Advancing model risk management with emerging tech

Protecting financial institutions during model development and validation

Model Edge

A PwC Product

The breadth and type of model usage — and the definition of what a model is — continues to evolve as models become more critical to the business operations of financial institutions.

More data, use cases, users and advanced capabilities increase the burden on business models, from known anti-financial crime models like anti-money laundering (AML) to model risk management (MRM) tools. In many cases, financial services institutions may not be aware of current model definitions, or they may not agree across the organization about what's within the scope of the MRM.

These disconnects can happen because:

- Each organization defines "model" differently
- Each organization applies their models differently
- The regulatory definition of "model" continues to evolve

For example, a small to mid-sized regional bank with a recently established MRM program might have identified just three models in use. But when regulators investigate, they find the institution failed to identify a dozen others based on changing model definitions — or even a model coming in via a vendor, which may go undetected and not be included in an inventory. Or, consider the plight of a fast-growing fintech that purchases a number of models in quick succession while still relying on spreadsheets to catalog and track each model's risk — a nearly impossible task.

In both scenarios, risk management, artificial intelligence (AI) and machine learning (ML) models should have the right level of governance, whether officially designated as models or not. Similarly, judgment-based models your organization may use today could soon be governed the way complex statistical models are, including those grounded in AI technologies.

Responsible AI and model governance

Models based on AI are garnering broader use. For these and other evolving modeling trends, your team should ask targeted questions around each model's ability to produce fair outcomes that don't disproportionately impact individuals based on their protected characteristics, like race or sexual orientation.

Using AI responsibly involves building models more effectively, considering unintended consequences, appreciating potential risks, building appropriate model governance and trust, and identifying where their performance may fall short. When AI is involved, you should apply the following lenses to your approach:

Organization strategy

Assess the role the company has and how AI models fit into that role and ask key questions. Will AI support decision-making, product development, product strategy or facilitate operations? Are there any areas in which your organization will not participate using AI, driven by regulatory and ethical considerations?

Responsible practices

These often go above and beyond mandated requirements, dictated by ethics and strategies. Views on transparency, fairness, privacy and responsibility cover a variety of systems and models that aren't regulated but may still require analysis and explanation.

Governance

Consider the structures in place to govern the models and provide end-to-end oversight of the systems. How does MRM play into all model development? Does the MRM team have the proper visibility and access it needs?

Core data science practices

Good data science and model development practices are crucial. Aim to have standard mechanisms for obtaining data and common view on checkpoints for model analysis to help instill confidence.

Beyond the challenges AI models bring, institutions face several hurdles to advance MRM. With the right approach, those organizations can stay ahead of the technology curve as models improve.

MRM challenges for financial institutions

MRM requires institutions to document, monitor and assess models periodically, and assign tasks and model users. MRM teams are working with technology and operational risk teams at their respective institutions to develop governance approaches to address the varied and inherent risks involved.

Six common challenges include:

01 - Human error

Collecting and analyzing data with spreadsheets isn't ideal — and the process can be error-prone. The rise of hybrid work also lends itself to human error, as teammates can be spread out across the globe and operate without as much IT oversight.

02 - Fast business growth

If your business is growing quickly, you might be prone to employing more models than you realize. Be on the lookout for this tendency, as it takes greater internal oversight to sift through programs with unknown models that require governance.

03 - Demand for greater efficiency for stakeholders

Global businesses have multiple stakeholders working together across geographic lines. This can reduce efficiency and the success of systemic checks and balances over time.

04 - A need for transparency and clear communications around the models

Larger organizations have multiple teams with unique risks. You should be direct and open with your messaging around model governance.

05 - Controls and a regulatory audit trail

Creating robust controls will demand both pre-planning and daily diligence. Maintaining a clear audit trail is important to tracking models within your organization.

06 - Constantly changing regulatory expectations

As technology and what's possible push the envelope on model creation, regulatory expectations evolve to match. Staying on top of this — with or without a dedicated team — can be daunting.

You need a roadmap to MRM success that can get you over the common hurdles in building and implementing effective models.

Enabling MRM success by avoiding common pitfalls

Models can enable you to process data, create actionable forecasts and insights, and evaluate potential transactions and screen for potential defaults.

Machine learning may require frequent recalibration, and although model development has sped up with the improvement of technology, there remain several challenges to overcome when developing, maintaining and tracking effective models.

Pitfall: The demand for speed to market

Development and documentation of a model can take up to six months. With machine learning, the pipeline to market is accelerated. This demand for speed can blur the line between the model validation and development teams.

Validation teams are sometimes expected to validate a model in parallel with development, a conflict of interest that can result in a loss of independence and create regulatory questions.

Solution: Your team should have a well-documented and controlled process with control points as well as templates and accelerators that can help speed up the time to market.

Pitfall: Extended use of vendor models

Institutions can lean on internal models for their processes, but third-party vendor-supplied models are available. These models tend to be purchased off-the-shelf with no customization or details from the vendor about the development or validation of the financial institution's needs and models used, or they may not be visible to the company stakeholders.

For example, employee management software may have some predictive capabilities, like flagging employees likely to leave. A company acquiring this software may not be aware of this specific feature of the AI/ML system. They won't know they should consider it as part of a holistic governance process despite regulations which will likely stipulate that these models need to be validated, recognized and included in model governance.

Solution: Financial institutions should follow Federal Reserve and OCC guidelines:

- First identify what is and what isn't a model to create a more accurate inventory across your financial institution.
- Define how you manage risk around the models. This can be a team effort and should include any vendors that have provided software or models to the institution.
- There should be a clear process to subject those embedded models to the company's MRM solution.

Pitfall: Unfamiliarity with new technology

AI/ML models can be more complex and difficult to validate and might require more frequent validation. But they shouldn't be treated differently from any other models. By default, AI models can use a much larger amount of complex data — as well as data that's novel to an organization — making exploration and validation more cumbersome. Additionally, AI machine learning models have been found to have a better use case for unstructured data. This can make it difficult to create a data summary or table to relay the information in an easy-to-digest format, increasing the need for more spot-checking or example-based validation.

ML systems and models are probabilistic. Understanding model sensitivity during validation might be more nuanced and require more experimentation to fully grasp it. Take online shopping sites, for example. They're continuously learning models that serve up products to the shopper based on their purchase, click and search habits. Those models can be extremely hard to validate because the models themselves are constantly changing.

Solution: Be intentional. Choose technologies that most closely suit the needs of your use case.

Finally, regulatory scrutiny around AI is highly uncertain, as they're more widely used and accessed across the industry in collections, marketing, fraud and broader financial crimes management.

Pitfall: Lack of MRM talent

In addition to the overall labor shortage that underscores hiring today, financial institutions face additional challenges in finding experienced talent to join their MRM teams. Model validation requires a very specialized skillset, and these individuals are highly coveted across the financial services industry and in development shops.

Even though some graduates are leaving school with data science, statistics, actuarial and machine learning expertise, institutions still struggle to find and retain the right talent to effectively challenge models during the validation process.

Solution: Automation can help with some of the repetitive exercises in the process, such as validation testing and performance monitoring, but people still need to step in and make judgment calls.

Control MRM with people, processes and technology

In a well-controlled and efficient MRM program, model validators can effectively challenge model shortcomings, which helps the development team create better models without imposing unnecessary burdens on them. To reach that ideal scenario, institutions should have the proper resources and tools: people with the right skill sets, embedded processes and technology.

Having an industry-leading MRM system like Model Edge, a PwC product, can help improve efficiency throughout the process and enable regulatory compliance at every turn.

With Model Edge, you have a centralized and automated MRM portfolio with a digital model inventory that tracks model documentation and signoffs from inception and design through testing and implementation. The digital platform captures updates and approvals with an audit trail to help meet MRM and regulatory standards. Collaboration between teams also is simplified to speed up model lifecycles and improve validation times.

Even the most complex models can become clearer to stakeholders through standardized and enhanced documentation and automation in Model Edge, allowing MRM team members to spend more time managing the high-level, more complex risk of the larger organization.

Model Edge can help you meet regulatory compliance demands and improve your MRM process efficiency in one affordable tool that addresses the biggest challenges in the industry.

Start a conversation with our team today.

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