and cell phone payment history, employment history and property ownership. Analysis of alternative data shows the potential to expand access to credit for those with a thin credit history or to counterbalance traditional indicators of lack of creditworthiness such as a low credit score.

On the other hand, as the RFI points out, some AI approaches can struggle with a lack of explainability – that is, it can be difficult to explain why they made a given decision after the fact. Highly complicated AI software like neural networks aim to simulate organic learning in order to generate progressively more accurate decisions – in the case of a credit underwriting AI, its goal would be to make loans that are ultimately repaid and deny applications that would end in default – but the process of an algorithm dynamically updating can make it difficult to determine exactly what factors the program considered to reach its conclusion.

However, the “black box” nature of deep learning AI models does not necessarily mean that they are conceptually unsound, nor impossible to explain with post hoc analysis. The simplest way to analyze the soundness of a model is to analyze its success rate. If its purpose is to underwrite loans, one could judge its soundness on the percent of approved borrowers that default. If its purpose is to flag suspicious transactions, a model could be evaluated based on the percentage of transactions flagged that are related to money laundering.

These types of analysis only demonstrate the effectiveness of the model, sometimes referred to as its global explainability. They may not be responsive, for example, to an individual who inquires why the model rejected their application for a loan. In our view, a relatively simple analysis of outcomes is sufficient to demonstrate a model’s global explainability and thus conceptual soundness – particularly if these outcomes compare favorably to traditional approaches to compliance or underwriting. Local explainability is admittedly more difficult, but we believe that (1) a list of inputs considered by a model (2) evidence that model is conceptually sound; and (3) an explanation-by-example of the model reaching the same output in a similar case are sufficient to provide local explainability and provide adequate insight into the operations of a “black box” AI.

Fair Lending

The agencies note that “it may be challenging to verify that a less transparent and explainable approach comports with fair lending laws.”⁴ In our view, the potential of AI to lower credit prices and expand access to credit against historically underserved groups, many of which fair lending laws are explicitly designed to protect, mean that it would be a mistake for regulators to discourage AI driven loan processing due to fair lending risk.

⁴ 86 Fed. Reg. 16841.

The Equal Credit Opportunity Act (ECOA) prohibits discrimination based on race, color, religion, national origin, sex or marital status, or age.⁵ While ECOA plainly prohibits facial and intentional discrimination (disparate treatment), it has also been used to prohibit and hold accountable unintentional and facially neutral activities that result in a discriminatory impact on protected classes (disparate impact). It is disparate impact liability that presents the biggest challenge for lenders in implementing AI-based underwriting because, under a disparate impact theory, a facially neutral algorithm that does not consider prohibited characteristics like race or sex, can give rise to liability even in the absence of a discriminatory intent.

In our view, the chilling effect of disparate impact liability on the implementation of AI-based underwriting does a disservice to the very people ECOA was enacted to protect. On November 30, 2020, the CFPB issued a No Action Letter (“NAL”) to Upstart Network, Inc., giving the firm a 36-month period where the Bureau will not bring a supervisory or enforcement action against upstart under ECOA or its Unfair, or Deceptive, or Abusive Acts and Practices Authority.⁶ The NAL was conditioned on Upstart’s adherence to a Model Risk Assessment Plan (“MRAP”), requiring Upstart to:

1. Notify the Bureau of significant changes to Upstart’s model prior to implementation;
2. Provide the Bureau with model documentation on a periodic basis, including a Technical Report (which describes certain aspects of each component of Upstart’s model) and Performance Monitoring Reports (which evaluate how Upstart’s customer population and model performance change over time);
3. Test Upstart’s model and/or variables or groups of variables on a periodic basis for adverse impact and predictive accuracy by group, with results provided to the Bureau;
4. Research approaches that may produce less discriminatory alternative models that meet legitimate business needs;
5. In addition to fair lending testing, conduct periodic access-to-credit testing to determine how Upstart’s model compares to other credit models in enabling credit access, with results provided to the Bureau; and
6. Provide the Bureau access to the software code that is used to implement the MRAP.⁷

We commend the Bureau for issuing the NAL to Upstart and see it as a model for future agency action to other firms that develop responsible AI underwriting algorithms. NALs like the Upstart letter give financial institutions the regulatory certainty they need to develop new technologies that reduce costs and benefit consumers. By ensuring that models are adequately governed and tested, this can be done without compromising consumer protection or creating significant risk of inadvertent fair lending violations.

⁵ 15 U.S.C. 1691(a).

⁶ CFPB, Upstart Network No Action Letter (Nov. 30, 2020), available at: https://files.consumerfinance.gov/f/documents/cfpb_upstart-network-inc_no-action-letter_2020-11.pdf.

⁷ *Id.* at 3.

ECOA and Reg B require creditors to provide consumers with the main reasons for a denial of credit or other adverse action.⁸ This notice requirement may present some challenges for AI, because of the issue of explainability, as discussed above – in short it can be difficult, though not impossible, to describe the reasons for a model’s behavior post-hoc if that model is dynamic and highly complex.

We believe that the CFPB’s current guidance strikes an appropriate balance on this issue. Reg B, as currently interpreted by the CFPB includes sufficient flexibility to account for adverse action notices resulting from AI underwritten credit denials. For example, the agency’s comments on Reg B state that “[A] creditor need not describe how or why a factor adversely affected an applicant. For example, the notice may say “length of residence” rather than “too short a period of residence.””⁹ Under this guidance, a lender would be able to satisfy the notice requirements by disclosing the variables considered by a “black box” AI without disclosing their specific weighting or relationship to each other.

Cybersecurity Risk

As with all technology, financial institutions thoroughly assess technology risks, including AI, as it applies to their institutions and customers.

Financial institutions face a number of data security and data privacy regulations, such as the Safeguards Rule of the Gramm-Leach-Bliley Act.¹⁰ While AI brings about a new use of data, the data held by financial institutions implementing AI technology is very similar to the data held prior to AI implementation and must be securely protected. Financial institutions work hard to maintain the security of their data and the privacy of their customer’s personally identifiable information.

A very positive use of AI is enhanced security for networks and processes through automation and expert AI detection and decision making. By working with companies who offer AI-based cybersecurity defense, community banks are able to leverage machine learning capabilities and provide better security with fewer resources. AI has already shown the ability to detect and stop malicious threats, enable behavioral analysis to detect suspicious account activity, and analyze network activity to identify zero-day threats, effectively protecting community banks against threats before vulnerabilities are even reported.

AI Use by Community Institutions

In general community banks do face greater challenges in developing, adopting, and using AI than large banks or fintech companies. For the most part, these challenges stem from a lack of

⁸ 15 U.S.C. § 1691(d)(2).

⁹ 12 CFR pt.1002, comment 9(b)(2)-3.

¹⁰ Pub. L. 106-102.

personnel with the highly technical expertise required to develop or evaluate AI software. These specialists are few in number, in high-demand, and out of the price range of most small banks. Without the relevant expertise, it can be difficult for community banks to develop their own AI software. This makes community banks more dependent on third party software providers. In the absence of a program by the agencies to certify that third party providers are conducting appropriate model risk management, it is a challenge to know whether a particular piece of AI software creates outsized compliance risks.

It is worth noting that community banks are not a monolith. How quickly they adopt AI and the use cases for which they adopt it will depend on competitive and regulatory pressures their individual institution faces. Because AI/ML are new technologies, some community banks will take a conservative approach, waiting until the technology and regulations fully develop. On the other hand, some community banks will take advantage of their nimbleness to quickly implement AI/ML.

At first, we foresee community banks interest in AI will be confined to back-office and compliance monitoring functions. Additionally, some community banks will choose to use customer facing and natural language AI such as chatbots to ensure that customers have 24/7 support when accessing online banking services. Likely the last place these technologies will be implemented is in underwriting, due to compliance risk. Furthermore, because relationship lending is what makes community banks unique, there is a significant portion of their lending business that cannot be replaced with AI, because AI will not have the personal connections and community knowledge that make relationship lending possible.

Oversight of Third Parties

Evaluating and overseeing third party providers of AI can be challenging for community banks. To alleviate this difficulty, we believe that regulators should provide safe harbors for using externally developed, industry-standard AI algorithms. To facilitate this, it may be appropriate for regulators to require more transparency from fintech companies. In the field of AI, software developers are reluctant to reveal the “secret sauce,” of how their algorithms analyze data. While it is understandable to be protective of proprietary business information, standardized disclosures of how AI providers conduct their model risk assessments can be useful.

Partnership with Federal Financial Regulators

We strongly urge the agencies to utilize their offices of innovation to keep an open line of communication with community banks and to help to educate the industry. In the past, agency staff have participated in ICBA’s ThinkTECH Accelerator Programs both to provide education to community bankers and collect feedback from members of the industry on AI/ML. We sincerely appreciate this outreach and see it as a critical component in our mission to ensure that the community banking industry can develop the talent and partnerships necessary to ensure that it is not left at a competitive disadvantage by emerging technologies.

Conclusion

Once again, ICBA appreciates this opportunity to provide feedback to the agencies in response to RFI on financial institutions' use of artificial intelligence and machine learning. These technologies have the potential to aid community banks in meeting the increasing burden of regulatory compliance and to expand access to credit to traditionally underserved and credit-invisible borrowers.

At the present time we do not believe there is a need for specific regulation of AI. The agencies' existing rules for fair lending compliance, data privacy, and conceptual soundness of computer applications contain sufficient flexibility to address problematic AI models. We believe that premature regulation of AI may prevent the development of technologies that expand access to credit and strengthen the banking system.

Please feel free to contact me at (202) 821-4411 or Michael.Marshall@icba.org if you have any questions about the positions stated in this letter.

Sincerely,



Mickey Marshall
Director, Regulatory Legal Affairs