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Phone: +1 646 783 7100 | Fax: +1 646 783 7161 | customerservice@law360.com

AI In Lending: Key Challenges And Practical Considerations

By **David Stein** (August 9, 2018, 1:03 PM EDT)

David Stein

Artificial intelligence, or AI, has enormous potential to enable the financial services industry to make better decisions in lending-related activities. The U.S. Treasury Department's recent report on nonbank financials, fintech and innovation discussed the use of AI in financial services and identified certain legal challenges presented by AI and related technologies.[1] Recognizing the potential benefits of AI, the Treasury Department recommended that regulators "not impose unnecessary burdens or obstacles to the use of AI" and related machine learning technologies, but instead "provide greater regulatory clarity" to promote "further testing and responsible deployment of these technologies" by regulated financial services firms.[2]

There is little risk of U.S. financial regulators taking proactive steps to restrict or quash the use of AI in financial services. Nonetheless, existing laws and regulations adopted long before the advent of AI-based financial services applications remain in effect and regulators must enforce them. The challenge, therefore, is how to deploy AI in financial services consistent with established legal and regulatory frameworks.

This article focuses on using AI in lending. Following a brief overview of AI, this article discusses similarities and differences between AI and traditional lending tools, identifies key legal and regulatory issues, and offers practical tips for using AI in lending applications.

Overview and Terminology

Artificial intelligence is an umbrella term for a group of technologies that enable computer algorithms to simulate aspects of human intelligence and behavior, such as decision-making, learning, generalizing and reasoning. Artificial intelligence encompasses, among other things, machine learning and deep learning.

Machine learning is a set of statistical techniques for coding a computer system or algorithm to parse data, identify patterns in the data, translate those patterns into rules, and make determinations or predictions based on the data. The translation of identified data patterns into rules gives the algorithm the ability to improve its performance over time or "learn" through experience based on the data it evaluates without explicit programming or human intervention.

Deep learning is a class of machine learning that uses multiple layers of neural networks to identify and process large amounts of raw data in a cascade or waterfall for the purpose of discovering nonlinear patterns or representations in the data. This layered neural network structure is modeled after a biological nervous system. The data patterns or representations detected by the algorithm can be translated into conclusions or rules and applied as additional data is evaluated. Advances in deep learning combined with the rich data sets available through big data is driving the development of commercial applications of AI.

Artificial Intelligence in Lending: What's the Same and What's New

Artificial intelligence-based algorithms can be used in a range of lending applications, including credit underwriting, credit scoring, target marketing, collections, fraud screening and identity verification models. AI-based algorithms bring new features and functionality to lending platforms, but also share many common attributes with current lending practices and tools.

Certain lending attributes remain the same despite the introduction of AI-based algorithms. First, automated algorithms have been used in lending for decades. Examples include automated underwriting systems, credit scoring models and fraud screening models. An AI-based lending algorithm is simply another form of automated algorithmic tool for evaluating loan applicants, borrowers or prospects.

Second, there is a long history of making credit decisions based on the output of proprietary "black box" algorithms, where the underlying computer logic — the secret sauce — is shielded from regulatory and public scrutiny. Proprietary credit scoring models and fraud screening tools are good examples of such "black box" algorithms. An AI-based lending algorithm is just another type of "black box" algorithm and the lack of transparency is nothing new. The inability of regulators or others to review and analyze the decision-making process followed by AI-based lending algorithms is no different than the current state with regard to many proprietary non-AI algorithms used in lending today.

Third, lending algorithms that do not rely on artificial intelligence increasingly consider nontraditional data and big data. For example, newer credit scoring models designed to evaluate consumers with limited credit histories consider utility and rental payment histories and other nontraditional data. Similarly, target marketing, fraud screening and identity verification models increasingly are programmed to evaluate big data even when the underlying algorithm does not use AI.

Two features of AI-based algorithms, however, represent a substantial change for lending models. First, the operational structure of AI-based algorithms differs significantly from non-AI algorithms. Traditional lending algorithms are programmed to make specific, repeatable decisions in different scenarios. These algorithms operate in a task-specific or deterministic manner. By contrast, AI-based algorithms are programmed to discover patterns in large amounts of data, translate those patterns into decisions or classifications, and automatically improve and refine algorithmic rules based on experience. AI-based lending algorithms are designed to simulate human decision making, learning, generalizing and reasoning and to apply what the algorithm discovers from its analysis of data across a range of scenarios with minimal human programming. As a result, decisions or classifications made by an AI-based lending algorithm may not be fully repeatable or explainable.

Second, AI-based algorithms have the capacity to evaluate large volumes of big data and identify patterns and relationships in the data that may be too complex or subtle for humans to identify or for human programmers to code. This ability to detect and analyze such data patterns or relationships sets

AI-based algorithms apart from traditional lending algorithms. At the same time, the power of AI-based algorithms to detect data patterns that humans cannot makes it challenging to track and monitor the bases for AI-based algorithms' decisions or classifications and to explain how these algorithms reach their conclusions.

Legal Issues With Using Artificial Intelligence in Lending

Legal issues related to the use of artificial intelligence in lending generally fall into one of three areas: (1) fair lending; (2) consumer reporting; and (3) unfair, deceptive, or abusive acts or practices. Each is discussed below.

Fair Lending

The Equal Credit Opportunity Act, or ECOA, and its implementing regulation, Regulation B, prohibit creditors from discriminating against any applicant for credit in any aspect of a credit transaction on a prohibited basis, such as race, color, religion, national origin, sex, marital status or age.[3] The prohibition against discrimination applies across the entire life cycle of the loan from the application process to servicing to collections. Discrimination may result from a creditor treating applicants differently on a prohibited basis (disparate treatment)[4] or from a creditor's facially neutral practice that has a disproportionately negative impact on a protected class of applicants (disparate impact).[5] Regulation B also extends to pre-application marketing by prohibiting creditors from discouraging applicants or prospective applicants from applying for credit on a prohibited basis.[6]

Discriminatory Factors or Proxies

To comply with fair lending laws, AI-based lending algorithms cannot consider discriminatory factors, such as race, national origin or gender, or proxies for discrimination, such as geography or level of education. A key fair lending challenge is to prevent AI-based lending algorithms from identifying and considering proxies for discrimination — even as these dynamic algorithms gain experience, refine their rules and evolve.[7]

Discriminatory factors or proxies may be introduced into AI-based lending algorithms in at least four ways. First, the initial programming instructing the algorithm to identify patterns and translate those patterns into new rules is a function of extensive human judgments, which may introduce human biases into the algorithm's DNA.

Second, most AI-based lending applications follow a practice of "supervised learning" where human monitors track performance, provide feedback and, where necessary, correct the decisions reached by the AI algorithm. Although such supervision and oversight is essential for the reasons described below, it also creates a risk that human-initiated course corrections may introduce biases or that close or unusual cases which prompt judgmental overrides may assume undue prominence in the algorithm's rules.

Third, absent human intervention, an AI-based lending algorithm refines its rules through the continual analysis of large amounts of data. In this process, an algorithm may identify and consider data patterns or relationships that correlate with a proxy for a prohibited basis. The fact that AI-based lending algorithms evaluate large amounts of nontraditional data and identify complex relationships between multiple data points amplifies the risk that one or more AI-based rules may correlate with a proxy for a prohibited basis.

Fourth, the performance of an AI-based lending algorithm depends upon the quality and quantity of data it evaluates. Fair lending risks can arise if the data evaluated by the algorithm is not robust or representative of certain protected classes of applicants or reflects past discrimination and biases. For example, some AI-based facial- and voice-recognition algorithms used for customer service and identity verification reportedly do not perform as well with racial minorities and nonnative English speakers, which could result in discrimination.[8]

Adverse Action Reason Codes

When a creditor denies an application for credit or takes other adverse action against an applicant, it must provide an adverse action notice to the applicant and either provide or make available upon request a statement of the specific reasons for the action taken.[9] Producing a statement of specific reasons, or adverse action reason codes, is perhaps the most vexing compliance challenge for the use of AI-based algorithms to make lending decisions.

AI-based algorithms are dynamic, not static; they modify their rules, including decision-making criteria, over time based on experience gained from evaluating large amounts of data. These algorithms also evaluate complex patterns and relationships among multiple data points, making it difficult to isolate one or more decisive factors in any decision. For these reasons, AI-based algorithms do not lend themselves to generating adverse action reason codes.

Nevertheless, AI-based algorithms cannot be used to make credit underwriting decisions unless the creditor is able to produce a statement of specific reasons for the adverse action taken. It is imperative that creditors seeking to use AI-based algorithms for credit underwriting develop programs to identify, extract and generate the primary reasons for the algorithm's decisions, regardless of the complexity of the algorithm's data analysis and the dynamic, evolving nature of the algorithm's rules.

Classification of AI-Based Algorithms

Regulation B differentiates between two types of systems for evaluating credit applicants. Empirically derived, demonstrably and statistically sound, credit scoring systems are systems based on data derived from empirical comparisons of recent credit applicants that are developed for evaluating creditworthiness using accepted statistical methodologies and periodically revalidated and adjusted to maintain predictive ability.[10] Regulators strongly prefer that creditors use empirically derived credit scoring systems to eliminate human judgment and bias from credit underwriting. All other credit underwriting systems are judgmental systems.[11]

AI-based credit underwriting or credit scoring algorithms share attributes of both empirically derived credit scoring systems and judgmental systems. Like empirically derived credit scoring systems, AI-based lending algorithms result in automated decision-making based on empirical comparisons of data without human intervention. But, like judgmental systems, these algorithms simulate human judgment and change based on experience. Further, the dynamic and complex data analyses performed by AI-based algorithms may not lend themselves to periodic revalidation and adjustment in the same way as static credit scoring systems. Therefore, it is unclear whether regulators will treat such AI-based algorithms as empirically derived credit scoring systems or judgmental systems.

Consumer Reporting

The Fair Credit Reporting Act, or FCRA, governs the sale of consumer reports by consumer reporting agencies.[12] Credit scores are consumer reports regulated by the FCRA that summarize large volumes of data to rank-order consumers based on risk. Creditors routinely rely on credit scores to make underwriting decisions.

Discriminatory Factors or Proxies

Given the central role credit scores play in credit underwriting, score developers have built deterministic credit scoring models or algorithms that do not consider prohibited bases, such as race, national origin or gender, or known proxies for prohibited bases, such as geography or education level. Credit scoring algorithms, like credit underwriting algorithms, must generate credit scores untainted by discriminatory bias. In fact, credit score developers warrant that their models comply with fair lending laws and do not take into consideration prohibited bases.

Like traditional credit scoring models, AI-based credit scoring algorithms cannot consider prohibited bases or their proxies. As with credit underwriting algorithms discussed above, ensuring that AI-based credit scoring algorithms do not consider such impermissible factors is complicated by the dynamic and iterative nature of AI-based algorithms and their evaluation of nontraditional data, detection of complex patterns or relationships between disparate data elements, and automatic refinement of algorithmic rules based on experience.

Key Factors Affecting the Credit Score

Creditors must disclose credit scores to applicants when they deny credit applications based in whole or in part on a score.[13] Consumer reporting agencies also must disclose credit scores to consumers upon request.[14] Any such disclosure of a credit score to a consumer must be accompanied by up to four key factors that adversely affected the credit score.[15]

Identifying and generating the key factors that adversely affected a credit score generated by an AI-based credit scoring algorithm poses the same challenges as generating adverse action reason codes, as discussed above. As dynamic AI-based credit scoring algorithms learn and recalibrate the scoring rules, score developers must ensure that such algorithms can generate the key factors that adversely affected the score even as the algorithm's decision-making process and rule set evolve.

Unfair, Deceptive, or Abusive Acts or Practices

Federal and state laws prohibit unfair, deceptive, or, in some cases, abusive acts or practices, or UDAAP. These include Section 1036 of the Consumer Financial Protection Act of 2010, Section 5 of the Federal Trade Commission Act and numerous state laws.[16] Unfair acts or practices cause or are likely to cause substantial injury to consumers (generally monetary harm) that consumers cannot reasonably avoid, and where the injury is not outweighed by benefits to the consumer or to competition.[17] Deceptive acts or practices involve material representations, omissions, acts or practices that are likely to mislead a consumer acting reasonably under the circumstances.[18] Abusive acts or practices materially interfere with a consumer's ability to understand a term or condition of a consumer financial product or service or take unreasonable advantage of a consumer's lack of understanding of material risks, costs or conditions, the consumer's inability to protect his or her interests, or the consumer's reasonable reliance on the provider to act in the consumer's interests.[19]

It is difficult to predict the ways that AI-based lending algorithms could lead to allegations of UDAAP violations. The examples that follow illustrate a few scenarios where the use of AI-based lending algorithms might raise UDAAP issues:

- Generating credit denials based on reasons that appear arbitrary with no clear nexus to creditworthiness, such as various social media metrics;
- Subjecting nonnative English-speakers to greater scrutiny when opening deposit accounts based on the poor performance of fraud detection and voice recognition algorithms with those populations;
- Penalizing consumers for engaging in certain types of transactions or for using certain types of service providers; or
- Providing inaccurate or misleading disclosures or other information in AI-generated advertisements or customer service chatbots.

Practical Tips

The legal challenges described above associated with using AI-based lending algorithms should not be viewed as showstoppers. Creditors and others performing lending-related functions can take steps to implement AI-based algorithms in their lending programs while minimizing legal risk. Practical steps to consider include:

1. Involving legal and compliance early in the assessment and development process for AI-based lending algorithms, and on an ongoing basis, to spot potential issues.
2. Using AI-based algorithms initially to make lending decisions only for persons who otherwise would be denied credit using traditional credit underwriting tools. The use of AI to expand access to credit for underserved borrowers likely will find favor with regulators.
3. Using AI-based algorithms for purposes aligned with regulatory objectives, such as fraud prevention and compliance with know-your-customer requirements. Again, regulators will tend to be receptive to such uses.
4. Starting small by applying AI-based algorithms to a small percentage of customer base. This pilot-based approach enables the creditor to gather data, gain experience, test performance and make adjustments before a more extensive rollout.
5. Conducting validation testing, including fair lending and UDAAP testing, for all AI-based lending algorithms.
    - Testing should occur before implementation and periodically after implementation to validate and revalidate performance.
    - Testing should be undertaken for each expected use case. For example, do not use an AI-based algorithm validated for fraud screening and apply it to credit underwriting without further testing specifically focused on credit underwriting.

6. Monitoring algorithm performance and making a person or a team responsible for supervising and adjusting AI-generated outcomes, as necessary, to avoid results that appear discriminatory or arbitrary. Judgmental overrides will continue to play an important role even as automated AI-based decisions become more commonplace.

Conclusion

Advances in AI create numerous opportunities for constructive applications in the lending context, as noted in the Treasury Department's fintech report. The Treasury Department's recommendation that financial regulators not impede, but provide clarity to facilitate, AI testing and deployment sends a positive message. Despite the Treasury Department's admonition, however, it remains essential to recognize potential legal and regulatory risks and develop appropriate strategies for managing those risks before launching AI-based lending applications.

David A. Stein is of counsel at Covington & Burling LLP.

[1] U.S. Dep't of the Treasury, "A Financial System That Creates Opportunities: Nonbank Financials, Fintech, and Innovation," at 53-59 (July 2018) ("Treasury Fintech Report").

[2] Id. at 59 and 200.

[3] 15 U.S.C. § 1691(a); 12 C.F.R. §§ 1002.2(z) and .4(a). The Fair Housing Act also prohibits discrimination in the sale or rental of housing on the basis of certain prohibited characteristics similar, but not identical to, the ECOA prohibited bases. 42 U.S.C. §§ 3601-3619. Because the ECOA covers a broader range of products than the Fair Housing Act, the balance of the fair lending discussion focuses on ECOA.

[4] 12 C.F.R. part 1002, supplement I, § 1002.4(a)-1 and -2.

[5] 12 C.F.R. part 1002, supplement I, § 1002.6-2. A creditor may rebut a disparate impact claim by showing that its practice serves a legitimate business need that cannot reasonably be met by less impactful means. Id.

[6] 12 C.F.R. § 1002.4(b).

[7] Financial Stability Board, "Artificial intelligence and machine learning in financial services: Market developments and financial stability implications," at 27 (Nov. 1, 2017) ("Even where data on sensitive characteristics such as race, religion, gender, etc., are not collected, AI and machine learning algorithms may create outcomes that implicitly correlate with those indicators[.]").

[8] See Kate Crawford, "Artificial Intelligence's White Guy Problem," New York Times (June 26, 2016), https://www.nytimes.com/2016/06/26/opinion/sunday/artificial-intelligences-white-guy-problem.html?mcubz=1.

[9] 12 C.F.R. § 1002.9(a) and (b).

[10] 12 C.F.R. § 1002.2(p).

[11] 12 C.F.R. § 1002.2(t).

[12] 15 U.S.C. § 1681 et seq.

[13] 15 U.S.C. § 1681m(a).

[14] 15 U.S.C. § 1681g(f).

[15] 15 U.S.C. §§ 1681g(f)(1)(C) and 1681m(a)(2)(B).

[16] 12 U.S.C. § 5536; 15 U.S.C. § 45(a)(1).

[17] Federal Trade Commission, “Policy Statement on Unfairness” (Dec. 17, 1980); Office of the Comptroller of the Currency, Advisory Letter AL 2002-3 (Mar. 22, 2002).

[18] Federal Trade Commission, “Policy Statement on Deception” (Oct. 14, 1983); Office of the Comptroller of the Currency, Advisory Letter AL 2002-3 (Mar. 22, 2002).

[19] 12 U.S.C. § 5531(d).