A LENDER'S ROADMAP TO AI ADOPTION

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Introduction

Pre-COVID, AI adoption across the financial services industry was gaining momentum. A recent World Economic Forum report revealed that a significant number of executives from 151 financial institutions say that within the next two years they expect to become mass adopters of AI and expect AI to become an essential business driver across the financial industry.

And then the pandemic triggered a massive shift to digital and accelerated new technology adoption, including AI and machine learning. “The industry crammed a decade’s worth of technology adoption and innovation into a few short months,” said Jo Ann Barefoot, CEO of Barefoot Innovation Group. Given the tougher environment financial institutions and credit unions now face due to the pandemic, the need for AI innovation is greater. According to McKinsey’s The State of AI in 2020 report, companies plan to invest even more in AI in response to the COVID-19 pandemic.

As AI becomes ubiquitous for banks and credit unions of all sizes, one of the most powerful AI use cases to emerge is in credit risk underwriting. As financial institutions and credit unions look for faster and more effective ways to assess credit and loan eligibility, machine learning models are fast becoming table-stakes to adapt to the new normal. Machine learning allows lenders to model using more variables, creating a more holistic, clearer picture of an applicant. Such a clear picture of borrower risk is increasingly difficult to get from traditional scoring methods and amidst shifting market conditions and demographics.

With machine learning models, lenders can identify risky borrowers who may have looked good on paper and swap them out for better, creditworthy borrowers overlooked by traditional underwriting techniques. Saying yes to more borrowers up and down the credit spectrum ultimately delivers growth, increased productivity, and more inclusivity.

With fresh urgency, leaders want to adopt AI but feel constrained by time, resources, and expertise. We get it. A roadmap to success exists and we want to share it with you. This guide provides a battle-tested approach and shares milestones and best practices from lenders who have moved to AI-powered to make more accurate risk assessments, accelerate modeling, and automate lending decisions. Read on to learn how lenders implemented machine learning models to deliver better results for every lending objective. Let’s get started!

Establish the Business Objectives

Every roadmap needs a destination. As an essential first step, you'll need to begin detailing answers to the following questions: What are the challenges your organization is trying to solve? What are the business goals you're looking to achieve?

Aligning AI Strategy with Overall Lending Strategy and Goals

Some of the most common business goals and results our customers, financial institutions and credit unions, are using machine learning for include:

Increase Approvals	Reduce Losses	Increase Yield	Decrease Disparity	Increase Automation
15%	30%	4%	13%	3x
Identify the best borrowers, safely increase approvals	Mitigate risk, limit losses, maintain performance	Enhance pricing, segmentation, and recoveries	Fairer lending with less discriminatory model alternatives	Gain operational efficiencies and decisioning speed

Identifying the goals and selecting KPIs will help set stakeholder expectations along with communicating progress and evaluating success for your AI investment.

→ Next: Assembe your A-Team

Assemble your A-Team

Change is never easy which is why it's critical to communicate the financial and non-financial benefits of investing in AI to secure buy-in. For many, AI elicits a range of responses from excitement about growth to confusion about its potential, to concerns about job displacement and potential biases. As a best practice, transparency, education, and speaking to business benefits such as competitiveness, revenue growth, and operational efficiency will be key to convincing stakeholders.

Here are the influencers that you will want to engage and how to communicate AI's impact:

The Champion

The business case for ML is your biggest asset — so there's plenty of common ground to go over when persuading executives and board members. Zest customers have seen approvals jump 15% with no added risk, or charge-offs drop by 30% while holding approvals constant when switching to ML underwriting. Calculating the business impact from such improvements forms the backbone of your business case. As a best practice, frame the business case using the goals set during AI strategy discussions, whether that's growing market share, driving member inclusion, or increasing operational efficiency.

AI-driven underwriting has multiple benefits across lending objectives. Reaching new borrowers, cutting losses by reducing your exposure to bad loans and setting more accurate prices for better yield can all improve the bottom line while being seen as forward-thinking. Tie the benefits of AI adoption to the goals every business executive wants to achieve.

→ Next: Assembe your A-Team continued

The Subject Matter Expert (Loan Originations)

For lending teams, AI provides better predictive abilities so they can avoid toxic borrowers and identify previously overlooked creditworthy buyers. For example, one lender achieved a **22% increase in portfolio approvals** while holding risk constant. Lending teams will also benefit from automation productivity gains by expanding their auto-decisioning thresholds.

With AI improving risk assessment accuracy, underwriters can deliver faster decisions to help teams meet customer experience goals. Their day-to-day drastically improves by spending more time on a smaller percentage of applications that require a more personal touch.

In addition to communicating the benefits, you'll also want to address explainability concerns. For lending teams, explainability is critical and they will be looking for answers to the following:

1. How does the model make decisions?
2. Why did an individual applicant receive a particular risk score?
3. How much control does the organization retain over decisions?
4. How quickly can decisions be made?
5. To what degree can/will decisions be automated?

The Credit Modeler & Model Validator

Overall, modelers can leverage ML to build more accurate, consistent, and efficient models with speed. Time-consuming manual tasks such as model documentation, validation, and monitoring will become automated, enabling teams to accelerate model development and production times.

Use these questions to help quantify the ROI for modelers:

1. What is the current cycle time to create, validate and deploy a new model?
2. How frequently are models updated, and how long does that process take?

The Regulatory Compliance Officer

For compliance teams, you'll need to address explainability concerns. The compliance officer is worried about bias and upholding the bank's Fair Credit Reporting (FCRA) and Equal Credit Opportunity (ECOA) obligations. These will be their top questions to address:

1. How does the model make decisions?
2. How do you ensure that models are fair?
3. How much influence do they have over what data is used in the model and whether they can influence how the model makes decisions?
4. How will they explain the model's decisioning process to regulators and demonstrate that they are in compliance with all of the regulations and guidelines?

The Head of IT

Overall, IT is mostly concerned with the implementation logistics. You'll want to be prepared and have answers to the following questions: How long will implementing an ML model take? What are the resource requirements for the project? What are the requirements for integrating with an LOS?

In the appendix, we've provided an ML underwriting vs Traditional Underwriting comparison table to help you communicate the benefits to all of your stakeholders.

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Paths to AI Adoption

There are multiple ways to build an effective AI capability. From building your own to buying a packaged solution, what's the best approach? Here are some best practices and considerations to help you choose the right approach for your organization.

Build Your Own

Pros:
Complete control over the process, with the ability to develop additional models for other products as needed.

Cons:

- Requires resources with a particular skill set.
- Long cycle times to build and validate models. Heavy compliance burden to document and explain models.
- Requires significant IT resources to translate the model built by data scientists into something like Python, and then to a software language like JAVA that supports integration into production systems.

Major Considerations:

- Do you currently have the resources, both from an employee skill set as well as technology standpoint?
- Are you able to meet the compliance obligations in addition to the performance goals?
- How long would model development and validation take?
- Have you defined the process for integrating the model into your production LOS?
- Have you defined a process for monitoring the model in production in accordance with SR 11-7 guidelines?

Next: Paths to AI Adoption continued

Buy

Pros:
Model is available very quickly. Comparatively less expensive than other options.

Cons:
Typically, a generic model is not tailored to an organization's specific customer base, region, or products. Customization is limited, and as a one-time purchase, updates require purchasing a new model.

Major Considerations:

- What data is used in making the model, and are you able to customize that data used within the model?
- What is the population the model was built to support?
- Have regulators reviewed and approved the model?
- How was bias addressed when building the model to ensure that it does not discriminate?
- How thorough is the model documentation?

Partner

Pros:
Generally offers more flexibility and customization than a pre-built model and much faster to build, validate, and deploy than models created "in-house". Provides ongoing relationship with domain experts that includes model performance analysis and model updates.

Cons:
Generally not as cheap or as fast to deploy as a generic, pre-build model.

Major Considerations:

- How much input will your team have on the model build process, such as the data used, variables included, target selection, etc.?
- How long does the process take and what are the resource requirements from your team during the project?
- How will the model be deployed and integrated into production systems?
- Have regulators reviewed and approved the model?
- How was bias addressed when building the model to ensure that it does not discriminate?
- How thorough is the model documentation?
- How often are models updated, and what is the process for identifying when an update is necessary?

→ Next: Adopt AI Responsibly

Adopt AI Responsibly

One of the biggest barriers to AI adoption and success has been overcoming regulatory and compliance challenges. To ensure successful adoption and to capture the gains of AI underwriting, it's critical to make sure you have plans to address AI responsibly. The good news is that due to advanced explainability techniques, you can now explain how a machine learning model made a decision and what factors contributed to that decision.

> "The AI community has made notable strides in explaining complex machine learning models."
>
> Lael Brainard,
> Federal Reserve Bank Governor

Lenders who are successfully adopting AI responsibly are doing two things:

1. Selecting the right explainability technique and making sure they can streamline model risk management (MRM) processes to address the specific needs of risk, data science, regulatory, IT, legal, and business functions.
2. Avoid downstream regulatory and compliance challenges by gathering stakeholder's concerns up front. By soliciting feedback earlier in the process, you can identify and mitigate problems before the model goes into production. These are some of the most common concerns you'll need to address from stakeholders and can be used to vet vendors if you choose to buy an AI solution.

→ Next: Adopt AI Responsibly continued

These are some of the most common stakeholder concerns you'll need to address and can be used to vet vendors if you choose to buy an AI solution.

Compliance

1. How does the model make decisions?
2. Why did an individual applicant receive a particular risk score?
3. How much control does the organization have over what data is used in the model?
4. How do we ensure that models are fair?
5. How comprehensive is the documentation provided with the model?
6. What influence do we have over how the model makes decisions?
7. How is the model updated with new information?

Regulatory

1. How are we ensuring that models are fair?
2. What variables are in the model?
3. How is the model compliant with regulations such as FCRA and ECOA Reg. B (Adverse Action)?
4. How will we explain the model's decisioning process to regulators and demonstrate that they are in compliance with all of the regulations and guidelines?

Additional ML Explainability resources

Robust Explainability in AI models

Video: How to Build Transparent Machine Learning Credit Models

Getting Adverse Action Notices Right for Machine Learning Models

Most AI Explainability is Snake Oil. Ours Isn't. Here's proof.

→ Next: AI Execution

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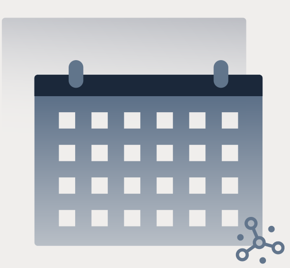
AI Execution

Great, you've selected your approach. What's next? This section covers all of the essential steps from building a project time plan, to data considerations, to model validation.

Build Project Time Plan

First things first, you need a project plan. According to Cornerstone's 2020 State of Credit Modeling report, **21% of financial institutions revealed that traditional models take more than 8 weeks to build and validate and another eight weeks to deploy**. While every model is unique, in general:



AI-Powered models can be built, validated, and deployed in 3 months

There are four stages: Data Collection & Analysis, Model Development, Model Evaluation, Validation and IT Consultation.

As you build your project plan, it will be helpful to account for these key tasks, deliverables, and stakeholder responsibilities:

Model Development:

Compliance will want to review the variables in the model, make sure they are FCRA compliant and that adverse action reason codes can be generated for them. They will also want to understand the steps taken to ensure that the model is fair and review appropriate fairness metrics to see how fair the model is, such as the Adverse Impact Ratio and the approval rate between protected class and non protected classes.

Model Evaluation:

The business team will want to see the economic lift of the model, including what the changes in overall risk and approval rates will be.

Note: This is done once the model is final

Model Validation and IT Consultation

Compliance and Model Risk Management will need to review the model documentation before pushing the model into production.

IT will want to know which historical data sources are needed to build the model, and which production systems they will need to integrate for live scoring.

→ Next: AI Execution continued

Data Gathering Considerations

In using machine learning to power credit decisions, more data put through the right models means better outputs. Lenders and credit unions using our machine learning (ML) modeling tools employ up to 10 to 100 times more variables than they used to when they built models with traditional math (linear regression).
That vastly improves their ability to make more good loans and fewer bad ones. But we also know that switching to ML models raises lots of data questions: how much, what kind, how clean, etc. Should just say Here are the most common questions we get asked about.

Data required for ML models
Typically, machine learning models rely on the following data sources:

- Application Data
- Bureau Data
- Historical Loan Performance Data

Learn more how financial institutions are using machine learning to swap out risky borrowers with good borrowers.

How to handle missing data or unlabeled data?
ML models are exceedingly good at finding a way to relate even messy and missing data in a meaningful way. They're also really good at dealing with unstructured data such as search and browsing history, and time-series structured data (CRM/transactions). You can come up with all kinds of creative ways to join these types of datasets in an ensembled machine learning model that unearths meaning from the mix.

For example, rather than merely looking at whether there is a bankruptcy or two in a file (about the most that a linear model can handle), an ML model can look at all the information for each bankruptcy event, the time between events and the length of time since the most recent event. In general, most lenders are implementing machine learning model with large swaths of missing data such as when data are only available if the customer applied online, or when data went missing due to an upgrade or change in the data source.

Should you use social media data?
No! Despite a lot of hype around insights that can be gained by stalking someone on Facebook or Twitter, the truth is that social data provides nowhere near the signal that typical credit variables do. Your customer bank data and the credit bureaus have plenty of great data that can build an accurate profile of a customer without having to find out where they went on their last vacation or if they're fond of IPAs.

Model Validation

Once a model is built, you will want to verify that its performance meets expectations. This is done by comparing your new Machine Learning model's performance vs. your incumbent model on a set of historical data. The results of this analysis will provide details on model accuracy, impact on approval and risk rates, and the economic impact of the new model compared to your previous.

→ Next: Track Ongoing Performance & Monitoring

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Track Ongoing Performance & Monitoring

Congratulations, your model is in production and you can begin to track and report on the KPIs you selected to demonstrate value from your AI investment. Depending on the lending objective you selected in the beginning, you can use these methods to show results:

Lending objective	How to measure
Increased Approvals	Construct a counterfactual portfolio to see the differences in the new models versus the old to understand who the new model will approve and deny versus what the old model did.
Reduce Losses	Same as above
Increase Yields	Using the same counterfactual, develop a pricing strategy to optimize yield.
Decrease Disparity	Report on the approval rate increase by protected class versus non-protected class.
Increase Automation	Calculate savings with increased automation: [manual process hours/year] x [rate] = [amount saved/year]

→ Next: Track Ongoing Performance & Monitoring

Monitoring

The Federal Reserve (SR11-7) offers guidance that models should be monitored in production to ensure safe operation. But what kinds of things should you be looking at? Here are some recommendations:

- **Operational Metrics:**
  Number of requests, time to score, etc.
- **Feature Stability:**
  Which features are most impactful to model scores and are those features changing over time?
- **Population Stability Metrics:**
  How closely do the applicants that your model is scoring today resemble the population that the model was trained on? If they vary, find out how they are changing and by how much.
- **Output monitoring:**
  How do the distributions of scores across segments compare with training distributions?

Monitoring should be an early warning mechanism to let you know it is time to update the model in response to changes that may potentially impact model accuracy.

Bottom line:

Robust ML-based monitoring should help lenders reap the increased profit potential of ML underwriting while staying fully compliant with regulatory guidelines and keeping the business on track.

→ Next: Conclusion

Conclusion

COVID-19's impact on the economy and lending industry has reinforced the urgent need to move to AI. In the current environment, lenders can't rely on credit scores as they previously have and need a new way to evaluate and monitor credit risk with limited visibility and access to reliable data. ML models provide a more holistic picture of borrowers, enabling lenders to assess risk more accurately and make the right decisions faster, even during a pandemic.

Change is challenging but the journey to AI is easier than you might think. With the right strategy and prescriptive approach, you can successfully implement ML models to deliver better results for every lending objective. And the best part is that you don't have to reinvent the wheel. We've helped banks and credit unions implement machine learning models and demonstrate a compelling return on investment for AI-powered underwriting.

We want to share our expertise and best practices to ensure your move to AI is successful and capture the gains, ranging from making better decisions and better loans to increasing credit access to underserved communities. Applying these roadmap development best practices will help you make a strong case for change and get you started on your journey.

To learn more, visit zest.ai

info@zest.ai

Schedule a Demo to learn how AI can help your organization make better and faster lending decisions.

About Zest

Zest AI makes the power of machine learning safe to use in credit underwriting. Lenders using Zest AI software make better decisions and better loans—increasing revenue, reducing risk, and automating compliance. Zest AI was founded in 2009 with the mission of making fair and transparent credit available to everyone and is now one of the fastest-growing fintech software companies. The company is headquartered in Los Angeles, California. Learn more at www.zest.ai and connect with us on Twitter and LinkedIn.

With Zest, you can:

Grow

Identify the best borrowers and safely increase approvals

Protect

Mitigate risk, limit losses, maintain performance

Optimize

Exchange pricing, segmentation, and recoveries

Automate

Gain efficiencies and return on high-value activities

Better Lending for you and your customers with more powerful insights and more accurate risk assessments, Zest gives you the ability to approve more credit-worthy borrowers, reduce existing losses, offer better rates, and develop more customized policies and rules engine for your business.

Thank You

Schedule a Demo to learn how AI can help your organization make better and faster lending decisions.

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LEARN MORE

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APPENDIX

How is ML Underwriting Different from Traditional Underwriting

	LOGISTIC REGRESSION	HYBRID ML + LR	AUTOMATED ML	ML FOR LENDING
Resilient to missing data and error	○	×	●	●
Uses large amounts of data (100s of variables) in production	○	○	●	●
Interpretable for Underwriting	●	×	○	●
Supports current model validation process	●	○	○	●
Easy to put into production	●	●	○	●
Duration of model build to production	6 months to years	6 months or more	Not possible to get models into production due to inadequate explainability	3 months
Preddictive accuracy	○	◐	◐	●
Stability over time	◐	◐	○	●
Fair lending	○	○	○	●