Grant Thornton

The Use of Machine Learning Techniques in Internal Models

Risk Advisory - Quantitative Risk Services

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Introduction

On 28th July 2025, The European Central Bank (ECB) has published a revised version of its *Guide to Internal Models*[1], incorporating significant updates to reflect changes in the regulatory framework under CRR3 and the revised Basel standards. Building on the experience gained since the guide's initial publication in 2019, this updated edition provides enhanced transparency which also allows for harmonisation in the supervision of internal models used for credit risk, market risk, and counterparty credit risk.

A key enhancement in this revision is the dedicated section on The Use of Machine Learning (ML) Techniques in Internal Models. Recognising the increasing adoption of ML in banking, the ECB sets out clear supervisory expectations to ensure that such models are:

- Developed using robust, replicable methodologies;
- Governed by well-defined internal policies specifying scope, limitations, and alignment with risk management and governance frameworks;
- Subject to appropriate levels of human oversight, explainability, and documentation, especially in relation to model outputs and override practices.

These principles aim to ensure that the use of ML does not compromise transparency, model reliability, or regulatory compliance. The guide also clarifies the need for institutions to justify the complexity of ML-based models with demonstrable performance improvements and to mitigate risks associated with their integration into credit decisioning, capital allocation, and stress testing processes.

The updated guide supports the simplification of model landscapes while reinforcing prudent model risk management practices. It has been informed by industry feedback and collaborative input from national competent authorities, ensuring that it remains a practical and forward-looking reference for both banks and supervisors.

Why inclusion of a section dedicated to the use of Machine Learning Techniques in Internal Models is significant?

The inclusion of a dedicated section on machine learning marks a significant milestone in the ECB's supervisory approach. Until now, the application of ML in internal models had operated in a regulatory grey area, with limited formal guidance despite its growing use across the banking sector. By explicitly outlining supervisory expectations, the ECB not only **acknowledges the increasing role of ML in risk management and decision-making** but also **addresses longstanding industry calls for clarity.**

This shift brings greater certainty for institutions, promotes consistent supervisory practices across jurisdictions, and sets a clear benchmark for the responsible development, governance, and auditability of ML-based models under the internal ratings-based (IRB) and other internal models frameworks.

[1] https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.supervisory_guide202507.en.pdf?4460c67ecb5d677bacabc2e19942912f

Background and Rationale

The use of machine learning in internal models has traditionally been restricted by European regulators due to concerns around transparency, explainability, and oversight. The ECB and EBA have emphasized that models used for capital requirements must remain interpretable and subject to effective governance. Under DORA, institutions must also ensure digital resilience and control over advanced technologies like ML. Until recently, ML was largely limited to supporting roles, not core risk modelling. The ECB's revised Guide to Internal Models, however, marks a turning point by formally recognising the use of ML—under strict conditions—to reflect evolving practices while maintaining regulatory safeguards.

2019 – Original Guide

- First issued in October 2019, the ECB Guide to Internal Models focused on governance, validation, and methodology for internal models under the IRB and Basel frameworks—without explicit reference to the use of ML techniques.

Implicit Treatment During 2019–2024

- Updates in 2024, including refinements to credit risk and default definitions, still lacked a specific ML section, leaving ML in a regulatory grey area despite rising adoption .
- ECB's supervisory publications on digital innovation and AI (2022–2024) acknowledged emerging ML risks and potential without formal guidance on internal models.

2025 Revised Guide – ML Explicitly Included

On 28 July 2025, ECB released the revised Guide to Internal Models—now featuring a dedicated section on ML within the "Overarching principles" chapter.

It formalised supervisory expectations on:

- Development, governance, validation and use of ML-based models
- Explainability, transparency, and human oversight
- Justification of model complexity versus benefits

ECB defines an ML Model as below:

- Uses many parameters
- Models non-linear relationships
- Needs large data volumes (structured or unstructured)
- Often complex and hard to explain

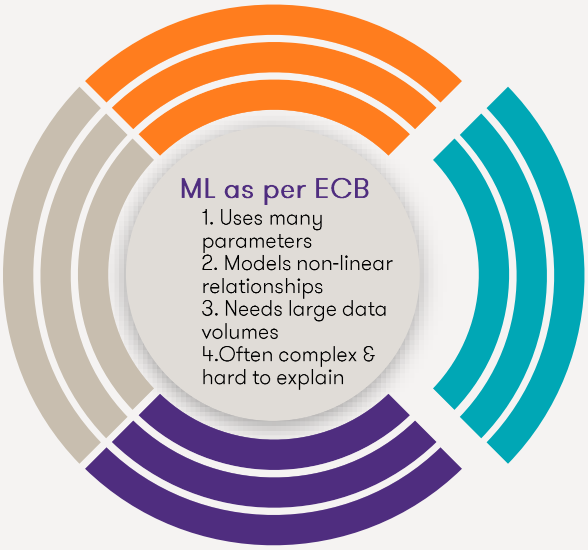
Significance of the New ML Section

- **Regulatory Clarity:** For the first time, ML techniques are formally addressed under ECB internal model supervision.
- **Consistency:** Promotes harmonised supervisory assessment across Euro-area jurisdictions.
- **Model Governance Upgrade:** Establishes explicit standards for explainability, validation, and human overrides—aligning ML-based models with established IRB expectations

General Principles on Internal Models Making Use of Machine Learning Techniques

The ECB sets out principles for using machine learning in internal models under Pillar 1, focusing on complexity, transparency, and governance. Though centred on credit risk, the guidance applies more broadly, with expectations scaled to model materiality and use.

Principles and expectations outlined in this guide are applicable on ML-based models in Credit Risk, Market Risk, Counterparty Credit Risk and Credit valuation adjustment (CVA).



Scope of Application

- ML principles apply to all internal models under Pillar 1.
- Though examples focus on credit risk, some principles extend to:
- Market Risk
- Counterparty Credit

Principle of Proportionality

Implementation must consider:
- The complexity of the ML-based internal model
- The model's role (e.g., data prep, core modelling, challenger use

Impact on Complexity & Materiality

ML is a driver of model complexity and triggers higher expectations for:
- Materiality classification
- Management reporting
- Internal validation

Legal & Supervisory References

- Principles cite credit risk regulations as default
- Market/counterparty risk references included where feasible
- Some expectations are credit risk-specific only

Governance of Machine Learning-based Internal Models

Institutions must embed ML-specific risks into their overall governance framework covery key areas of **Model risk governance**, **Data governance**, **Validation governance** and **Change management**. All three lines of defence—<u>risk control, compliance, and internal audit</u>—must understand ML-related risks.

Skills & Expertise

- Stakeholders involved with ML models including **developers, validators, auditors, users, senior management, and risk committee** must possess adequate ML knowledge.
- All legal entities (if group-level) must maintain sufficient internal ML capabilities.

Model Change Management

ML-specific changes must be clearly defined in the **internal change policy.**
- **Thresholds, significance levels**, and **classification criteria** should reflect ML-related **complexity.**
- Distinguish between: **Material changes** (e.g., switching from traditional to ML models) and **Maintenance** or **non-material changes.**

Dynamic Models*

Dynamic ML models require special attention:
- Institutions must justify their use.
- Regularly **monitor** model evolution, performance, and impact on outputs.
- Identify and prevent **model drift** and unintended changes.
- Avoid **splitting** material changes into smaller unreported ones.

*A dynamic ML model is one that evolves over time, typically retraining on new data or adapting its parameters in response to changing conditions—introducing added complexity, monitoring challenges, and heightened supervisory expectations.

Data Governance, Maintenance & IT for ML-based Internal Models

IT & Data Principles

01
Data Standards & Quality

Institutions should set **data standards** aligned with industry best practices and academic research, especially for **Synthetic data and Unstructured data** (e.g. text, social media, videos) and perform exploratory data analysis to understand data formats, handle missing values and dentify potential biases.

ML-based internal models must be:

- Explicitly included in outsourcing policies.
- Subject to proper risk identification, assessment, and management.
- Align with EBA Outsourcing Guidelines to ensure proper oversight.

02
IT Infrastructure Expectations

IT systems must support:

- **complex data inputs,**
- **high computational needs** of ML models and,

should enable:

- Model **versioning,**
- Process **traceability,**
- **Auditability** & **replication** of model decisions.

Mathematical Methodology of ML-based Internal Models

Model Development

Justification of Structure:

- ML model structures and parameters must be based on sound statistical or optimality criteria.
- Explicitly address risk of overfitting, especially when reusing training data in stages (e.g. PD estimation).
- Ensure model complexity balances fit vs. generalisation.

Hyperparameters & Generalisation:

- Identify all hyperparameters.Tune using data independent from training (e.g. validation sets).
- Avoid feedback loops or bias introduced by repeated use of the same dataset.

Replicability:

- For stochastic models, record and store:
    - Parameters
    - Hyperparameters
    - Random seeds
    - Order of training data
- Ensure complete replication of results is possible.

Complexity Managemt

Avoid Unnecessary Complexity

Complexity must be justified relative to:

- Performance improvement,
- Organisational use
- Model governance effort

Input Feature Justification

Features must be:

- Economically justified,
- Relevant to the risk being modelled
- Input selection should involve business experts
- More features will more need for transparency and scrutiny.

Explainability

Interpretability of Predictions:

- ML outputs must be: Plausible, Intuitive & Aligned with economic logic

Explainability Tools:

- Show Global feature impacts & Local (prediction-level) explanations by using state-of-the-art explainability techniques.

Documentation:

- Tools used & Evaluation criteria
- Limitations & assumptions

Expectations for Explanations:

- Robust, Accurate, Actionable for decision-makers and overrides

Internal Validation of Machine Learning-based Internal Models

Extensive ML use requires stronger internal validation structures, with independent and well-resourced teams. Organisational arrangements should scale with model complexity. Below are the set Validation Requirements for ML based Internal Models:

Internal Validation Requirements

Model Challenge & Robustness

- Validate the justification for ML **use, stability of outputs, hyperparameter** choices, and **training** randomness.
- Detect **risks** like **overfitting** and ensure proper testing with **out-of-sample** and **out-of-time** data.

01

Explainability Checks

Use explainability tools to:

- Identify when models **fail** to perform
- Understand why **performance deteriorates**
- Explain deviations in **predicted vs. realised** risk

02

Validation & Tool Review Frequency

- Perform validation **more frequently** for **complex** ML models to **detect deficiencies early.**
- Conduct **annual** reviews of the **explainability techniques** themselves for adequacy and appropriateness.

03

Internal Audit of Machine Learning-based Internal Models

Internal audit must adapt resources, tools, and methods to reflect the **unique characteristics** and **complexity** of ML techniques.
Internal audit must **identify** any additional **ML-specific risks** not already covered in existing credit risk audit frameworks. <u>These should be incorporated into the general risk assessment</u>.

Appropriate Audit Techniques

Institutions must ensure **audit methods** used are suitable and effective for assessing ML models' **complexity** and **behaviour.**

01

Risk-Based Audit Planning

In case of an **increase in Model Risk:**

- Audit **intensity** and **frequency** should **increase.**
- Deep dives in the annual audit plan.
- Schedule **ad-hoc** audits.

02

Use of ML-based Internal Models

In order to use ML-based Internal Models for Decision Making, as a part of Internal Policy Requirements, **scope, purpose, applications** and **functionalities** as well as **limitations** of such models should be defined in **Credit Approvals, Internal Capital Allocation, Risk Management** and **Governance Functions.**

Strategic Alignement & Partial Use or Exclusions

- Use of ML must align with **broader business strategy.**

If certain ML outputs are **not** used in internal processes (e.g. risk management or approval):

- Provide clear justification
- Explain discrepancies with model output

Risk Awarness

- Be aware of additional risks from adapting ML models for broader use (e.g. bias from adding variables like social media data).
- Adjust update frequency or model configuration accordingly.

Internal Capital Models

If ML is used in **ICAAP**, ensure outputs from:

- **Stress tests, Scenario analysis**

Are:

- Explainable, Plausible, Not overly optimistic

IRB: Human Judgement in Model Use

Override Policy Design

Excessive or unjustified overrides may indicate:

- Model design weaknesses
- Misalignment with business use

Monitoring of the Overrides

Assess impact of overrides on model performance:

- Compute marginal contribution of human judgement
- Distinguish input vs. output overrides

Documentation

Store override records in full:

- Data not captured by model
- Relevance to creditworthiness
- Justification for override

*Especially important for high-dimensional ML models.

Personal Competence

Staff responsible for overrides must:

- Understand pre-override risk drivers
- Use appropriate explainability tools
- Be able to interpret inputs and model logic.

Inputs Overrides

- Personnel should have access to full set of input variables used in model estimation
- ECB expects input overrides to be treated as exceptionally as output overrides.

How can Grant Thornton support you?

We provide end-to-end development and advisory services to help institutions align with evolving supervisory expectations, including the ECB's latest guidance on machine learning. Our support spans governance integration, materiality assessment, data and methodology development, model explainability, scenario analysis and stress testing, override monitoring, model integration, risk plan implementation, and internal control assurance.

Gap Assessment & Readiness Check

Conduct tailored reviews of existing ML models and documentation to identify gaps against the new ECB expectations—especially around explainability, scope definition, and override policies.

Model Simplification & Use Case Alignment

Support clients in refining their ML model landscape—helping determine which portfolios justify ML complexity and where simpler or traditional models may suffice, in line with ECB's guidance on model efficiency and use.

Policy & Governance Enhancement

Help define or update internal policies to explicitly cover ML model use, including purpose, functionalities, limitations, and alignment with internal capital, credit approval, and risk management frameworks

Stress Testing & Scenario Analysis Validation

Validate and enhance ML-based models used in ICAAP by ensuring outputs under stress and scenario testing are plausible, explainable, and not overly optimistic.

Explainability & Transparency Support

Implement or improve explainability tools (e.g., SHAP, LIME) and techniques to meet ECB's expectations for model interpretability—particularly for override justification and senior management understanding.

Override Monitoring Frameworks

Design monitoring solutions to track input and output overrides, quantify the marginal impact of human judgement, and ensure proper documentation and justification.

Our Recent Publications on ML

Machine learning is not a new topic in the regulatory space, and our team has previously published guidance on its integration within internal risk models. We have explored the development, explainability, and alignment of ML models with evolving regulatory expectations, as well as examined practical use cases of ML-based models across the financial sector. Below is a selection of our most recent publications.

The study conducted by Grant Thornton Cyprus Quantitative Risk team in collaboration with SEKASA Technologies, investigates Logistic Regression, as a benchmark, against various Machine Learning models' performance in mortgage default prediction. Key points investigated are:

- Predictive accuracy,
- Balancing complexity and explainability,
- Alignment with EBA Recommendations (EBA's follow-up report on Machine Learning for Internal Ratings-Based models published on August 2023)

https://www.grantthornton.com.cy/insights/quantitative-risk-articles/Credit-Default-Forecasting-with-Machine-Learning/

This paper will provide an overview of the current and future uses of Machine Learning in the world of Internal Rating Based (IRB) Models which allow banks to model their own inputs for calculating Risk Weighted Assets.

https://www.grantthornton.ie/insights/publications/machine-learning-in-irb/

Model risk management is a regulatory priority and has a significant impact on financial decision making and strategy. Vivian Lagan and Miles Davis explore how emerging technology, including generative AI, can support the model inventory – the foundation of any good model risk management approach.

https://www.grantthornton.co.uk/insights/leveraging-generative-ai-in-model-risk-management/

Machine Learning is, as its name defines it, a machine who learns. The first reference of Machine Learning dates back to 1959 and attributed to artificial intelligence and computer gaming pioneer; Arthur Lee Samuel. 63 years later and "self-teaching computers" (another term for Machine Learning) are revolutionising every industry, from healthcare to finance, marketing, and agriculture. Monica Odysseos in this paper takes us through a fundamentals of Machine Learning.

https://www.grantthornton.com.cy/insights/ai-and-data-lab/ml-what-is-it-really/

Contact

Our team specialises in supporting institutions with the design, deployment, and oversight of internal models in line with evolving supervisory expectations. From governance integration and data methodology to performance monitoring, model explainability, and control frameworks, our services cover the full model lifecycle—including traditional and machine learning-based approaches.

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