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# **Shaping the Future of Finance:** How Explainable AI is Transforming Credit Decisioning

# Executive Summary

Artificial intelligence (AI) and machine learning (ML) are transforming how financial institutions approach credit decisions and traditional banking processes. In this white paper, we explore the significance of explainability and interpretability in AI models, and the imperative for transparency, accountability, and human relevancy when leveraging AI in the financial services industry.

Key takeaways include the importance of the "human in the loop" concept for model optimization, the role of interpretability in maintaining regulatory compliance, and the substantial challenges posed by data quality assurance.

By incorporating AI into the credit decisioning process, financial institutions can help create a more inclusive, intuitive, and impactful financial services landscape. It begins by starting with targeted AI projects, fostering an innovative culture, and collaborating with experienced AI partners for a successful AI implementation journey.

# The Promise of **Artificial Intelligence**

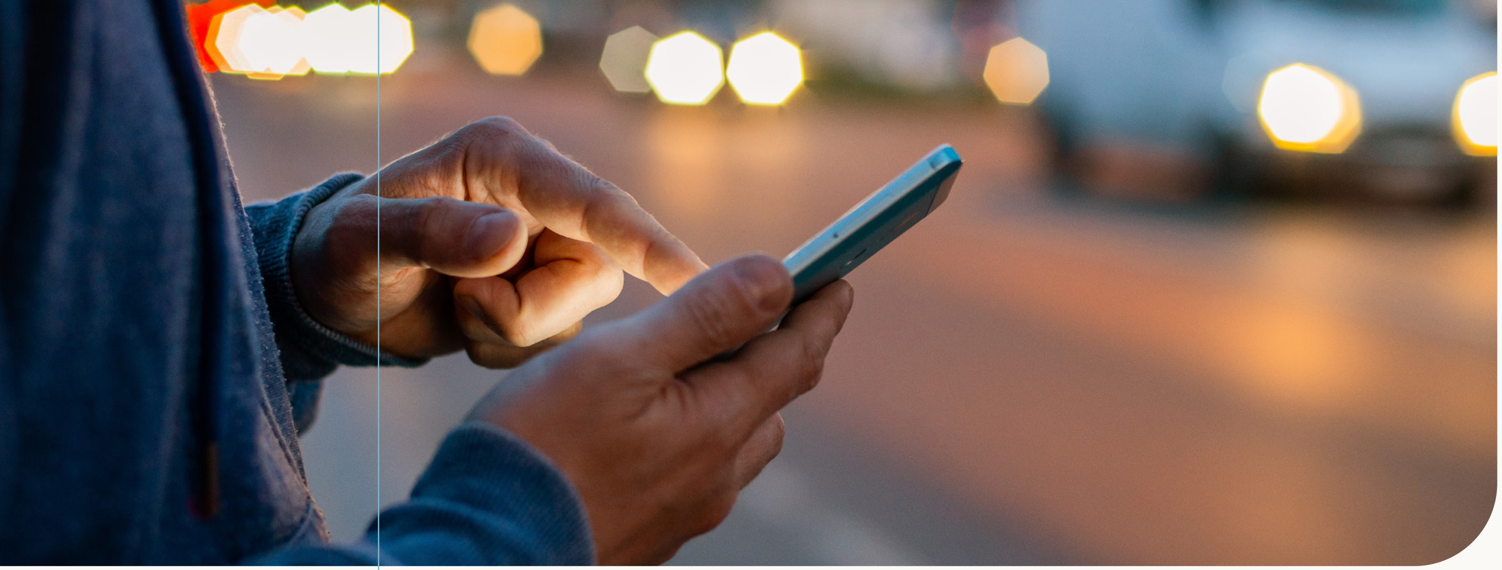
When it comes to credit decisioning, the most innovative and forward-thinking financial institutions aren't satisfied with yesterday's status quo.

They're focused on becoming experience-driven instead of simply transactional by bringing their customers personalized, efficient, and secure financial services. One of the ways they're accomplishing this is by leveraging artificial intelligence (AI) and machine learning (ML).

This evolution isn't surprising. AI and ML, often used interchangeably but fundamentally different, have the potential to redefine how financial institutions make credit decisions.

AI refers to the capacity of a machine to mimic human intelligence by learning from experiences, adjusting to new inputs, and performing tasks—some simple, others deeply complex—that traditionally require human intellect. ML, on the other hand, is a subset of AI that leverages algorithms to allow systems to learn from data, improve over time, and make informed decisions without being explicitly programmed.

AI and ML, along with the power of the cloud, can empower financial institutions with the insights that enable them to provide bespoke services to their clients, streamline operations, and lead to remarkable improvements in efficiency, risk management, customer experience, and decision-making capabilities.



Lending has traditionally been straightforward; if your credit score was high, your odds of being approved for a loan were also high. However, with the evolution of AI models, the decision-making process is now multi-layered—financial institutions can make credit decisions based on a multitude of real time data points, rather than a single credit score.

In this sense, infusing AI into the lending process is not a radical departure from traditional banking technology, but a more evolved solution to the same age-old problems. It's about reshaping the familiar and improving it, with more sophistication and accurate insights.

"All this is possible because we're now at a technical standpoint that we weren't at thirty or even ten years ago," says Mark Doucette, Data and AI Leader. "The phones in our pockets right now are more powerful than our computers from fifteen years ago. We have vast amounts of data, and now we have machines that can process that data faster than ever before. For the first time in human history, we're ready to put that technology to work."

In the next 5-10 years, as we move toward a world with no room for black boxes, explainability in AI is expected to play a pivotal role in its acceptance and integration across domains. Leveraging AI to make financial decision-making more efficient is no longer just about automation, but also about maintaining transparency, accountability, and human relevance in the process.

The phones in our pockets right now are **more powerful than our computers** from fifteen years ago

# Credit Decisioning: **Past, Present, Future**

One of the areas of banking that AI is revolutionizing is how financial institutions assess risk.

In the past, traditional statistical models have been the backbone of various financial activities, offering a blend of historical data analysis, probability theory, and mathematical computation to predict future events, assess risks, and make informed decisions. At their core, traditional statistical models analyzed past data to forecast future outcomes.

Predictive AI represents a significant advancement over these models, marking a transformative leap in how data is analyzed and utilized. This evolution stems from predictive AI's ability to learn from data, improve over time, and make increasingly accurate forecasts.

Lending tools that leverage predictive AI can enable financial institutions to access real-time metrics and decision points that shape the overall decision, providing even more clarity. For example, instead of relying on outdated historical financial statements, financial institutions can now analyze a business's most recent transaction data for a proactive, rather than reactive, approach to risk.

What sets AI and machine learning models apart from traditional statistical models in credit decisioning is their enhanced accuracy and proactive nature. This improved precision allows lenders to extend credit to an increased number of deserving businesses and individuals, which can promote financial inclusivity. Additionally, these models offer a diverse range of machine learning algorithms to better understand borrower behavior, aiding in effective risk assessment and serviceability evaluation.

While these tools are powerful, they aren't perfect—an important distinction to make when the stakes are so high. "AI is not always better," says Doucette. "When you look at the ethical aspects of AI, you must be aware of some red flags. For example, models built on historical data will make the same historical mistakes based on biases that existed then. As we build these models, we must take precautions with the sample set to ensure it's fair and equal. That can be tough, but it's necessary."

Improved precision allows lenders to **extend credit to an increased number** of deserving businesses

# The Importance of **AI Explainability**

When it comes to AI and the financial services industry, the concept of explainability–i.e., the ability to clearly communicate the process behind AI's decision-making and understand the model's inner workings–is of the utmost importance. But not all AI is explainable.

Take generative AI (Gen AI), for instance. Gen AI can be compared to a 1930s phone operator connecting party A to party B. The difference is that a phone operator can make one connection at a time; AI can accomplish the same type of task with billions of data points almost instantly. While it's theoretically possible to understand this process, the complexity and speed involved makes this quite daunting.

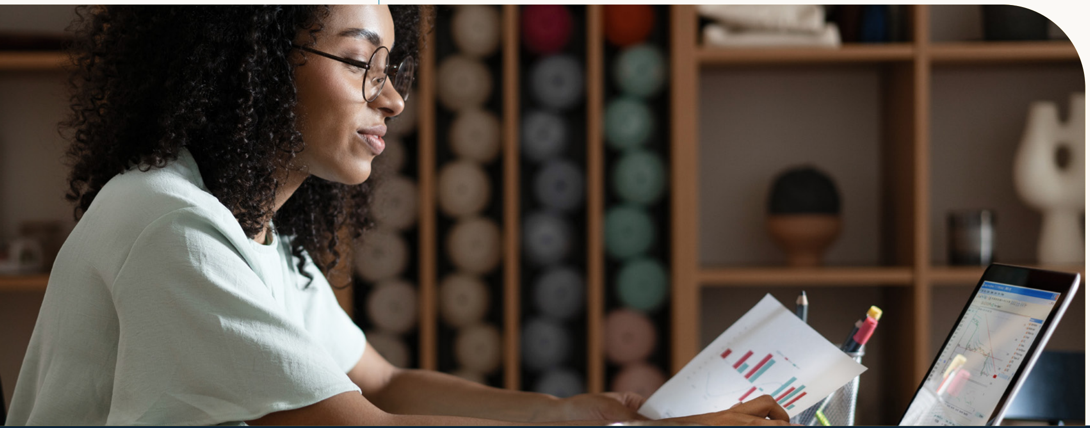
This is why AI has, in some circumstances, functioned like a black box–it produced results without explaining the how's and why's.

Initially, when users were solely concerned with the accuracy of predictions, the need for explainability didn't seem pressing. But as AI advances and permeates various sectors, including ones with strict regulatory requirements such as financial services, the need to understand AI's inner workings has grown immensely.

Credit modeling is one example of a situation in which explainability is critical throughout the entire model lifecycle. Traditionally, statistical credit monitoring has provided a clear line of sight from the features used in the model to the final outcome, allowing modelers to explain the rationale behind the model's score. However, as ML algorithms such as predictive AI have become more sophisticated, there is a need to trace explainability from the raw data.

"Explainability in AI is similar to the transparency required in traditional banking models—both center on clear communication of inputs and outputs," says Chris Gufford, Executive Director – Commercial Lending at nCino. "Within the model development cycle and data interpretation, explainability is essential for maintaining trust and understanding. At its heart, explainability is about achieving this transparency, regardless of the advanced nature of the AI or the mathematical complexity of the models."

Gordon Campbell is the CCO and Co-founder of Rich Data Co (RDC). The RDC AI Decisioning platform provides lenders with deeper insight into borrower behavior, enabling faster and more accurate decisions that empower confident lending to Business and SME lending segments. "In the model development cycle," Campbell says, "explainability plays a crucial role in several stages. During model building, it ensures that the features selected are meaningful and contribute to the model's predictive accuracy. In model documentation and validation, it helps ensure the model's outcomes align logically with domain knowledge and support regulatory requirements. Furthermore, in model deployment and monitoring, explainability provides insights into how the model behaves in real-world execution, enabling stakeholders to monitor model behavior and detect population or model performance issues."



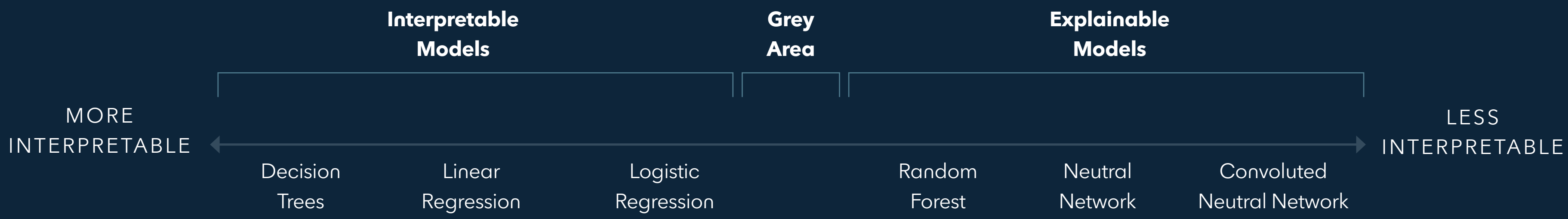
Overall, explainability fosters trust and accountability in AI systems, enhances regulatory compliance, and facilitates model improvement and optimization over time. It empowers stakeholders to make informed decisions based on AI outputs and creates greater understanding and acceptance of AI technology in various domains, including credit modeling.

One of the ways companies like nCino and RDC ensure explainability is through a concept called "human in the loop."

The "human in the loop" concept facilitates ongoing model optimization and refinement, and integrating this concept is crucial for model comprehension and optimization. It involves incorporating human expertise throughout the AI model development, deployment, and execution. Human experts, such as domain specialists or risk analysts, can provide valuable insights into the data, model assumptions, and business context, which are essential for understanding and interpreting the model's outputs. In the model development phase, human experts can collaborate with data scientists to select relevant features, define appropriate model constraints, and validate the model's performance against real-world scenarios. During model execution, human experts can monitor the model's behavior and intervene when necessary to address issues such as bias, fairness, or ethical concerns.

"Those humans, who are experts in their fields, can also continuously evaluate the model's performance, gather feedback from end-users, and incorporate new data or insights to improve the model's accuracy and relevance over time," says Campbell.

# Interpretability in **AI Models**




"Explainability" is one thing, whereas "interpretability" is another. While explainable AI hinges on the ability to communicate the reasoning behind decisions, interpretable AI seeks to make the inner workings of AI models understandable to humans. It's about achieving a balance where AI models are used thoughtfully with full consideration of the end-users– in this case, financial institutions and their customers.

"Financial institutions can ensure explainability in their AI models through several key practices," says Campbell. "First, they can adopt transparent and interpretable AI techniques, which provide clear insights into how the model arrives at its decisions. Additionally, employing techniques such as feature importance analysis or sensitivity analysis can help identify which features have the most significant impact on the model's outputs, enhancing its explainability."

A good example of this is the decision tree, commonly used in many machine learning models, which provides the ability to trace how a decision is reached. When it comes to something as complex as neural networks, however, the theory becomes harder to articulate and explain, and therefore impacts whether it is "interpretable."

Gen AI, on the other hand, works on the statistical probability of outcomes, similar to predicting the end of a well-known sentence based on the beginning. The difference is that Gen AI does this for all sentences, predicting the most likely next word based on patterns and numeric values from extensive data training. However, its dependence on available information often leads to "hallucinations" or fabricated data. This necessitates the installation of guardrails or controls to monitor its processes.

## How and Why to Ensure Interpretability

### There are a few methods that can explain and interpret model predictions.

XGBoost stands for Extreme Gradient Boosting, which is an implementation of gradient boosted decision trees designed for speed and performance. While boosting models, including XGBoost, are not inherently interpretable in comparison to linear models, they offer significant predictive accuracy. When using tree models like XGBoost, hyperparameters can be used to tune and control the model to aid in explainability.

SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) are two methodologies used to enhance the interpretability of machine learning models, including complex ones like those created using XGBoost. RDC, for example, leverages SHAP and package baselines from model build into the model runtime to assist in understanding how a particular customer received a specific score.

No matter what model a financial institution uses, choosing one that is interpretable and understandable is key. Interpretability in AI models, especially those used for credit decisioning, is not just a technical requirement but a necessity to support fairness, regulatory compliance, and to build trust with both customers and regulatory bodies.

"The goal of explainable AI is not to remove or bypass the human interaction, it's to enhance and augment the human and support their decision," says Peter Fabbri, Master Product Manager - AI Solutions at nCino. "It gets the decision in front of the banker and their customer sooner. That additional lead time means more time to react and ultimately build a stronger credit portfolio."

### nCino Banking Advisor

One example of a tool that is both interpretive and explainable is nCino Banking Advisor, a generative AI tool built specifically for the financial services industry that can, among other things, drastically streamline review processes. Instead of pouring over pages of credit policies, Banking Advisor can pinpoint exactly where relevant information is located. Furthermore, the "human in the loop" concept ensures that AI doesn't replace human judgment but supplements it, helping experts navigate through contradictory sources and drive informed decisions.

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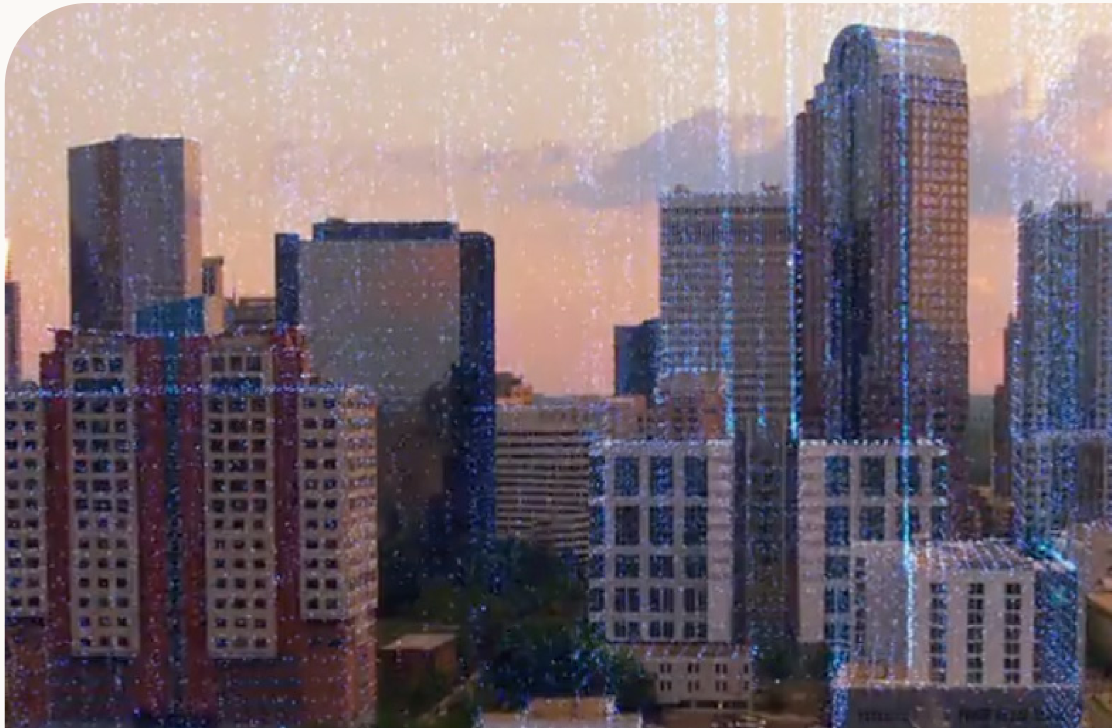
# **What Next?** How Financial Institutions Can Start their AI Journey

The idea of embarking on an AI journey may seem daunting to some financial institutions, perceived as a Herculean task requiring massive data set and extensive clean-up operations. This, however, is a misunderstanding. The key to leveraging AI in a banking environment lies in starting small, concentrating on specific use cases, and focusing on particular data elements.

"Financial institutions should not wait to harness the power of AI," says Fabbri. "The necessary data for transformation is readily available, particularly for nCino customers. Starting small is viable, given the strategy we've developed. Over the long term, AI will revolutionize the banking industry. We've seen impressive advancements in AI technology recently allowing us to finally realize our visions. The time is now to leverage these transformative tools." While starting small is ideal, financial institutions should be aware of some of the challenges facing them when it comes to data quality assurance, given the nature of the industry.



# A few core issues include:

**Volume and Variety of Data:** Financial institutions deal with large volumes of data from diverse sources daily. Ensuring the accuracy, consistency, and completeness of this data across different systems can be overwhelming.

**Regulatory Compliance:** The financial sector is one of the most heavily regulated industries. Institutions must ensure their data meets stringent regulatory requirements, which can vary by region and over time. Failure to comply can lead to significant penalties.

**Data Silos:** Within many financial institutions, data is often siloed across different departments or IT systems, making it challenging to have a unified view of data quality. This fragmentation can lead to inconsistencies and errors.

**Legacy Systems:** Many financial institutions rely on legacy systems that may not integrate well with newer technologies. These systems can be inflexible and may not support efficient data quality management practices.

**Real-Time Data Quality:** With the increasing demand for real-time banking services, ensuring the quality of data in real-time becomes a challenge. Any delays in identifying and rectifying data quality issues can lead to customer dissatisfaction and financial losses.

**Advanced Data Security Threats:** Financial institutions are prime targets for cyberattacks. Ensuring data quality must go hand in hand with securing data against unauthorized access and breaches, adding an extra layer of complexity to the challenge.

Because of these issues, data quality assurance is an ongoing endeavor for financial institutions, with specific challenges stemming from the sheer volume of sources contributing to their data pools. “Everyone has data quality challenges – consistency, error prone processes, unstructured data, mono data drifts, to name just a few,” says Doucette. “These are everybody’s problem, whether you’re a sports team, a health company, or a financial institution.”

The task of integrating vast amounts of data into a single accessible platform can feel daunting. The goal is to streamline the process, reduce human errors, and effectively leverage the data for insightful analysis. This process is not a one-off task. It's a continuous cycle, constantly assessing, enhancing and improving data quality for an increasingly robust and effective strategy.

"Quality assurance for data within financial institutions is not about cleaning up all data, but rather about identifying and focusing on the right data required to solve specific business challenges," Gufford explains. "You don't climb Mount Everest in a day; you do it gradually. Data is the same way – you tidy it up bit by bit, focusing on the data that is essential for specific tasks, like credit decisioning or remote deposit capture, which might need less than 40 data elements. Think about it like driving – you don't need a Bugatti to get to where you need to go. A Toyota Camry will get you there just fine. The key is time to value, prioritizing crucial data based on the task at hand."

The journey to AI optimization does not require an overbearing amount of data. Instead, it begins with a strategic direction and a decision to focus on a particular segment of your bank. The essential data is already within your reach, nestled within your daily transaction data and monthly deposit account statements.

Starting with targeted, small-scale AI-driven projects not only allows for better management of data quality, but also makes it much easier to measure impact and results. These improvements and outcomes can then serve as a stepping stone to expand your AI implementation, paving the way for a broader, more sophisticated AI strategy.

"When leveraging AI in lending decisions, financial institutions must take a balanced approach," advises Gufford. "The wise strategy is to implement AI models while still maintaining traditional methods, essentially operating these systems simultaneously to measure and discern the variations in results. Such a strategy allows banks to assert and ensure the integrity of the AI system, providing confidence to both the institutions and the regulators. It's the most responsible way to deploy. Banks might start by applying this approach to smaller loans before moving on to larger-scale applications."

In essence, AI adoption in the financial sphere is a project that can be launched today, rather than a distant dream that's still years away. The journey can start right now, with the data you already possess. It's about taking those initial steps, identifying a direction, and building your AI capability from there.

**In formulating an AI strategy for credit decisioning, financial institutions should first assess their readiness by:**

- **Choosing an experienced partner who has invested time, resources and talent into its AI tools**
- **Evaluating current capabilities, infrastructure, and company culture**
- **Defining clear objectives aligned with broader business goals**
- **Prioritizing AI use cases based on value and alignment with organizational strengths**
- **Fostering an innovation-centric culture to encourage experimentation and learning**
- **Embedding regulatory compliance and ethical considerations throughout AI implementation**
- **Investing in training and development to build internal competencies**
- **Collaborating and partnering with technology providers and industry players to accelerate AI adoption and drive innovation in credit decisioning processes.**

The first consideration involves digitizing processes and identifying the data that will solve your business problem. An AI-led journey starts with making your data readily available for use. This ideally involves opting for a single vendor to ensure that data is easily accessible, promoting efficient integration with AI capabilities.

Next, the selection of an AI partner should be driven by a strategic focus. Look for a partner who can empathize with the banking challenges and offer prudent advice. The shift towards AI means embracing a fresh perspective on efficiency in credit decision-making and notably reducing risk. Therefore, grasping the problem and envisioning the AI journey through this new efficiency lens are pivotal for a successful transition into the future of financial services.

"If AI isn't your core competency, outsource it," says Doucette. "There are other companies who can do it better than you. Your job is to find the right partner based on what you need. Find someone you trust, who is excited about the future of AI, who tries new things, who is on the bleeding edge but doing it responsibly."

Lastly, it's essential to assess the governance processes. A robust governance process will ensure that the AI partner is not just a short-term solution, but an integral part of the organization's long-term transformation strategy.

As financial organizations embark on this journey towards becoming AI-empowered, the selection of an AI partner must be done thoughtfully, with careful consideration of technology, domain expertise, and governance processes.

# Conclusion

It's clear that the transformative potential of artificial intelligence with machine learning in banking cannot be overemphasized. From offering personalized, efficient, and secure experiences to reducing bias and improving model accuracy, AI is poised to completely redefine the banking industry.

However, it's crucial that financial institutions and their technology partners place explainability and interpretability at the core of these AI models, affording transparency, accountability, and human relevance. The path forward involves beginning with specific use cases, prioritizing data quality, and fostering a culture of innovation. It's time for financial institutions to assess their readiness, set clear objectives, invest in training and development, and collaborate with the right partners.

This is an exciting era where innovation meets efficiency, empowering institutions to not only fulfill but exceed customer expectations. With the help of these new technologies, industry leaders are shaping a world where financial services are more inclusive, intuitive, and impactful than ever before.

## About nCino

nCino (NASDAQ: NCNO) is the worldwide leader in cloud banking. Through its single software-as-a-service (SaaS) platform, nCino helps financial institutions serving corporate and commercial, small business, consumer, and mortgage customers modernize and more effectively onboard clients, make loans, manage the loan lifecycle, and open accounts. Transforming how financial institutions operate through innovation, reputation and speed, nCino is partnered with more than 1,800 financial services providers globally. For more information, visit www.ncino.com.

## About Rich Data Co.

Rich Data Co (RDC) is an industry leader in AI decisioning for business and commercial lenders. The RDC AI platform enables banks to make high-quality lending decisions efficiently and safely. Leveraging advanced explainable AI technology, the platform delivers efficiency and transparency in both origination and portfolio management decisions. With the RDC platform, banks can deliver more meaningful customer interactions, improve credit outcomes, and increase lending. For more information, visit richdataco.com.

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