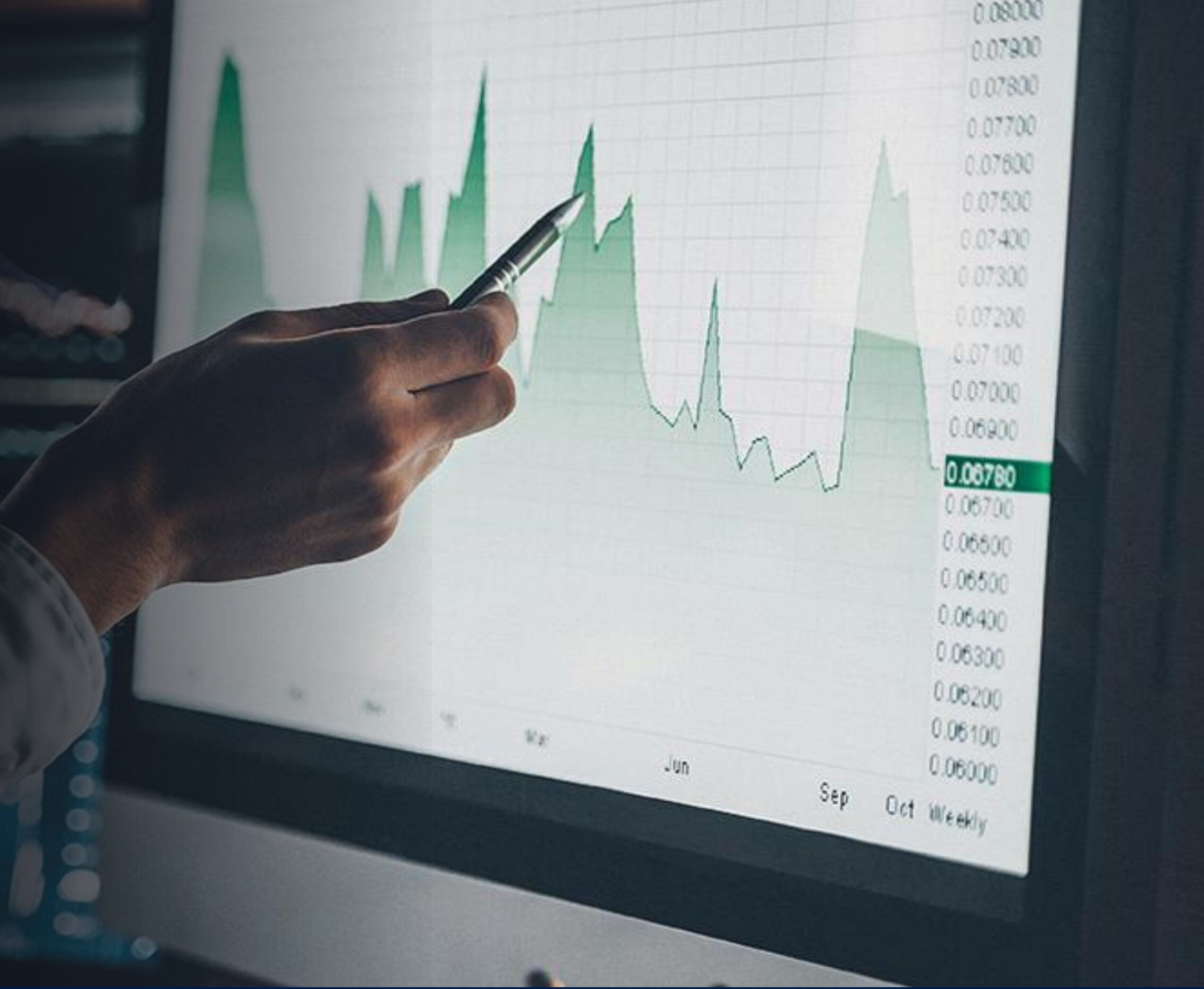
Management Solutions
Making things happen

Machine Learning for IRB models

Executive summary



Executive summary

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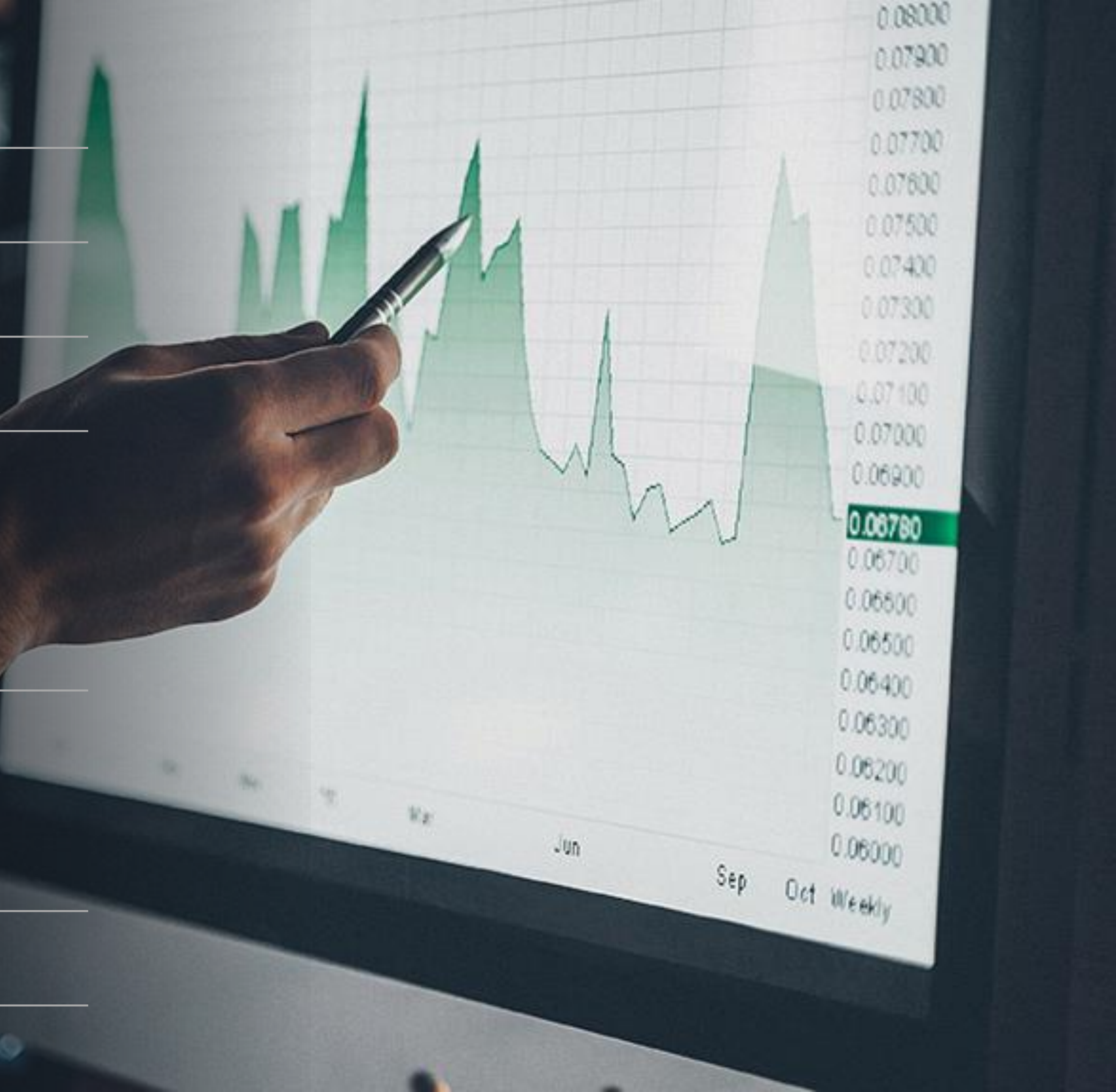

1 Executive summary

The follow-up report aims to summarize the main conclusions from the consultation on ML used in Internal Ratings-Based (IRB) models and discusses the interaction between prudential requirements, GDPR, and the AI Act

Introduction

ML models offer **improved predictive power** in credit risk assessment, they also pose challenges due to their complexity and limited transparency. Financial institutions are using ML techniques primarily for **PD** estimation during risk differentiation, but to a lesser extent for model validation and collateral valuation in IRB models

Topics

The key challenges identified in using ML techniques are related to **explaining results**, ensuring **traceability**, and addressing **statistical issues** like overfitting. Acquiring a sufficient level of skilled labor is also a concern. The report emphasizes the importance of alignment with prudential requirements on material model changes when using ML techniques and provides clarifications on this point.

Additionally, the report addresses concerns outside the scope of **prudential considerations**, particularly focusing on the impact of **GDPR** and the **AI Act** on IRB models utilizing ML techniques. The aim is to ensure compliance with these legal frameworks to protect consumer data and maintain ethical considerations.

2 Introduction
Background

Financial institutions are increasingly using ML for fraud detection, Money Laundering (AML), Terrorist Financing (CFT), and real-time monitoring, but less so for credit risk due to regulatory concerns. The EBA aims to address this through its recommendations in the "Machine Learning for IRB Models" document, fostering compliance and harmonized capital requirements

Current ML Landscape in Banking

Increasing Availability and Analysis of Financial Data:

i. Availability of financial markets data has seen exponential growth.
ii. Improved computing capabilities and utilization of Big Data and ML techniques have bolstered the capacity for data analysis.
iii. Enables more in-depth insights into financial trends and behaviors.

ML Techniques in Banking:

i. Detecting fraudulent activities to enhance security.
ii. Combating AML and CFT.
iii. Profiling and clustering client behaviors and transactions for better risk management.
iv. Real-time monitoring of payment activities for transaction security.

Challenges in Credit Risk and ML Techniques:

i. ML techniques are widely embraced in banking, but their use in credit risk assessment for determining capital requirements is limited.
ii. Concerns arise due to doubts about ML techniques' adherence to regulatory standards for IRB models.
iii. Majority of financial institutions rely on regression analysis in internal models for credit risk capital assessments.

EBA's Perspective and Insights

EBA's Publication on Machine Learning for IRB Models:

i. The EBA published a document on November 11, 2021.
ii. Aimed to engage industry and supervisory community in assessing ML's potential within IRB models.
iii. Explored challenges and opportunities of employing advanced ML techniques for regulatory capital calculations in credit risk.
iv. Addressed concerns and sought to build a common understanding of ML's role in IRB models.

Principle-Based Recommendations for ML Techniques:

i. Ensure consistent understanding of prudential requirements.
ii. Demonstrate alignment of novel ML models with regulatory demands.
iii. Maintain harmonized capital requirement standards across European financial institutions.
iv. These recommendations serve as a foundation for developing and integrating ML models.

Selective use of ML for IRB models

ML Techniques in PD models

Institutions predominantly focus on applying ML techniques to PD model development. The Discussion Paper (DP) examined the potential benefits and challenges of using ML techniques in different IRB modeling stages, with consultation revealing their partial application. ML techniques are found to be utilized selectively in specific steps of the IRB Approach, detailed further in subsequent sections

1. Core Modelling Steps

The usage of ML techniques in the core steps of IRB modelling includes their application in PD model development, validation, and risk differentiation. On the other hand, other parameters like LGD, EAD, ELBE, and CCF models see comparatively less use of ML techniques.

Their application improves model performance, especially in cases of historical poor risk differentiation.

- ML techniques are employed to validate PD segmentation in the expected credit loss (ECL) model.
- Risk differentiation is the primary area where ML techniques are used.
- Random Forests and Gradient Boosting Trees are employed for selecting risk drivers.
- Clustering techniques assist in the estimation of PD and LGD score ranges.
- ML techniques enhance discriminatory power and identifies relevant risk drivers and are particularly beneficial for input data selection, transformation, and ranking exposures.

Complex ML techniques are deemed less essential for risk quantification due to data availability challenges.

2. Validation via Model Challengers

During the model validation phase, ML techniques are particularly helpful in improving challenger models and addressing challenges.

The DP highlights the respondent's desire to integrate ML techniques into model validation. **Improving the performance of challenger models is a primary focus of ML technique implementation.**

- ML techniques enhance challenger models through robustness analysis and variable challenge.
- Benchmarking purposes are served by ML techniques during initial and ongoing validation.
- Challenges identified include interpreting validation outcomes and resolving findings.
- Operational requirements increase, including considerations for data quality, storage, and maintenance.
- Technical expertise and specific skills are highlighted for conducting validation when ML techniques are employed in internal credit models.

3. Collateral Valuation

In collateral valuation, the usage of ML techniques is useful when performing real estate value estimation and monitoring.

Supervisors anticipate more frequent ML technique adoption for collateral valuation than initially indicated.

The DP shows that a few respondents mention the use of ML techniques for collateral valuation.

- ML techniques primarily aid in estimating and monitoring real estate values.
- Ongoing projects involving ML techniques for collateral valuation are in the implementation phase.
- External providers play a role in the development and implementation of ML systems for real estate value estimation.

4 Challenges in Developing and Validating IRB Models Using ML Techniques

Developing and validating IRB models using ML techniques pose specific challenges that can be summarized into three categories: statistical issues, human skill-related issues, and interpretability issues

Statistical issues	**Overfitting Challenge:** Financial institutions must take this issue into consideration and compare model performance within development data to out-of-sample and out-of-time data. **Data Representativeness and Quality:** Careful evaluation of input data quality is essential to avoid using ML scores as explanatory variables for other models, leading to feedback loops.
Human Skill-Related issues	ML techniques introduce complexity, leading to increased time, computational, IT, and human resource requirements. Assessing model assumptions and economic meaning of risk drivers becomes more difficult with complex ML models (Article 174(e) of the CRR). Compliance with the requirement for human judgment in model development and application becomes challenging. Expert judgment may be required for setting hyperparameters in specific ML techniques. Validation functions must analyze and challenge complex model designs, assumptions, and methodologies (Article 185 CRR), requiring appropriate training.
Interpretability of results	Complying with Article 171(1)(a-b) of the CRR, which calls for consistent and appropriate assignment criteria documented for human judgment, presents a challenge with ML models being them harder to interpret than analytical models.

Categorization of Model Changes and Model Stability:

The **categorization** of model changes and ensuring **model stability** are important considerations in the development of ML models for IRB.

The EBA emphasizes that any **updates** to the **rating system** used for calculating own funds requirements must be **assessed** under the prudential model change framework. Specifically, changes in the algorithm used to assign obligors to grades or pools may require approval from competent authorities.

On the other hand, as long as the rating system for calculating own funds requirements remains unchanged, the model change framework **does not restrict** the use of **self-training** and **self-development** model challengers. This means incorporating additional data for yearly reviews or estimate updates is allowed without constraints.

4 Statistical Issues:
Overfitting and strategies to overcome it

Overfitting Challenge:

- Industry confirms overfitting as a key challenge in developing ML models.
- ML techniques pose greater challenges for low-default portfolios due to larger dataset requirements for proper model training, validation, and testing.

Complexity and Adaptability:

- Complexity of ML models hampers the use of standardized model development and validation processes.
- ML model effectiveness relies on case-by-case choice of the best methodology, hindering standardized approaches.

Strategies to Overcome Overfitting:

- Use methods for risk driver selection (feature selection and normalization).
- Ensuring model stability and validation with out-of-time and out-of-sample tests (cross-validation).
- Utilization of additional dedicated tools for ML model hyperparameters.
- Focus on model consistency with economic theory to improve explainability and increase generalization capacity.

Human Skills-related issues:
Complexity challenges in ML model development

Additional Know-How Skills Required:

- Theoretical and statistical knowledge of ML techniques
- Evaluation of model stability and overfitting.
- Practical knowledge of ML: hyperparameter tuning, alternative stability testing methods, and statistical & programming skills using standard ML libraries.

Challenges in Enabling Human Judgment:

- Expertise with ML methods is crucial to ensure adequate and well-understood model development tools.
- Human judgment needed for feature selection and final model assessment.
- Treating large data requires advanced IT expertise and controls.

Balancing ML Expertise and Human Intervention:

- Financial institutions strive to have ML expertise in-house through hiring and training.
- Human intervention crucial during model development and application to maintain business and economic perspective.
- Limited outsourcing to third-party support during internal model development.

Model Validation Challenges:

- Complexity of ML techniques increases time, computational, IT, and human resources needed for validation.
- More tests and methodologies required for stability checks and challenger models.
- Frequent model monitoring and validation due to rapidly changing models.

4 Interpretability issues:
Interpretability of ML models: challenges and potential solutions

Challenge: Balancing Model Performance and Interpretability	• Higher complexity improves model performance but reduces explainability and understanding. Finding the right balance between performance and interpretability is a key challenge for banks. • This requires hiring experts with good knowledge of ML models and increasing interaction among stakeholders. • Proper documentation of the model is crucial.
Measures to Ensure Interpretability:	• Financial institutions ensure explainability at the global and local levels of ML models. • Common interpretability tools used are Shapley values, graphical tools, enhanced reporting/documentation of model methodology, and sensitivity analysis.
Traceability and Root Cause Identification:	• Implementing methodological choices in model design facilitates traceability. • Sensitivity analysis and interpretability tools help mitigate explainability and traceability issues.
Communication and Acceptance:	• ML model communication and acceptance within financial institutions is crucial. • Training stakeholders and providing targeted documentation, including interpretability tools, aids in explaining model results to less statistically knowledgeable stakeholders.

Complying to (Non-CRR) Regulatory Frameworks: GDPR and ML Techniques in IRB models

Interaction with the General Data Protection Regulation (GDPR)

Decision on using ML techniques in credit risk models should include ethical, legal, consumer, and data protection. These aspects are mainly governed by two frameworks: GDPR and AI Act

Limited Feedback	Financial institutions and supervisors have provided limited feedback on the current interaction between the General Data Protection Regulation (GDPR) and IRB models using ML techniques.
Proposed CCD Directive	In June 2021, the European Commission proposed a new directive on consumer credit (CCD) to replace Directive 2008/48/EC and adapt rules to digitalization trends. The CCD references GDPR and prohibits the use of specific personal data for creditworthiness assessment, even if received from databases in other EU Member States. It also restricts the use of data collected from social networks and emphasizes GDPR's minimization principle for assessing consumers' creditworthiness.
Challenges with ML Techniques	ML techniques require a significant amount of data, raising concerns about identifying data subject to GDPR restrictions. Compliance with GDPR requirements may become more difficult once ML techniques are used, necessitating additional review by financial institutions and supervisors.
Unstructured Data Complexity	Financial institutions using unstructured data to build ML models may face challenges in detecting GDPR-defined personal data. Ensuring GDPR compliance in such cases may require extra time and expertise during validation.
Limited Use of Unstructured Data	Currently, only a few financial institutions utilize unstructured data due to business needs and technical challenges. However, the future use of unstructured data is not ruled out, and ensuring compliance would involve implementing adequate control functions.
GDPR Data Retention	The majority of financial institutions do not see GDPR data retention as a problem, particularly concerning ML techniques. They believe that personal data collected for capital requirement purposes under the Capital Requirements Regulation (CRR) justifies data storage

5 Complying to (Non-CRR) Regulatory Frameworks: AI Act

Interaction with the AI Act

The European Commission's AI Act proposal, published in April 2021, seeks to establish a secure and innovation-driven AI environment while enhancing the EU's global competitiveness. Following responses from the European Council and European Parliament, a trilogue will follow, aiming to finalize the AI Act by the end of 2023

Clarification on the scope of application of the AI Act

- Recital 37 of the AI Act proposal explains that AI systems for creditworthiness assessment are high-risk due to potential discrimination and perpetuation of biases. Creditworthiness evaluation and credit scoring are high-risk use cases due to potential adverse impacts on individuals' access to financial resources.
- The AI Act's scope targets systems that may jeopardize access to financial resources, reflected in various legal framework parts and definitions.
- Article 83(2) of the AI Act applies to existing AI systems with substantial changes after the date of application.
- The EBA suggests limiting the AI Act's scope to credit scoring at loan origination and clarifying its non-direct application to areas like IRB models for capital requirements. Indirect effects on IRB models may occur through prudential use-test requirements.

Additional requirements from the AI Act

Mapping of the AI Act requirements with the prudential ones

- To avoid legal uncertainty, it's crucial that the AI Act aligns with existing regulatory frameworks and doesn't conflict with IRB models affected by use-test. Prudential risks related to IRB models are addressed through CRR/CRD, which includes governance, risk management rules, and further details in level 2 legislation.
- Comparisons between high-risk AI system requirements in the AI Act and IRB model requirements were made by the EBA, revealing similarities. Most AI Act requirements, particularly those for loan origination, align with financial sector laws or CRR/CRD standards applicable to IRB models for capital requirements calculation
    a. Administrative AI Act obligations for high-risk AI system providers, such as EU declaration and reporting, aren't pertinent to IRB models.
    b. Requirements for CWA/credit scoring pertain to procedural obligations, like documentation and in-house instruction, not affecting model performance. Adjustments can comply without altering IRB model operation.
    c. Requirements for CWA/credit scoring may impact model use and performance, involving bias testing and human oversight for rights protection

Clarification on the interaction between the intended use of the model and the risk to fundamental rights

- The AI Act's impact on creditworthiness assessment models for loan granting is uncertain due to interpretation.
- EBA supports AI Act's intentions but notes varied interpretations of undue differentiation and risks of legal uncertainty.
- The importance of accurate creditworthiness assessment for financial stability and consumer protection is highlighted.
- EBA suggests clarifying AI Act requirements, ensuring AI systems align with their intended purpose and comply with law.
- CRR/CRD framework's plausibility requirement supports IRB models' justification for differentiation in credit scoring based on purpose and risk analysis.

6 Why MS?

Management Solutions has differential expertise in IRB related projects and with extensive working with supervisors and in main European financial institutions in the scope of IRB models and internal validation frameworks

Supervisory experience: selected as the **reference consultant**, being **best valued service provider by different regulators in the area of IRB models**. **Deep knowledge of supervisory expectations** provided by practical experience.

Deep knowledge of regulation and its application in top institutions and vast experience in the European financial industry in the area of IRB providing us with a global perspective of our clients' needs and allowing us to provide differential QA capabilities

Vast experience in the area of internal validation in main G-SIBs y D-SIBs: framework and guidelines, model validation, automatization and development and implementation of related tools

Best-in-class experts and R&D team with distinctive capabilities in Capital IRB, international perspective and knowledge of European financial institutions, providing differential benchmarking capacities

Top class team with multidisciplinary profiles and skills (regulatory knowledge, modelling, IV, …), proven delivery capacity and track record of projects developed with outstanding results.

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International
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Multiscope
Team

Best practice
know-how

Proven
Experience

Maximum
Commitment

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