

DeRisk

CRISIL's insights and analyses of regulations, macroeconomic factors, guidance and trends affecting the insurance industry

Governance for Machine Learning models

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Financial models relying on Artificial Intelligence (AI), particularly its Machine Learning (ML) branch, are in the high risk-complexity-materiality spectrum in the model inventory of banks and insurers. Some of these have increased their popularity with the advent of Big Data analytics.

To establish common ground, ML applies and refines – or trains – a series of algorithms on a large dataset by optimizing iteratively as it learns in order to identify patterns and make predictions for new data¹.

Financial services and other industries are expected to increase the use of such Big Data from 7.9 ZB in 2016 to 44 ZB by 2020². They are also expected to increase the use of non-traditional data and change the mix of internal and external data used.

Such use of data and reliance on the results they produce – including diverse commercial uses that involve analytics, model benchmarking and decision-making – is likely to increase with ~55% of the insurers using or experimenting with AI and ML solutions⁵.

Consequently, attention is focussed on how financial institutions and regulators are responding in terms of governance of these models and providing appropriate oversight while maintaining proportionality to conduct model development and validation activities.

Potential problems

ML models have different oversight

ML model developers and users have to confront the natural model lifecycle and explain how results or decisions were obtained to model validation experts or regulatory examiners. Some models require limited human intervention in the training (non-supervised) process. In some others, they are completely absent in the results and decision-making process. Thus, ML models diverge from typical classification and have different oversight.

Guidance is emerging in various jurisdictions to address some of the challenges of ML model governance. The Financial Stability Board (FSB) produced a report on Artificial Intelligence and Machine Learning in financial services in 2007¹. In the United States (US), the Algorithmic Accountability Act, 2019³, deals with issues that lie at the core of ML models.

The term ML is not specifically used in the US, where it is referred to as automated decision systems

On the other side of the world, the Bank of Japan released a report by a study group on legal issues regarding financial investments using algorithms/AI⁴ (2019).

¹<https://www.fsb.org/wp-content/uploads/P011117.pdf>

²https://www.iif.com/system/files/32370132_insurance_innovation_report_2016.pdf

³<https://www.wyden.senate.gov/imo/media/doc/Algorithmic%20Accountability%20Act%20of%202019%20Bill%20Text.pdf>

⁴http://www.boj.or.jp/en/research/wps_rev/lab/lab19e01.htm/

⁵https://eiopa.europa.eu/Publications/EIOPA_BigDataAnalytics_ThematicReview_April2019.pdf

In Europe, the EIOPA (2019) produced a Big Data Analytics (BDA) report⁵ that aims to show different aspects of BDA on complex tools for motor and health insurance.

New York City has issued guidance on the use of data in underwriting life insurance (2019).

And as we learn more about ML applications, an important question that surfaces is on the ownership of model risk. An ABA Banking Journal article addresses this⁶.

Governance framework for ML models

Regulators, practitioners, and financial institutions together are driving the future of ML techniques

Governance for ML models is critical to address regulatory concerns and industry challenges. But ownership of ‘who’ is accountable is complicated. A few considerations include the view of regulators to conduct consultations to drive model governance policy. This is an important view we share, where regulators, practitioners, and financial institutions together drive the future of ML techniques.

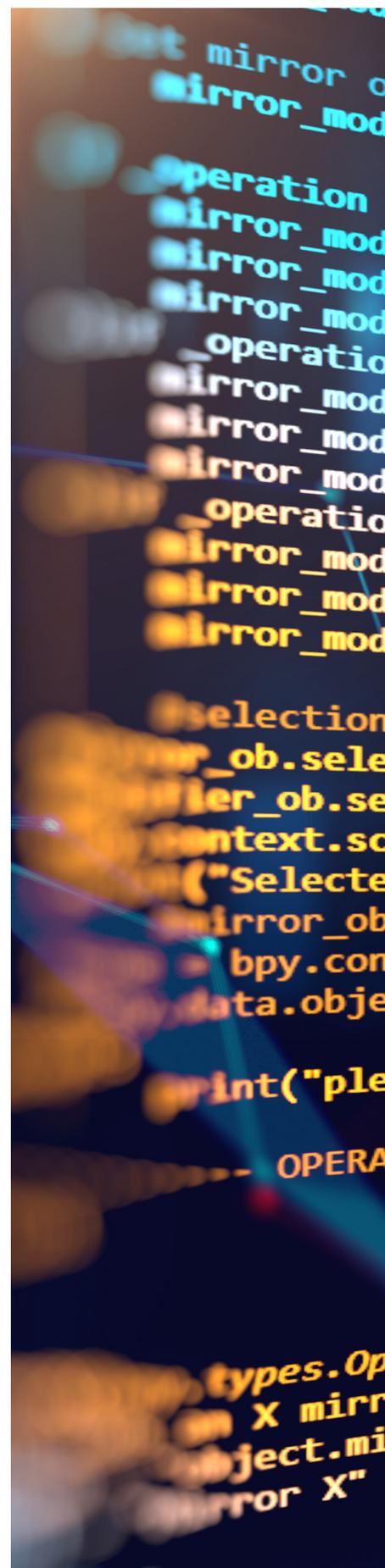
Some guidelines such as SR11-7, OSFI E23, EBA, PRA, and EIOPA SII L1 provide clear details on how to handle model governance. But recommendations around model risk management will be effective only if they are supported by a robust and holistic governance framework. For example, the E-23 guidelines make it clear that a strong model governance framework must cover the process from end-to-end, clearly allocate ownership, and provide unambiguous guidance on exceptions. The governance approach endorsed by E-23 guidelines is similar to the SR 11-07 guidelines and is summarised in Table 1 below.

Table 1: Typical guidance on model governance

Encompasses each lifecycle stage of model management cycle
Identifies stakeholders and articulates roles and responsibilities
Developed and operationalised by senior management
Sets out ownership clearly
Provides for materiality assessments of model risk to be reviewed periodically

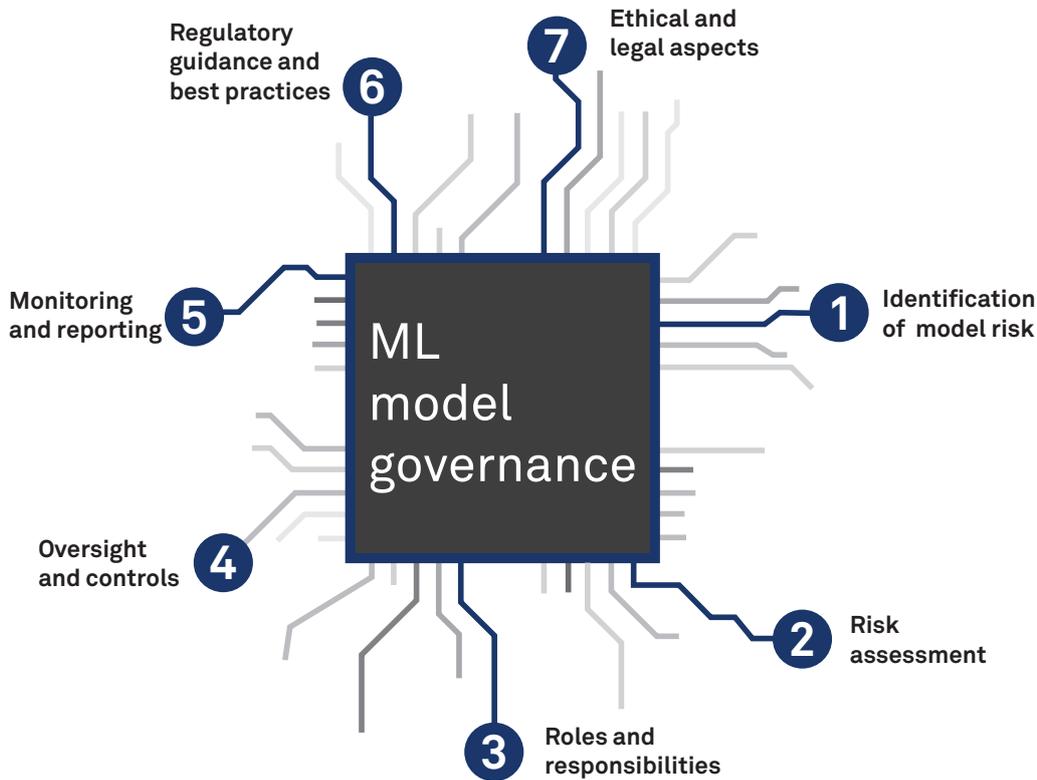
⁵https://eiopa.europa.eu/Publications/EIOPA_BigDataAnalytics_ThematicReview_April2019.pdf

⁶<https://bankingjournal.aba.com/2019/04/who-owns-model-risk-in-an-ai-world/>



Our proposed governance framework for these automated decision systems, including AI and ML models, includes the following considerations:

Figure 1: CRISIL model governance frameworks for ML models



1. Identification of risk

One of the major risks arising from ML models is algorithmic bias and the extent to which the models can make inferences from data sets without establishing a link.

Input data may be inherently biased, which may result in unfair outcomes.

Moreover, model users may lack adequate understanding of complex model limitations and provide an incorrect interpretation of output, leading to poor outcomes.

Financial institutions must perform periodic reassessments to determine whether the risk model profile is adequate and appropriate as the model life cycle advances through each of its stages.

2. Risk assessment

Since models can evolve over time, the current risk-assessment matrix-tiering may not address the aspects based on which the model arrives at the results, or derives them for its automated decision systems. Hence, the risk assessment process must be more frequent and dynamic. It must also prescribe mandatory sign-off from subject-matter experts, ensure regulatory compliance and be representative of the business. Assessment must include the technical, business, and operational parameters of the model.

3. Roles and responsibilities

Financial institutions need to assess talent needs, especially how responsibilities are differentiated between actuarial and non-actuarial functions. This is to comply with internal policies, statutory requirements, actuarial and accounting standards,

and rigorous code of ethics, in addition to other best practices and activities required for ML models. Authority and independence to challenge the model owner is also important. Currently, this demarcation is not so clear for actuarial models that use ML techniques, with actuaries signing off on models.

4. Oversight and control

The models must adhere to the internal policy and compliance requirements established by each financial institution, as different stakeholders need to review, approve, attest, and certify each stage of the model lifecycle, while maintaining suitable and proportionate risk controls. Control and testing processes must be more dynamic and proportionate to the risk tiering, materiality, and complexity of the model. This includes frequent testing and monitoring of models beyond the development stage.

Key performance metrics must be designed to gain assurance that the model is meeting expectations. In order to control model risk, multiple smaller algorithms are typically used to determine output, rather than one complex algorithm. Once the assessment process identifies variances, if any, firms must put in place certain model constraints.

Having predefined tools in place is another way of controlling the model. Certain tools such as Model Cards, Facets, Flow Algorithms, and What if, increase the ability to analyse datasets, make them more transparent, reduce the risk of bias, and help understand complex models in order to make automated decision systems fairer.

5. Monitoring and reporting

As algorithms continuously evolve, a more dynamic monitoring approach must be followed. While banks have found the value of model validation, insurers and other financial institutions are starting to define more pointed monitoring processes for their automated decision systems.

Model users must monitor potential market or regulatory changes that could impact the design of models in their inventory. Ongoing and circular/ bottom-up feedback must be given to ensure accurate reporting. The internal audit team must ensure that ML models are regularly monitored and steered towards model validation units in the event their performance does not meet the thresholds defined in the oversight and controls policies.

6. Regulatory guidance and best practices

Regulators expect financial institutions to adopt best practices and adhere to the guidance, laws, and practice notes emanating from practitioner societies. Regulators also understand that it is critical to think through processes to ensure best practices, that it is a timely exercise, and may require adaptation in case of a complete cultural shift from rooted practices – for e.g., standards that actuaries use in many of the models for insurance companies. For multinationals, convergence may be a challenge and local entities may require different practices due to differentiated regulations or demarcation of responsibility and accountability, including model ownership.

7. Ethical and legal aspects

This is a massive topic in itself and requires interdisciplinary groups to address it. For example, many legal risks may be mitigated in vendor provided models, with rigorous contractual agreements at the licensing stage. The intervention or supervision of the models by adding a human layer is important, as an ‘assistive intelligence’ mechanism, as a means and not as an end.

Another important aspect is disclosure, especially in the use of personal data. Compliance, legal, and technical teams and committees must rigorously

review aspects such as whether it relevant or not to gather 'certain data', instances it is better not to know, etc. Financial institutions would need to take risk to maintain a good deal of innovation, while mitigating ethical and legal detractors.

Concerns around ML models

It is still not clear at this stage if regulation and guidance might stifle innovation and distort the market

Financial institutions need to thoughtfully design their governance frameworks for ML models so that they ensure risks are appropriately mitigated but, at the same time, not stand in the way of responsible innovations that might expand access and convenience for consumers and small businesses, or bring greater efficiency, risk detection, and accuracy⁷.

Despite an analytical process in setting up a framework, it is still not clear at this stage if regulation and guidance may stifle innovation and distort market. Some problems include:

- **Data accessibility:** Huge datasets are required in order to train ML or AI models but these datasets could lack authenticity, verification and ethical issues. This includes Internet of Things data, online media data, digital data owned by insurance firms, geocoding data (people geolocation), genetics data, bank account and credit card usage, and other digital data (selfie to estimate age). In Figure 1, the points 1 and 7 are particularly important as they establish correct use of data depending on model risk identification, while staying on course for possible ethical and legal challenges.
- **Explainability:** Enhancing the ability of model developers and validators to improve visibility in model design is required. This need is commonly found in deep learning models such

as neural networks, where layers of nodes are set up by the model developer with a selection criteria that is difficult to explain. Additional documentation regarding training/learning methods and use of intermediate outputs that may derive decisions are key. Yet, it becomes challenging to explain credit decisions to consumers, which would make it harder for consumers to improve their credit score. In the near future, explaining decline in insurability rates will also become important. In Figure 1, point 2 and 6 are focused on setting up correct risk assessment and oversight and controls to increase the explainability of the model.

- **Opacity and understandability:** This concern is tied with explainability, but encompasses the so-called 'black box component'. It uses extraction of complex patterns of data, which are incomprehensible to the human mind. Financial institutions need more powerful and adaptable tools, but models may not be transparent due to the rise in vendor models from fintechs and insure-techs that makes it difficult to understand how model works. This also enters legal ground due to intellectual proprietary. In Figure 1, points 3 and 5 are aimed at decreasing model opacity by having clear roles and responsibilities for each of the stakeholders and transparent model monitoring.
- **Accountability and skills set adequacy:** Many financial institutions, especially insurers, are struggling with finding the right talent. At first glance, this does not appear as a regulatory concern, but it becomes clear when it comes to liability and model risk accountability. Model developers need to have the right experience and credentials to defend their models. In fact, based on our experience working with 3,000 model validation projects in 2018 of banks and insurers, we found that lifting and shifting skills across functional teams was difficult, particularly between actuarial and non-actuarial functions for ML-oriented solutions. In Figure 1, point 3 addresses the problems arising in the roles and responsibilities for complex models.

⁷<https://www.federalreserve.gov/newsevents/speech/brainard20181113a.htm>

- **Cyber security:** Though outside the scope of this paper, data privacy-security is a highly relevant issue. It is observed that automation decisions create issues related to data privacy which imposes ethical and legal challenges for financial institutions dealing with complex tools relying on BDA. In some cases, though model owners can use non-traditional data (for e.g., credit card use), they decide not to use it to eliminate cyber risk or liability, i.e, they prefer not to know. Some of the major overhauls of data privacy include the GDPR⁸ that has transformed the way various data providers, consortiums, and users deal with personal data. In Figure 1, points 6 and 7 cover many of the best practices to mitigate cyber security, along with flagging its underlying legal challenges.

How the future looks

ML models will increasingly become the core

The next couple of years will see the rise of BDA use, automated decision systems, and ML models. We anticipate these models will move to the center of financial institutions' agendas for model risk management. Financial institutions will continue to overcome challenges by implementing targeted governance for ML models, especially those which have Model Risk Management (MRM) programs under development. This means, while adopting and using ML, institutions will have to adopt an exemplary model governance structure to ensure their ML models are meeting the fast-evolving environment of automated decision systems. Improving end-user experience for banking users and policyholders, better customer service, and improved MRM effectiveness to help financial institutions strength their competitive advantage will be central to the industry's agenda.

⁸<https://eugdpr.org/>

How we can help

We have made a strong commitment to industry research and thought leadership, and produced regular reports highlighting topical issues within the insurance industry. A dedicated team of market risk experts, actuaries, quantitative analysts, and small and medium enterprises are engaging with clients to provide them with the best possible regulatory and insurance-related solutions, including actuarial modeling and statutory reporting.



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- Insurance Operations and Operational Risk
- Statutory and Tax, Reporting & Analytics
- Fraud Reporting and Analytics
- Financial Crime and Compliance

Insurers have a long road ahead to transform themselves by riding the revolutionary wave and CRISIL is well-poised to become a relevant partner in the journey. CRISIL has been proactive in collaborating with financial institutions to help them devise analytics and technological strategies to succeed. Moreover, we are constantly acquiring necessary tools and skill sets, and are strategically placed to help the insurance industry transform itself.

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