June 30, 2021

Via Electronic Submission

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RE: "Request for Information and Comment on Financial Institutions' Use of Artificial Intelligence, including Machine Learning"[1]

To Whom It May Concern:

SAS Institute Inc.[2] (SAS) welcomes the opportunity to submit this comment letter in response to the joint Request for Comment (RFC) regarding financial institutions use of artificial intelligence (AI), including machine learning (ML). There has been a growing interest and speculation regarding these analytic techniques in recent years as the availability of data and computing power have made it possible for companies to adopt both AI and ML techniques at scale, especially within the banking and financial services sector. As AI and ML adoption becomes more wide-spread and integrated into financial

[1] Office of the Comptroller of the Currency	Docket ID OCC-2020-0049
Board of Governors of the Federal Reserve System	Docket No. OP-1743
Federal Deposit Insurance Corporation	RIN 3064-ZA24
Bureau of Consumer Financial Protection	Docket No. CFPB-2021-0004
National Credit Union Administration	Docket No. NCUA-2021-0023

[2] Headquartered in Cary, North Carolina, SAS is one of the largest privately held software companies in the world. For over 40 years, SAS has established itself as an industry leader in advanced analytics and data management, a standard that has been repeatedly recognized by independent third-party researchers, including Gartner, Forrester, and Chartis Research.

institutions operations and decision-making, we support the Agencies' interest in understanding more about the potential benefits and risks associated with these technologies and we appreciate the opportunity to submit comments.

AI and ML systems, when properly designed, deployed, and governed have shown clear promise and benefits to industry and customers alike. These systems can enable innovation in financial products, improve efficiency in operations and risk management practices, and lower operating costs by automating mundane and repetitive tasks. Additionally, by utilizing a wider range of data sources and identifying complex non-linear patterns in data, AI systems can be leveraged by financial institutions to expand access to credit to a larger population by improving the accuracy of existing credit models.

Yet the promise of AI must be tempered for potential risks that can lead to undesirable or unintended outcomes. These risks include the lack of explainability in some AI systems, potential data privacy and data accuracy risks, as well as the potential risk of bias when human intervention in decisioning is limited. This risk of unintentional bias, especially in the case of vulnerable or historically disenfranchised populations, can be particularly acute. While automation or innovation of any kind can introduce new ethical considerations, at SAS, we believe AI systems should be designed to promote and preserve human dignity, agency and overall well-being – all with an eye towards equity.

For over 45 years, SAS has been a pioneer in the advanced analytics industry, including in the areas of AI and ML with SAS being recognized as a Leader in 2020 Gartner Magic Quadrant for Data Science and Machine Learning Platforms. SAS supports more than 3,500 financial services customers world-wide, including more than 90% of the top global banks. Our responses to the RFC are based upon our extensive industry and subject matter expertise, as well as our commitment to the core concept of "Responsible AI"—AI that is governed, transparent, interpretable, and ethical.[3] SAS has responded only to those questions where our expertise in AI and ML was most relevant to the topics raised within the RFC. We look forward to future opportunities to contribute to this important discussion.

Sincerely,

Gavin Day
Senior Vice President, Technology
SAS Institute Inc.

[3] *See* SAS Institute Inc., *Artificial Intelligence & Ethics Whitepaper* (2020) (available at https://www.sas.com/content/dam/SAS/documents/marketing-whitepapers-ebooks/ebooks/en/artificial-intelligence-and-ethics-111452.pdf, or https://bit.ly/3gxuND0).

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Question 1: How do financial institutions identify and manage risks relating to AI explainability? What barriers or challenges for explainability exist for developing, adopting, and managing AI?

In SAS' experience, the primary risks related to AI explainability are:

- the AI system develops the logic or algorithm that generates the outcome based on the data being fed – a process that may lack transparency and human intuition,
- limitations regarding the size and scope of the required data to train AI methods for employing algorithms in business processes,
- the lack of standards or methodologies across the industry on usage and deployment of AI,
- the manual nature of labeling data and associated potential for human error, and
- the use of synthetic data in testing can limit variability present in the testing population and impair the ability to detect bias or gauge out-of-sample performance.

SAS is not aware of any universal approach that has been adopted by financial institutions (FIs) across the industry to identify and manage risks relating to AI explainability. However, on balance, most FIs have long used established risk control assessment and audit practices, built on the core principles of safety, soundness, and accountability against bias, as part of their governance process for advanced analytics and algorithms. SAS believes these existing practices, in many cases, can be well-suited to manage risks related to AI explainability. As adoption of AI and ML techniques have grown in recent years, some major financial institutions have also created executive positions to oversee methods and strategies to enhance corporate-wide governance to address the use of AI specifically. Additionally, a few leading software vendors, including SAS, provide state-of-the-art analytical solutions with technologies that have built-in controls to mitigate the explainability risks associated with AI. These controls include providing self-documenting, interactive explanations, and interpretation of inferences through the iterations of development, deployment, and monitoring.

Based on SAS' industry experience, the major challenges to the ability to effectively develop, deploy, adopt, and manage AI algorithms are often related to the opacity of the model itself, especially if the model is "black-box." Specifically, the complexity and non-linear nature of variables in some black-box AI models may be difficult to explain or understand. This includes explainability of the model logic (global explanations) as well as the individual decisions made by the model (local explanations). In addition, the relative lack of transparency challenges model development and model validation teams to foresee unintended consequences from model usage, which could create an operational risk if the model is implemented in production.

Another potential challenge relates to the model development process itself. As AI approaches are data driven and automated, it can be challenging to decipher, for example, the choices for tuning parameters, as well as the choices for justifiable data sources and inputs. These challenges can be managed through a defined internal governance process.

Finally, SAS believes that one common barrier to explainability is a shortage of people with the right skills to develop, validate, and manage AI models.

Question 2: How do financial institutions use post-hoc methods to assist in evaluating conceptual soundness? How common are these methods? Are there limitations of these methods (whether to explain an AI approach's overall operation or to explain a specific prediction or categorization)? If so, please provide details on such limitations.

As a general matter, SAS believes that post-hoc testing alone, while effective in traditional use of statistical modeling and data mining, may only partially interpret or explain an AI system. In some instances, post-hoc explanations rely on the accuracy of an underlying surrogate model which requires validation and oversight once the model has been deployed.

To control for these limitations, model developers can add constraints to maintain domain-specific rules (for example, developing interpretable AI models with constrained inputs). Additionally, model developers can apply post-hoc explanations to better understand the model logic. These methods are applied at the global and local level. Global interpretability methods include Feature Importance, Partial Dependence graphs and sensitivity analysis. Local interpretability methods include, Individual Conditional Expectations (ICE), Local Interpretable Model Agnostic Explanations (LIME), and Shapley values.

Finally, to develop robust and unbiased AI systems, it is not enough to only focus on the explainability of AI algorithms – consideration must also be given to all aspects of the overall approach to the planning, development, deployment, and production use of an AI system, including the data, the algorithms, the infrastructure, the business processes, and the people involved.

Question 3: For which uses of AI is lack of explainability more of a challenge? Please describe those challenges in detail. How do financial institutions account for and manage the varied challenges and risks posed by different uses?

The importance of explainability in AI relates to the consequence of the use case and the complexity of the AI system. For example, outcomes produced by less complex AI systems, such as deep learning algorithms trained using data for image recognition or language translation, can be easier to understand and interpret using available tools. In a more complex use-cases, such as decisioning for investments and capital adequacy, the levels of abstraction in the deep learning algorithms can make explainability of the outcome more difficult.

Lack of explainability also poses challenges with credit underwriting decisions and other processes related to the credit risk management cycle where alignment with fair lending laws and the lending policy is required. While FIs are well attuned to controlling for potential bias in lending or credit decisions today, imposing similar controls in AI systems can be complicated by the data driven changes to the algorithms. Because of this, FIs have typically limited AI-approaches for these use-cases to experimental phases that also rely on human input and collaboration.

Question 4: How do financial institutions using AI manage risks related to data quality and data processing? How, if at all, have control processes or automated data quality routines changed to address the data quality needs of AI? How does risk management for alternative data compare to that of traditional data? Are there any barriers or challenges that data quality and data processing pose for developing, adopting, and managing AI? If so, please provide details on those barriers or challenges.

Data quality is integral to any aspect of analytics modeling. Because AI systems tend to utilize larger quantities of data, data quality and data processing become more prominent. To control for data quality issues, FIs may rely on several established techniques, including lineage tracking, labeling, design of datasets for specific purposes, and prevailing risk and control self-assessment frameworks and audit approaches to manage AI risks. These include tracking the accuracy, integrity, and completeness of data used for risk measurement and management. Additionally, technological controls such as comprehensive data catalogs, data pipelines, and model pipelines can be leveraged to further enhance data quality and reliability.

With alternative data sources, data quality controls can be more difficult to implement than for traditional data sources. Typically, traditional data sources are structured and stored in relational databases, allowing FIs to administer and implement data quality controls directly. Alternative data, on the other hand, may include structured and unstructured data in the form of real-time transactional data, mobile phone data, news feeds, web browsing, online ratings, property data, supplier or shipping data, and geospatial data. In some cases, this alternative data may be provided by third parties or stored in forms that may make it difficult to test and validate the underlying quality of the data. Unless an AI model using alternative data is well explained and understood, underlying data issues could be masked, resulting in unintended outcomes. Further, consideration should be given to whether alternative data sources have sufficient time history and data volumes (as data capture may have only started recently) for back-testing purposes.

Question 5: Are there specific uses of AI for which alternative data are particularly effective?

Alternative data sources can provide important insights and enrich the outcomes of AI models, especially in circumstances where data from traditional data sources may be limited, lagging, or incomplete. For example, during the recent COVID-19 pandemic, alternative data sources were leveraged to approximate macro-economic activity by using online sales numbers and traffic information. With little traditional data regarding modern economic behavior during a global pandemic available, alternative data was leveraged to gain insight and identify patterns that could then be used by policy makers to help address the economic impact of the pandemic.

In the banking context, some alternative data could benefit AI-driven credit decisioning models. For example, alternative data could be used to evaluate the creditworthiness of an individual that is unbanked, underbanked, or without a traditional credit score. Where existing credit information may already exist, alternative data can provide a more nuanced view of a consumer's creditworthiness and identify early indicators of changes in financial situations otherwise missed by traditional credit scores. Anecdotally, several financial institutions across the globe have begun to report that alternative data have potentially improved the accuracy and fairness of credit scoring and as a result, those FIs are incorporating it as part of their credit decisioning processes. However, as noted in our response to Question 4, the accuracy of such models is dependent on an institution's capability to effectively collect, process, manage, and use alternative data.

Additional, specific examples (including those outside the financial industry) where SAS has found AI-based approaches that incorporate alternative data sources to be particularly effective include:

- chatbots,
- short-term high frequency forecasts using alternative data (nowcasting of macro/micro economic indicators),
- sentiment analysis,
- climate risk modeling using spatial data,
- process automation in commercial lending,
- fraud detection and anti-money laundering, and
- cybersecurity.

Question 6: How do financial institutions manage AI risks relating to overfitting? What barriers or challenges, if any, does overfitting pose for developing, adopting, and managing AI? How do financial institutions develop their AI so that it will adapt to new and potentially different populations (outside of the test and training data)?

Overfitting is a common modeling issue when developing either statistical or machine learning models. It happens when a model learns the noise or random fluctuations in the training data to the extent that it impacts the model ability to generalize. Overfitting can be a common issue in applied machine learning with high dimensionality in input data and highly flexible machine learning methods. For example, a neural network is a typical machine learning algorithm that is subject to overfitting training data. Some ways to address this issue can be to leverage analytics software that includes options to mitigate overfitting when training machine learning models, such as regularization, early stopping, pruning, and validation on out of sample/out of time datasets.

It is important to note, however, the conventional understanding of overfitting may not be applicable to all AI systems. For example, the model's ability to generalize is determined by several factors such as data design, model architecture, and use definition. It is not necessarily limited to the number of parameters or complexity of the model, especially with large model architectures that inherently generalize well. Thus, each of the above factors should be property assessed to minimize the risk of overfitting in AI systems.

Question 8: How do financial institutions manage AI risks relating to dynamic updating? Describe any barriers or challenges that may impede the use of AI that involve dynamic updating. How do financial institutions gain an understanding of whether AI approaches producing different outputs over time based on the same inputs are operating as intended?

Companies, including financial institutions, that deploy AI systems are increasingly looking for efficiency gains by automating aspects of the model lifecycle. Models that are more frequently updated and have faster model development and deployment cycles are said to deliver superior benefits in terms of accuracy and relevancy. Automated machine learning and self-learning models are particularly well-suited to recalibrate dynamically based on new information. AI systems that are dynamically updated (i.e., continuously learning as new data become available) will require additional workloads for model governance teams to validate the calibration process on a continuous basis. This will require more rigor and increased need for comprehensive data management. In addition to the data and the models, the model changes and model performance will require continuous monitoring, requiring institutions to have robust model risk management systems in place.

Question 9: Do community institutions face particular challenges in developing, adopting, and using AI? If so, please provide detail about such challenges. What practices are employed to address those impediments or challenges?

The successful development, adoption and use of AI is related to the ability of any institution to employ AI talent, have access to analytical tools, and have access to the right data and analytics infrastructure. These technology and talent gaps also extend beyond data scientists to people and processes, such as business analysts, marketers, and loan officers who must also understand how to apply results of the AI systems appropriately. As a likely consequence of insufficient and/or incongruent investment, community institutions commonly rely on an ecosystem of third-party providers, such as data consortia and other data and results providers, which may require consideration of other risk mitigation controls.

Question 12: What are the risks that AI can be biased and/or result in discrimination on prohibited bases? Are there effective ways to reduce risk of discrimination, whether during development, validation, revision, and/or use? What are some of the barriers to or limitations of those methods?

Like all human designed systems, AI systems can be subject to bias which may impact compliance, model accuracy, and fairness. Bias may arise from poorly diversified input data or algorithms that lead to insufficiently or incorrectly trained AI systems. For example, if the sample data used to train the models does not sufficiently represent the population the model will operate on, or if the data over- or under-represent certain groups, it increases the risks of potential bias. Further, if the AI system includes unfair biases due to the training data, that bias can be perpetuated and potentially amplified through automated decision making. Potential sources of bias in AI systems can be especially difficult to discern if there is limited explainability of the model outcomes.

The following approaches are commonly used to limit or mitigate the risk of bias in AI models.

- FIs can, in areas with strict requirements for explainability, extend model governance frameworks with indicators and validation processes specific to AI/ML models.
- FIs can strengthen data validation and sampling processes to ensure models are trained on representative data. This is critical to ensure that certain groups are not over or under-represented.
- FIs can apply data quality checks to prevent data measures from contamination or influence by subjective errors.
- FIs can employ statistical methods to ensure correlations with protected characteristics are identified and understood.
- FIs can ensure the methods used to debias the data are fully documented and validated.
- FIs can utilize feature attribution analysis to identify drivers that impact customer decisions and that the drivers are justifiable.
- FIs can utilize disparate impact analysis to validate that there is no significant disparate treatment for protected groups compared to non-protected groups.
- FIs can utilize outcome analysis and cross-referencing to assess model accuracy across both protected and non-protected groups.
- FIs can analyze sensitivity by perturbing sensitive features to assess the reliance on sensitive features of a model.
- FIs can develop AI systems that are accessible and reflect diverse perspectives and experiences. Inclusivity should be reflected in the design, development, deployment and decisioning processes. For example, FIs can consult community leaders and subject matter experts studying equity during the AI design, development, and deployment stages to ensure they are taking proactive measures to mitigate unforeseen harms.
- FIs can carefully test against a range of inputs and real-world scenarios to reduce unforeseen bias. If conditions do not support accurate and consistent output, safeguards—such as human intervention--should be put in place to minimize the potential for error.

While the risk of bias in AI is an appropriate area of concern and focus, it should also be noted that if bias is properly addressed, AI-based decision making has the potential to be more consistent and traceable compared to human decision making.

Question 13: To what extent do model risk management principles and practices aid or inhibit evaluations of AI-based credit determination approaches for compliance with fair lending laws?

As a general matter, model risks associated with AI systems become more pronounced as complex algorithms and larger datasets are typically involved in modeling process. For example, intercorrelation or interdependence of model variables can make it more challenging to uncover hidden patterns that may be considered under fair lending laws. Thus, it is more important for institutions to apply model risk management (MRM) principles and governance to control for potential risks related to AI systems.

By applying MRM principles to AI systems, institutions can monitor model development, implementation, and use; the effective validation of models; and the effectiveness of existing governance, policies, and controls to mitigate potential sources of compliance risk.

Question 16: To the extent not already discussed, please identify any additional uses of AI by financial institutions and any risk management challenges or other factors that may impede adoption and use of AI.

Financial institutions are already leading the way on exploring the application of AI in various aspects of their operations. Bots have proliferated across the industry, especially chatbots in the areas of customer service for routing and prioritizing human intervention. Several Fintech startups have supplemented risk underwriting with AI. It is not a coincidence that most of the innovation in the AI space is coming from technology companies that have exceptionally substantial amounts of data to refine their algorithms.

The benefits and use of AI are currently being tested in the following areas (among others):

- feature generation and engineering,
- pricing approximation,
- collateral valuation,
- trade surveillance,
- personalized financial planning,
- taxation,
- cashflow forecasting,
- insurance underwriting and pricing,
- sentiment analysis,
- short term ML-based liquidity forecasting,
- customer management (CI),
- cybersecurity,
- AML/BSA compliance,
- data quality,
- compliance, and
- process automation.

Question 17: To the extent not already discussed, please identify any benefits or risks to financial institutions' customers or prospective customers from the use of AI by those financial institutions. Please provide any suggestions on how to maximize benefits or address any identified risks.

Please see the cover letter.