Model Risk Management in 2024

Survey Report April 2025

Contents

Foreword

Over the past year, significant regulatory changes have reshaped the Model Risk Managment (MRM) landscape. The European Central Bank (ECB) has expanded its guidelines on internal model validation and governance, with an increased emphasis on Artificial Intelligence (AI) and machine learning models. The Prudential Regulation Authority (PRA) in the UK has reinforced its stance with the release of SS1/23, outlining new expectations for managing model risk in a digital-first era. Meanwhile, in the United States, the Federal Reserve and the Office of the Comptroller of the Currency are tightening oversight on AI-driven financial models, reflecting growing concerns about explainability and accountability.

In this technology-driven era, financial institutions must keep pace with rapid digital transformations while aligning with shifting consumer behaviours and regulatory mandates. AI and machine learning have advanced, becoming widely accessible across financial services. More than the others available, generative AI techniques have not only progressed in quality of outputs and overall performance, but have also become much more accessible and widely used in practice. These innovations enhance efficiency and predictive capabilities but also introduce new risks, such as algorithmic bias, transparency issues, and governance challenges. To mitigate these risks, regulatory bodies worldwide have started establishing clear expectations for AI-driven models, requiring institutions to incorporate robust validation, explainability, and monitoring mechanisms.

This year, we are focusing on:

- How financial institutions define models and what type of models they consider in their MRM framework, including vendor models.
- Use of AI and the importance of enhancement of existing MRM practices to address risks associated with AI-driven models.

At PwC, we believe that you will find valuable insights in this report, which could help you enhance the current MRM practise in your organization. We would like to thank all the respondents for their valuable time and answers.

Rostislav Černý
Partner

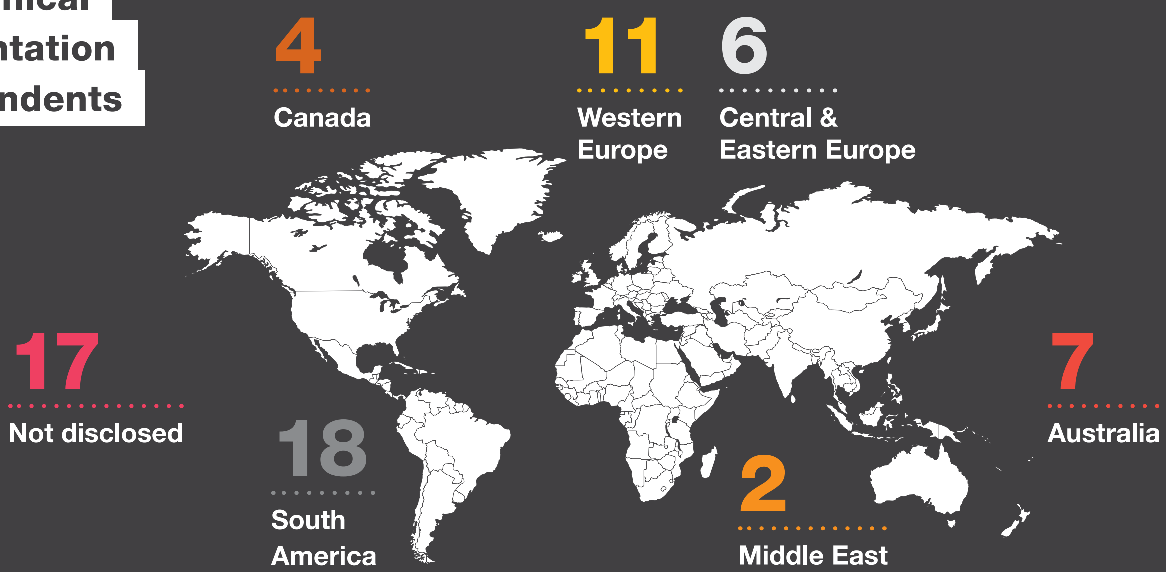
About This Survey

Between September and December 2024, PwC conducted an in-depth survey centred around Model Risk Management. The respondents consisted primarily of banks and insurance companies contacted via connections from the PwC internal network. The answers were anonymous and optional, however, not all respondents answered all the questions. In our analysis, we only considered respondents that completed the survey. The section regarding personal data was facultative. We used Qualtrics as the data gathering platform.

We have collected complete answers from 65 respondents from various financial institutions. These institutions are geographically distributed, with a significant presence in South America 18 (**28%**), followed by Western Europe 11 (**17%**), Australia 7 (**11%**), Central & Eastern Europe 6 (**9%**), Canada 4 (**6%**) and Middle East 2 (**3%**). 17 (**26%**) respondents chose not to disclose their geographical location.

These organizations were stratified based on various attributes, such as the number of risk-relevant models, including institutions with few (0-20) models to those with many (501+) models. The survey brings a diversity of collected answers and provides a comprehensive view on MRM areas that were the focus of the analysis.

Geographical representation of respondents



Executive Summary

The survey uncovered the following key findings:

- **Strong commitment:**
  The survey reveals a strong commitment to MRM, with more than 50% of financial institutions having teams of four or more professionals dedicated to MRM activities.

- **Defining a model:**
  A significant portion of institutions prefer to follow regulatory guidelines rather than developing their own definitions. This trend underscores the importance of regulations in shaping model definitions across different regions.

- **Current technology landscape:**
  95% of surveyed institutions have some form of inventory. 82% of respondents have employed more advanced solutions, either internally developed or provided by dedicated vendors.

- **Consideration of vendor models in the MRM framework:**
  According to our survey, 80% of respondents incorporate models provided or serviced by external vendors into their model inventories.

- **Artificial Intelligence is on the rise:**
  The survey indicates that 70% of financial institutions have already integrated AI-driven models into their operations. Additionally, among the institutions not currently utilizing AI, 50% have expressed intentions to adopt these models in the near future, underscoring the growing trend and recognition of AI's potential in the financial sector.

- **Risk-tiering as a critical component:**
  The survey highlights the importance of risk tiering in MRM, with 82% of respondents having integrated risk tiering into their MRM framework. The decision tree method emerges as the dominant approach for assessing model risk tiers, employed by over two-thirds of the institutions.

Growing Significance of Model Risk Management

Reaction to the use of more sophisticated models

The importance of Model Risk Management is increasing. Financial institutions are now using advanced modelling techniques on a daily basis, especially those related to artificial intelligence (AI) and machine learning (ML). These advanced models are critical in operations such as credit risk assessment and trading strategies. However, their complexity presents new challenges in managing risks, prompting regulatory bodies to issue guidelines to ensure proper governance. The PRA in the UK, in its Supervisory Statement 1/23 effective from May 2024, stressed the need for a strategic MRM approach. This includes principles for model identification, governance, development, validation, and risk mitigation, aiming to ensure robust risk management as AI and ML models become more integrated.

The Reserve Bank of India (RBI) has acknowledged the growing significance of MRM in the context of AI and ML models. Its 2024 draft guidelines highlight the necessity for regulated entities to establish comprehensive MRM frameworks. These guidelines mandate validation of all models, particularly those using AI and ML. Additionally, the regulator requires annual reviews and independent validation processes, underscoring the importance of effective model risk management in ensuring financial stability.

The Monetary Authority of Singapore (MAS) has recently addressed similar concerns in an information paper on AI Model Risk Management. It emphasizes the importance of strong governance frameworks as AI becomes more central to financial operations. Key issues include operational risks, data governance, model explainability and AI model biases. The Monetary Authority advocates for a balanced approach that supports innovation while mitigating risks. This includes integrating AI governance into existing risk management frameworks, updating control standards, and ensuring transparent and ethical AI use across organizations.

Robust MRM frameworks are essential as more and more sophisticated models become an integral part of financial operations. Regulatory bodies across the globe have issued guidelines emphasizing the need for comprehensive governance, validation, and risk mitigation strategies. These measures aim to balance innovation with risk management, ensuring financial stability and ethical use.

Selected regulation over time and geographies

> While existing control functions continue to play key roles in AI risk management, most banks have updated governance structures, roles and responsibilities, as well as policies and processes to address AI risks and keep pace with AI developments.
>
> **(MAS AI MRM, December 2024, Principle 4.)**

2011

FED (SR 11-7)
This guideline sets the standard and basis for the model risk management in the U.S. and across the globe.

2014

EBA (SREP)
Outlines the high level expectations regarding the model risk assessment in the EU.

2015

KNF (Recommendation W)
The list of 17 detailed recommendations on MRM for Polish banks.

2016

OSFI (Guideline e23)
Expectations around sound policies and practices for an enterprise-wide MRM framework in Canada.

2017

ECB (TRIM)
Structure of 3 lines of defense and expectations about a model risk framework.

Banco Central do Brasil (CMN 4557)
Risk management regulation including basic requirements for MRM.

2021

FSA of Japan
The regulator sets out "Principles for Model Risk Management" for systemically important financial institutions in Japan.

2022

CB of United Arab Emirates
"Model Management Standards" for all licenced banks in UAE.

2023

7th amendment to MaRisk
"Minimum Requirements for Risk Management" for German banks.

PRA (SS1/23)
Detailed regulatory expectations on model risk management in the UK.

2024

The Reserve Bank of India
Draft of new regulatory principles for managing model risks in credit.

MAS of Singapore
A thematic review of banks AI model risk management practise.

2024

Bank of Israel
New directive (2792-06) on the banking sector on Model Risk Management.

Model Landscape

The Number of Risk-Relevant Models in Financial Institutions

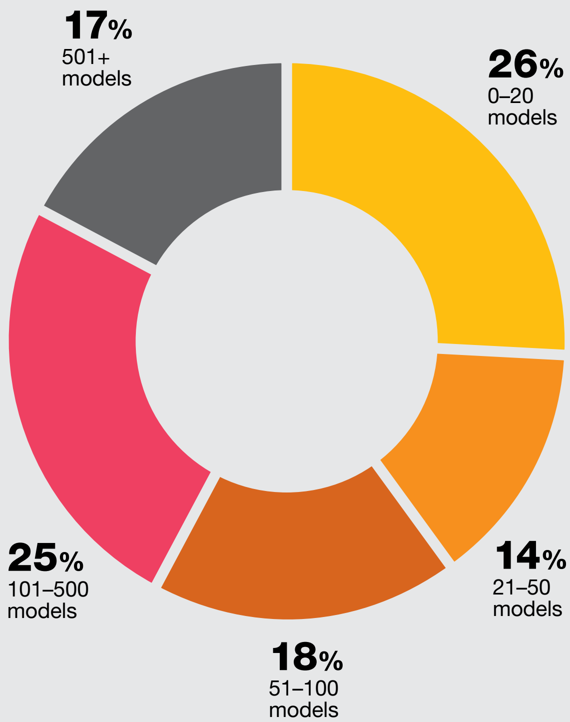
Representation of risk-relevant models in the organizations in the financial sector

The number of risk models in the financial sector is substantial and increasing over time. Financial institutions often have dozens or even hundreds of such models.

Our survey reveals a varied distribution of risk models across financial institutions. This year, **17%** of institutions reported having more than 500 models, while **25%** have between 101 and 500 models. Conversely, **26%** of the financial institutions in our survey manage 20 models or fewer. Additionally, **14%** maintain between 21 and 50 models, and **18%** manage between 51 and 100 models.

This diverse range highlights the complexity and scale of model management within the industry. As financial institutions increasingly rely on these models, the need for effective identification and evaluation becomes even more critical.

How many models do you have within the Model Risk Management framework in your organization?



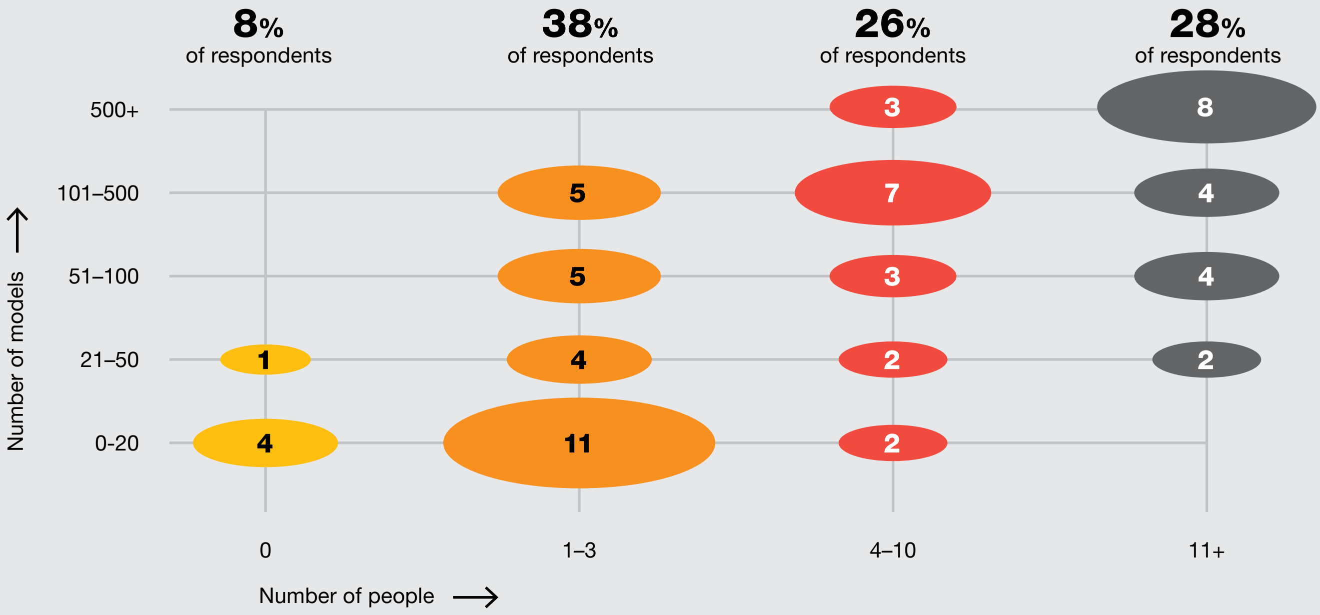
MRM Organization

A Look at Organizational Headcount, Leadership and External Resources

Having dedicated MRM teams is a recognized practice, playing a crucial role in overseeing models and preventing errors. The team is often composed of quantitative analysts, risk managers, and model validators, and is generally overseen by senior leadership, such as the Chief Risk Officer (CRO) or a Head of Risk Management. This structure ensures effective oversight and governance across the firm's model risk framework.

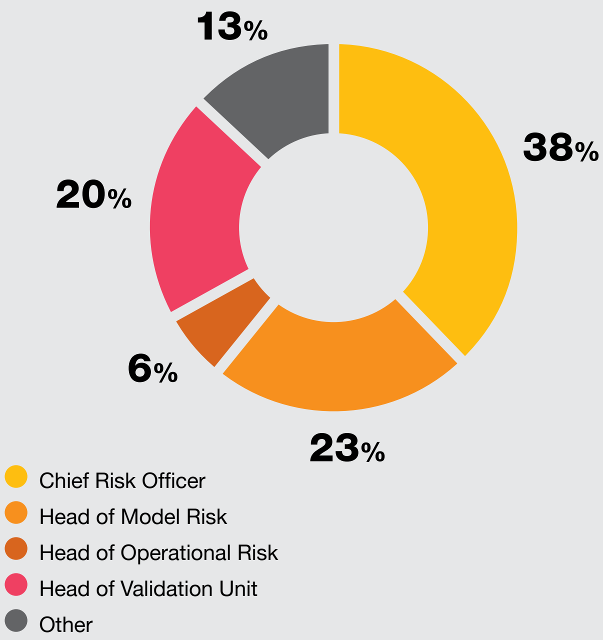
Our survey found that **26%** of financial institutions have strong MRM commitment with teams of four to ten professionals, and **28%** have shown even greater dedication with over eleven individuals engaged in MRM activities. **38%** of respondents have one to three individuals dedicated to MRM matters, while **8%** of respondents have no dedicated team.

How many people dedicated to Model Risk Management activities are there in your organization?



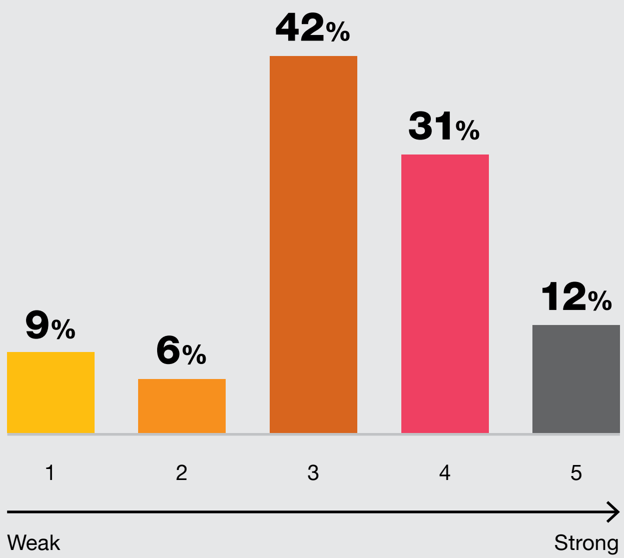
Who oversees Model Risk Management in your organization?

Firms designate senior management to ensure accountability for the Model Risk Management framework and its ongoing execution and maintenance. This role is typically associated with the Chief Risk Officer's reporting function within the institution. More than one-third (**38%**) of the surveyed financial institutions have a Chief Risk Officer directly leading their MRM team. The Head of Model Risk supervises the MRM team in **23%** of surveyed institutions, while the Head of Operational Risk oversees it in **6%** of cases. The Head of Validation Unit is responsible in **20%** of cases. Additionally, **13%** of respondents stated that their MRM team is led by other individual, such as MRM expert, the Head of Analytics, or the Head of the Non-Financial Risk Unit. 4 respondents did not specify the person responsible over MRM.



On a scale from 1 to 5 (5 being the strongest and most advanced), how strong and fit for the purpose do you consider the current Model Risk Management function in your organization?

Despite a strong commitment indicated by the number of individuals engaged in MRM activities, just **12%** of respondents view their MRM functionality as highly robust and advanced. Meanwhile, **31%** of institutions consider their MRM function strong and advanced but acknowledge certain deficiencies, primarily concerning AI modelling, validation and governance. Over **40%** of respondents evaluate their MRM as only halfway fitting, citing similar issues with AI model governance and a lack of adequate staffing or expertise in the MRM area. Additionally, **15%** of respondents report that their MRM function is not fit for purpose or is very weak, primarily due to limited resources and underdeveloped teams.



Use of external resources within MRM

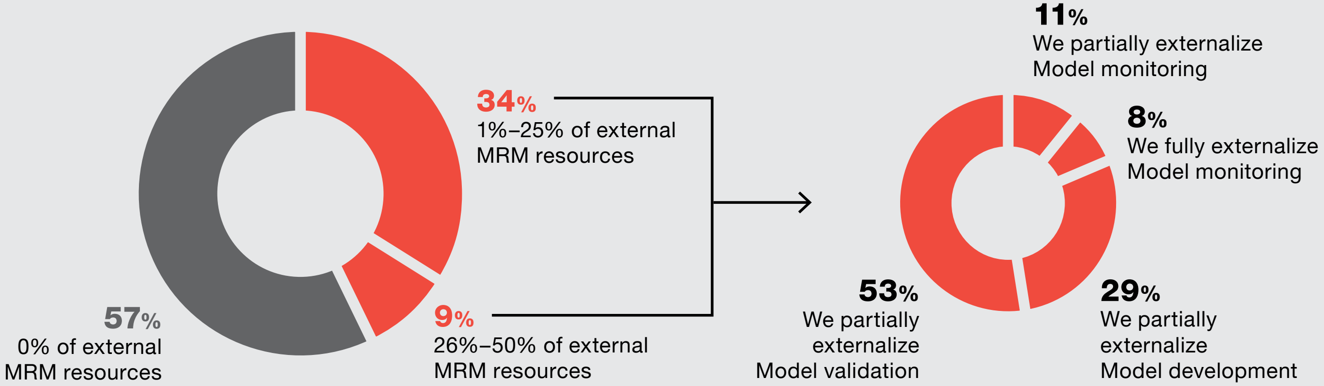
In the evolving landscape of financial risk management, the question of externalizing full-time equivalents (FTEs) in the MRM has gained significant attention. As organizations strive to optimize their MRM processes, many are considering the strategic benefits and potential challenges of leveraging external expertise. This survey provides insights into current industry practices and attitudes toward the outsourcing of MRM functions, emphasizing key trends and considerations for financial institutions. More than half of the respondents (**57%**) do not utilize any external resources.

43% of our 65 respondents use some form of externalization of MRM function. Among those who do engage external resources, **53%** of respondents partially outsource model validation, **29%** partially model development, and **11%** partially model monitoring. Full outsourcing is considered only in the case of model monitoring among **8%** respondents.

> **Use of externally developed models, third-party vendor products**
>
> In line with PRA SS2/21 – Outsourcing and third party risk management boards and senior management are ultimately responsible for the management of model risk, even when they enter into an outsourcing or third-party arrangement.
>
> **(PRA SS1/23, 2023, Principle 2.6)**

What percentage of total FTEs dedicated to Model Risk Management in your organization are external recouces?

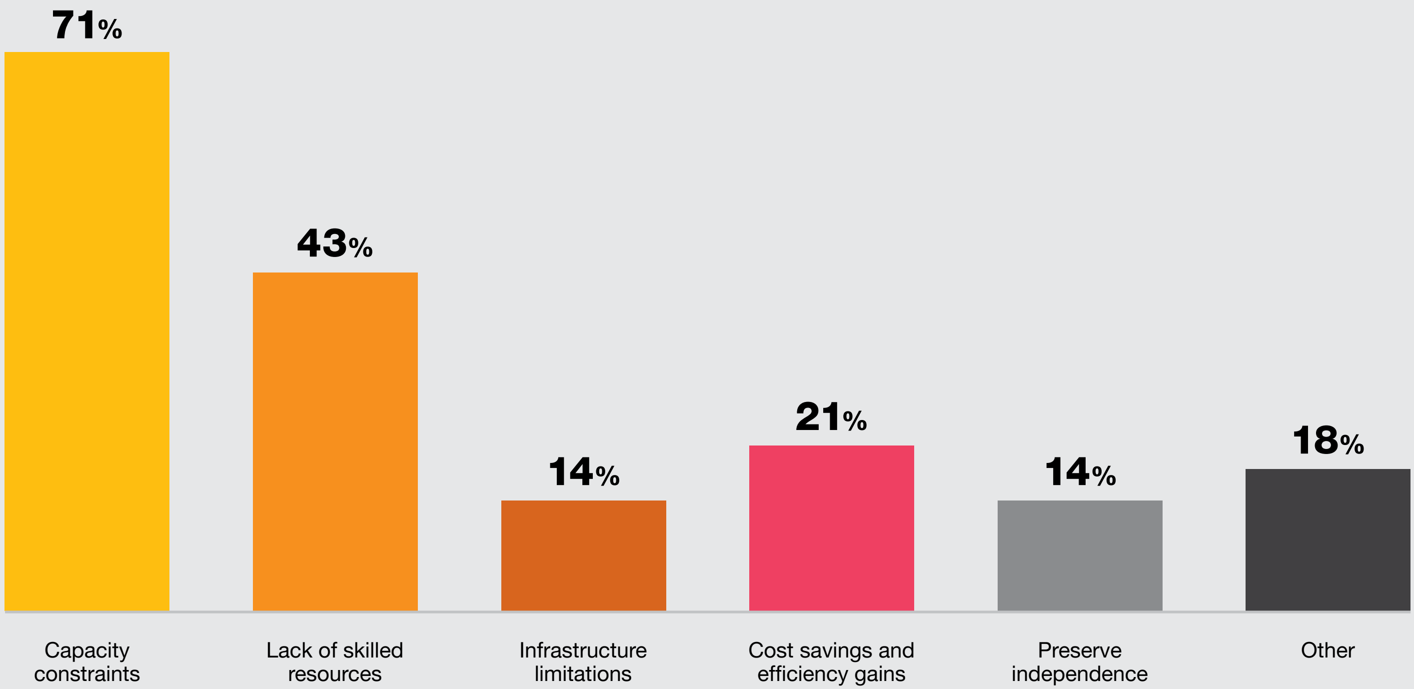
Which parts of the Model Risk Management framework in your organization are fully or partially externalized?



What are the key reasons for externalizing Model Risk Management activities in your organization?

Furthermore, those who engage external resources cite capacity constraints as the most significant factor, with **71%** of respondents indicating that the volume of work surpasses their current capabilities for handling MRM internally. Additionally, **43%** of respondents point to a lack of skilled resources, with either small or developing teams lacking the necessary expertise, driving them to seek external support. Infrastructure limitations also contribute, as **14%** of respondents indicate their institutions may not possess the required technological or operational infrastructure to manage MRM effectively.

A graph depicting the reasons for outsourcing MRM activities reveals that **21%** of respondents cite cost savings and operational efficiency as key motivations, highlighting the benefits of specialized expertise and technologies from external providers. Additionally, **14%** of respondents emphasize the importance of preserving independence and objectivity in risk assessments, valuing the unbiased evaluations that external providers offer for robust risk management. Furthermore, **18%** of respondents report other reasons, such as that externalizing MRM offers a better industry perspective, enabling organizations to benchmark their practices against market standards. These factors collectively illustrate the diverse motivations behind institutions opting to externalize their MRM functions, driven by both internal constraints and strategic considerations.



Model Identification Process

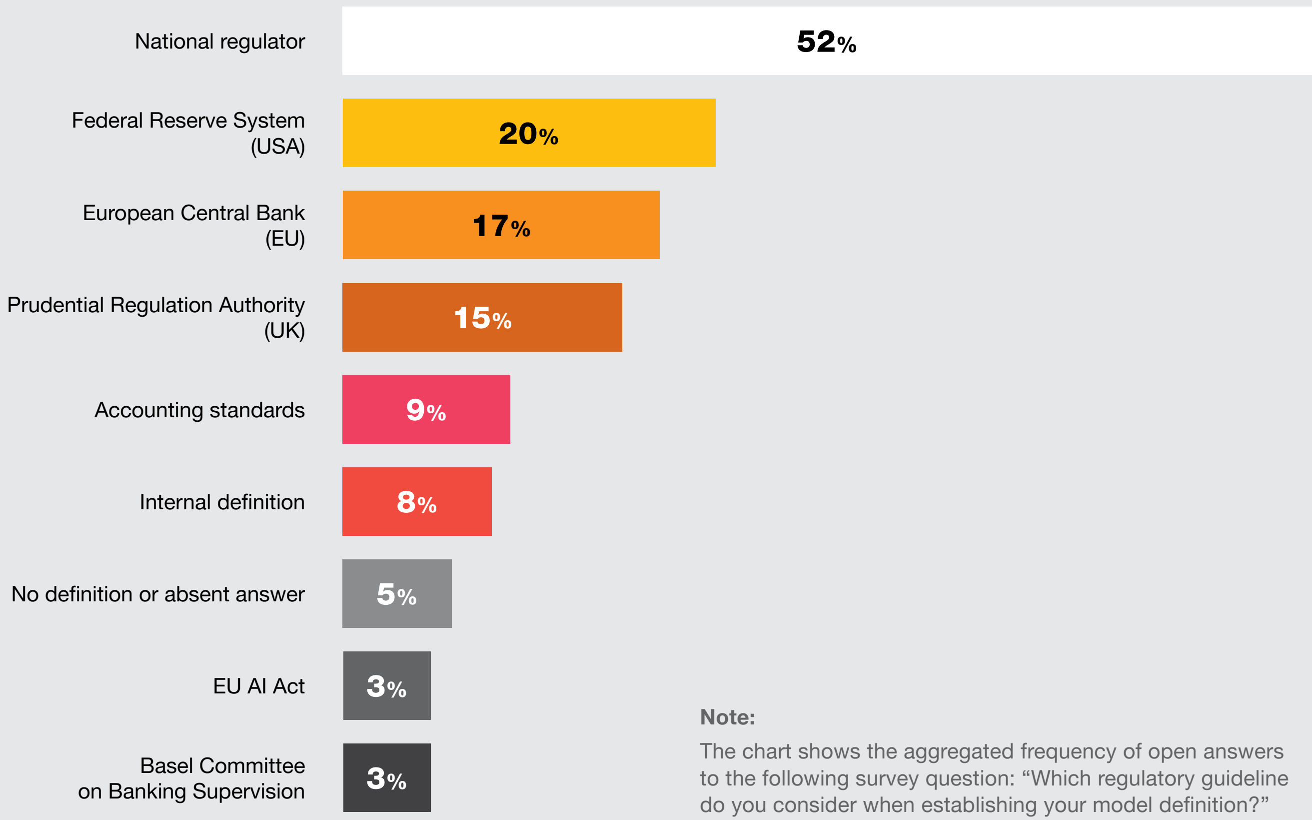
Model definition

Model risk management begins with the model identification process. This process requires a firm-wide model definition. A model is broadly defined as a method that employs theoretical and expert assumptions, combined with complex algorithms or techniques, to process inputs into meaningful outputs. It has 3 essential components:

- Input component: It may include data, assumptions, other models (upstream models) or expert judgements.
- Processing component: It may be associated with a formula, method, theory or algorithm that translates the inputs into estimates.
- Output component: It may express the quantitative or qualitative estimates in a format that is useful and meaningful to business or control functions.

The definition of a model differs from institution to institution. From 65 respondents, only **8%** of financial institutions reported that they are following an internal model definition, which often includes local or internationally recognized regulations. Additionally, **52%** of respondents consider local national regulations to some extent when defining a model. Examples of such regulations include MaRisk in Germany, OSFI-23 in Canada, and CMN 4557 in Brazil. Furthermore, guidelines from larger regulatory bodies, such as SR 11-7 from the Federal Reserve System in the USA and SS1/23 from the Prudential Regulation Authority in the UK, are regarded as best market practices and are considered when defining a model.

Source of guidelines for establishing model definition



Note:
The chart shows the aggregated frequency of open answers to the following survey question: “Which regulatory guideline do you consider when establishing your model definition?”

The evidence highlights a key point: a significant portion of institutions prefer to follow regulatory guidelines rather than developing their own. This trend underscores the importance of regulations in shaping model definitions across different regions. Institutions that follow internal definitions often do so to align with specific local or international standards, ensuring compliance and consistency in their practices.

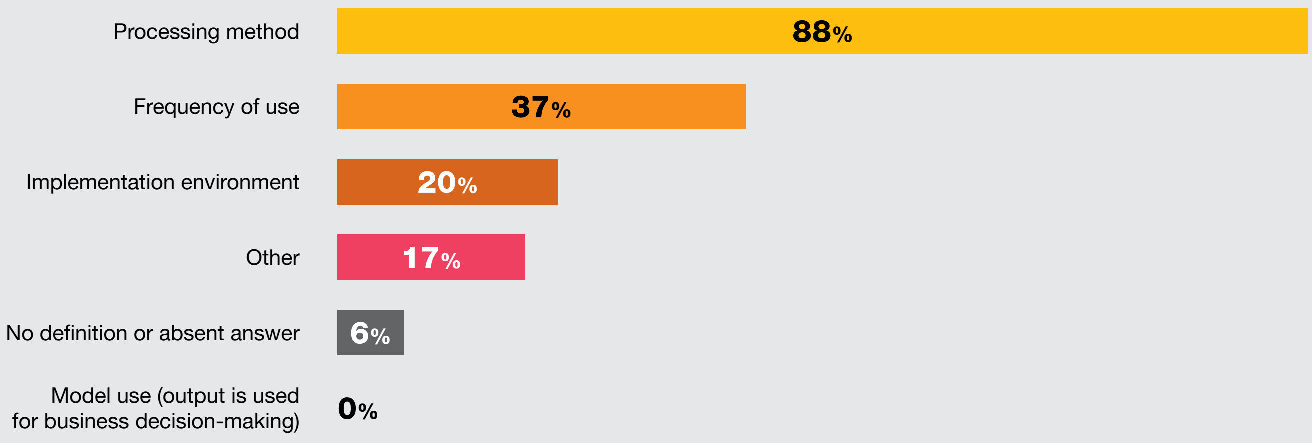
A new trend in model risk management is the consideration of the EU Artificial Intelligence Act, as noted by two survey participants. In our practice, we observe that certain financial institutions are beginning to incorporate these new requirements to address model risk, with a focus on AI literacy, bias detection, and human oversight.

Criteria for model definition

The survey results reveal a variety of criteria used to identify algorithms or techniques as models. Almost all respondents (**88%**) see a processing method, such as statistical techniques, mathematical approaches, or expert judgments, as a key criterion for identifying a model. Out of these, a half of respondents think it's the only criterion. Other important criteria include how often the model is used (**37%** of respondents) and the environment in which it is implemented (**20%** of respondents). In the "Other" category, respondents mentioned criteria like materiality, regulations, uncertainty of output, and input data. Interestingly, no one identified models based on how they are used in business decisions.

> **Model Definition by Bank of England**
>
> A model is a quantitative method, system, or approach that applies statistical, economic, financial, or mathematical theories, techniques, and assumptions to process input data into output. The definition of a model includes input data that are quantitative and / or qualitative in nature or expert judgement-based, and output that are quantitative or qualitative.
>
> **(PRA SS1/23, 2023, Principle 1.1)**

Which specific criteria do you use to define a model?

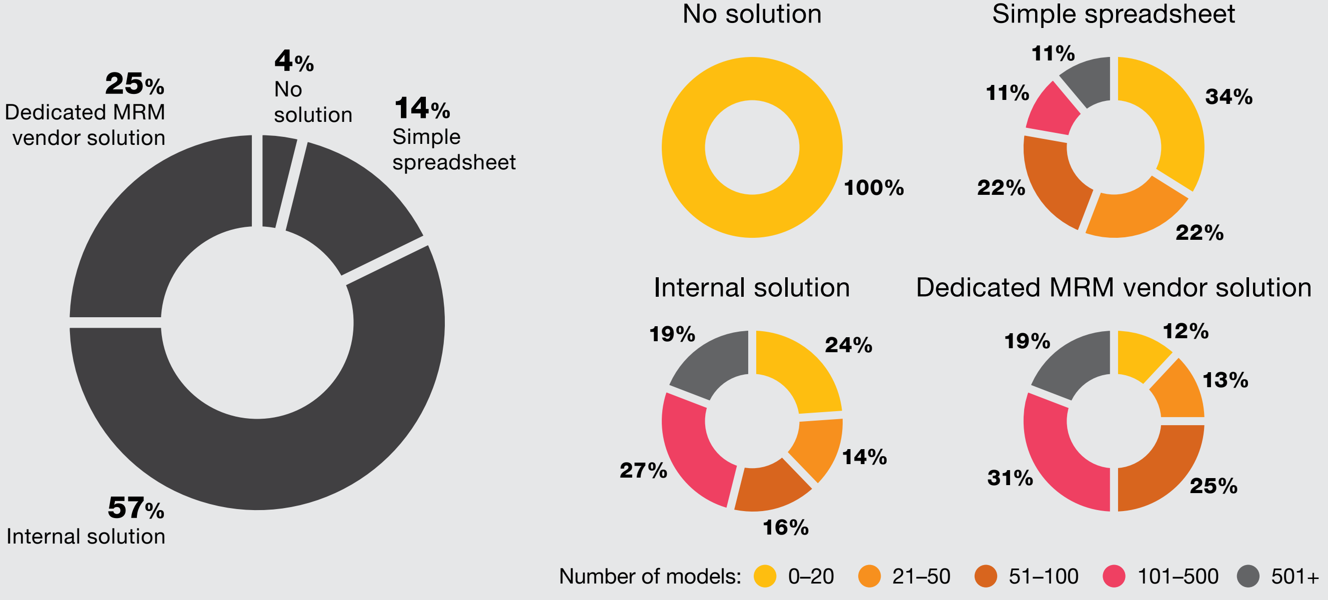


Inventorization

Model inventory in financial institutions

Financial institutions should “maintain an inventory of models implemented for use, under development for implementation, or recently retired” (SR 11-7). This is a common regulatory requirement and standard market practice. Our survey shows that this practice is followed by the vast majority of institutions. More than **95%** of respondents have some form of inventory. A simple spreadsheet solution without specific functionalities is used by **14%** of respondents, typically those with fewer than 50 models. More advanced solutions, either internally developed or provided by dedicated vendors, are used by **82%** of respondents, particularly those with more than 100 models. Only **4%** of respondents, who generally have 20 or less models, do not have any inventory solution.

What type of technical solution supporting the Model Risk Management function do you have in your organization?



> In our business practice, we have observed that model inventory has become a standard tool for effective model risk management in medium and large financial institutions, especially those with over 50 models.
>
> **David Dolejší**
> MRM Subject Matter Expert

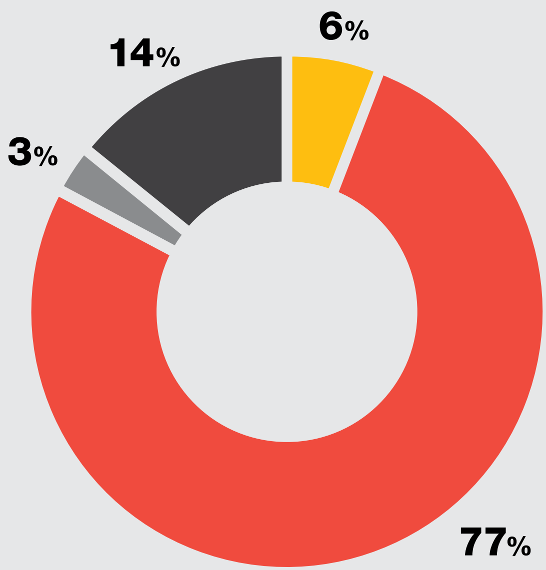
Model inventories are typically centralized, firm-wide solutions used across relevant departments. Although an inventory might be department or entity-specific, the best practice is to maintain a company-wide one. This approach is not only practical but also aligns with the principles set by the Bank of England for model risk management: "While each line of business or legal entity may maintain its own inventory, firms should maintain a firm-wide model inventory which would help to identify all direct and indirect model inter-dependencies in order to get a better understanding of the aggregate model risk" (PRA SS1/23, 2023, Principle 1.2).

This survey confirms such a practice in the market. **80%** of respondents reported using company-wide solutions, with two of them also maintaining specific inventories. In contrast, **14%** of respondents use only specific inventories, typically associated with functional roles, geography, or departments. Only 6% did not state any form of inventorization.

95% **of respondents have some form of model inventory**

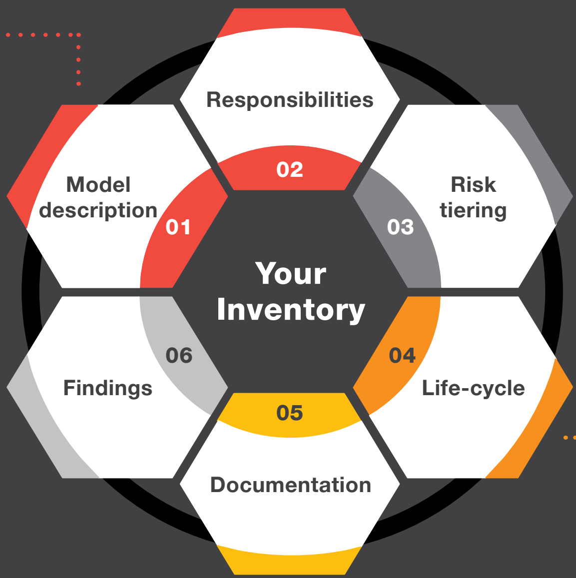
Is your model inventory company-wide or specific with respect to various attributes?

- No solution or absent answer
- Company-wide
- Company-wide and Specific
- Specific



Inventory requirements from regulation to best practice

The model inventory should cover a range of relevant information to support effective model management and mitigate model risk. This information falls into the following six categories:



Roles and responsibilities

- **Model owner identification**
- Model users
- Model developer
- Model validator
- **Model approver (for use)**

Model description and categorization

- Model inputs such as data inputs
- **Key information about the model and scope**
- Model approval specification
- Model limitations
- **Purchased from vendors**
- **Model versioning**

Risk tiering

- **Materiality of models**
- Risk ranking of models based on specific categories such as model use, materiality, complexity

Model findings

- References to outcomes analysis (e.g. back-testing results)
- References to internal audit or validation findings as they pertain to the model

Life-cycle information

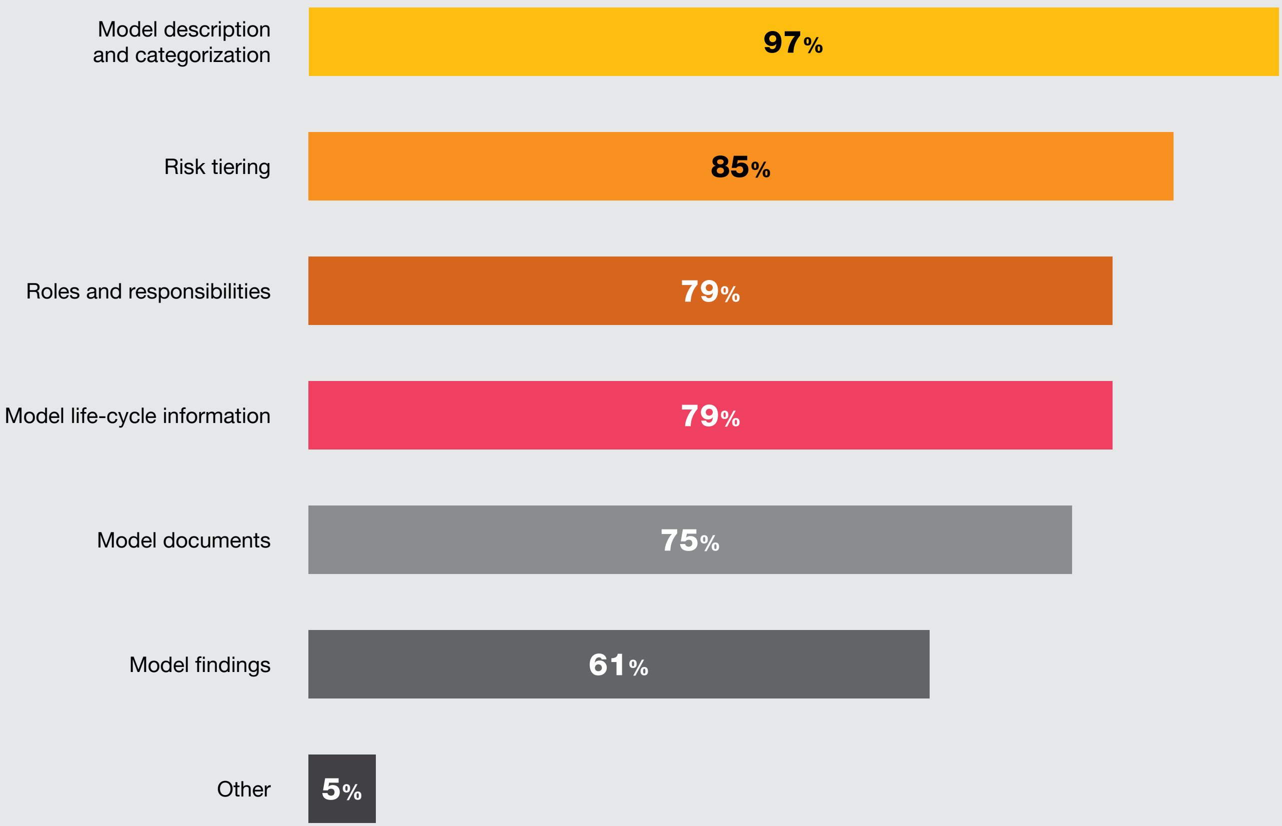
- **Date of inception / production**
- **Model changes history**
- Validation date
- **Approval date and notification date**
- Time frame during which the model is expected to remain valid

Model documents

- Inventoryof documentation
  - Validation report
  - Development documents
  - Implementation documents
  - Approvals

According to our survey, most important set of data is the model description and categorization, mentioned by **97%** of 61 respondents who indicated collecting model attributes in their inventories. This is followed by risk tiering, highlighted by **85%** of respondents. Other categories include roles and responsibilities (**79%**), model life-cycle information (**79%**), model documents (**75%**), and model findings (**61%**). Additionally, respondents mentioned the importance of including information about non-models and the statuses of documentation.

What is the key information collected in the model inventory of your organization?

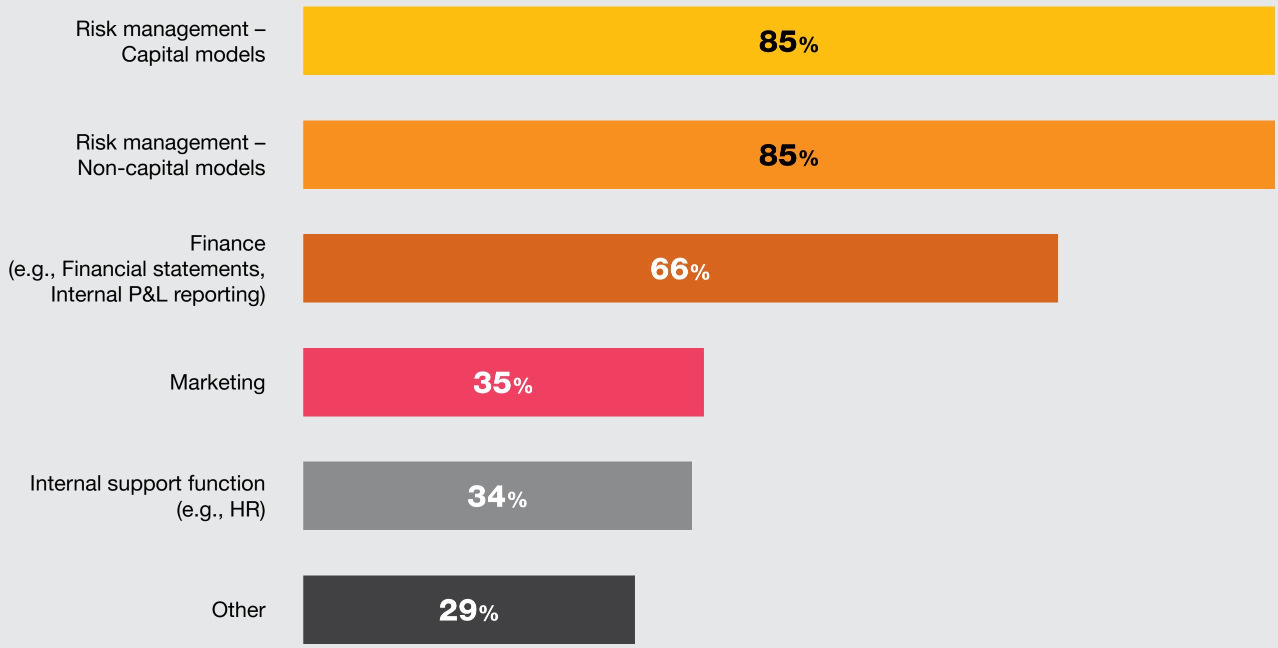


Note:
The chart is based on 61 respondents who indicated that they collect information in their inventories.

Model inventories cover a range of models from the perspective of their use; from capital management to marketing campaigns. The regulated models are typically those which enter inventories first, often associated with capital or provision calculations. These are followed by other models used by risk, business, and finance departments.

Financial institutions reported that the Risk management category of models associated with capital and non-capital models is the most frequent in their inventories (**85%** of responses). The second most frequent category of models is Finance models (**66%** of responses) covering P&L or financial statements. Less frequent categories of models come from Marketing (**35%** of responses) and Internal support function (**34%** of responses), such as human resources. Other categories include financial crime models, pricing models, GenAI tools, or valuation models.

What categories of models do you consider in your model inventory?



Note:
The chart is based on 62 respondents who consider specific categories of models in their inventories.

Vendor Models in MRM

Role of external models

Proper treatment of third-party vendor models plays an important role in model risk management. These models, often outsourced or purchased, require validation, monitoring, and oversight to ensure they perform accurately and meet regulatory requirements. Managing vendor models involves assessing risks associated with reliance on external providers and ensuring proper governance and compliance.

According to our survey, a significant ratio of respondents (**80%**) incorporate models provided or serviced by external vendors into their model inventories. Majority of them (**79%**) report that vendor models represent only 0% to 25% of their total model inventory. This highlights a reliance on internal model development, even among those who utilize external models. The remaining **20%** of respondents that do not include vendor models cite reasons such as their inventory being in development stages, lack of a specialized inventory process, or a focus solely on internal model development. These statistics reflect the varied approaches organizations take in integrating vendor models into their MRM frameworks, indicating potential areas for further standardization and development.

Do you consider models provided or serviced by external vendors in your model inventory?

80% YES

What percentage of overall model inventory constitutes models provided or serviced by external vendors?

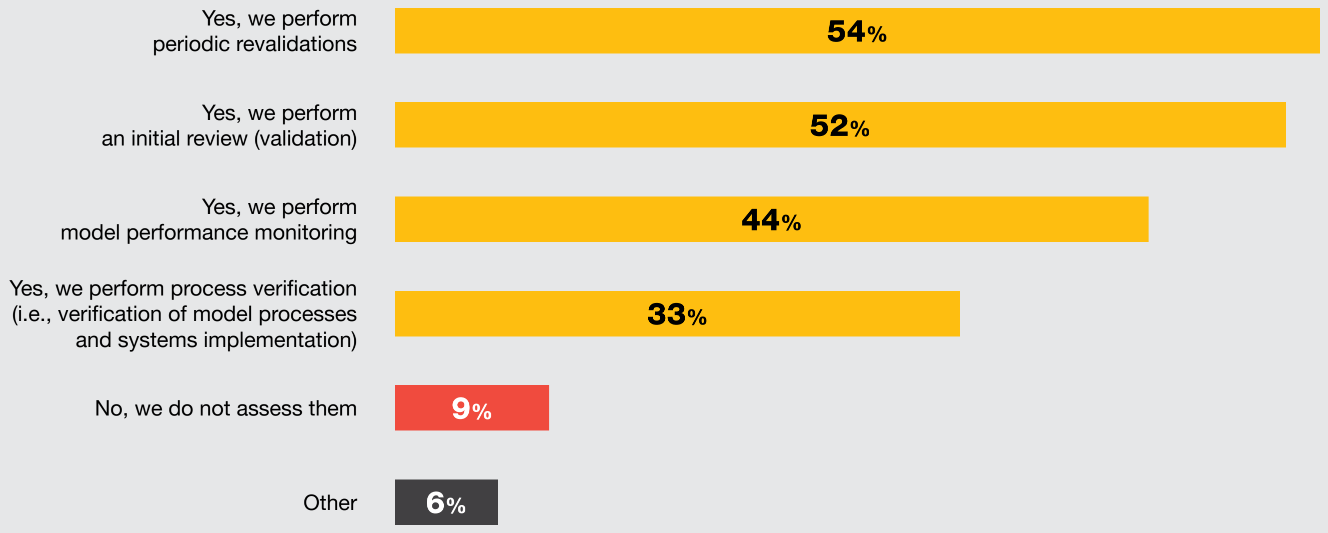
Note: The chart is based on 52 respondents who consider externally serviced or provided models in their inventories.

20% NO

Reasons why:

- Inventory in development
- No special inventory
- No external models / internal development only

Do you have a specific MRM framework for models provided or serviced by external vendors (to the extent possible with respect to the particularities of vendors)?



Note: Percentage out of respondents that have vendor models in their inventory.

External models require maintenance and governance. More than **90%** of respondents assess third-party models as part of their MRM activities. Common practices include periodic revalidation (**54%**), initial review (**52%**), ongoing performance monitoring (**44%**), and process verification (**33%**). Notably, about **8%** of respondents do not conduct specific assessments of vendor models. About **15%** of organizations adopt a unified framework for both external and internal models to streamline MRM processes and ensure consistency. These insights reveal diverse industry strategies and suggest areas where further standardization could be beneficial.

The survey results underscore the importance of robust Model Risk Management practices, particularly concerning the integration of vendor-provided models. With **80%** of organizations utilizing these external models, there is a clear reliance on third-party services. By adopting more consistent practices within MRM, organizations can enhance their oversight and governance of vendor models, ensuring they meet regulatory requirements and contribute effectively to decision-making processes.

Artificial Intelligence

Our survey reveals diverse perceptions of AI's usefulness and complexity within financial institutions, highlighting even the absence of a universally accepted definition. Some view AI as systems with advanced machine learning, such as facial recognition or generative AI using neural networks, while others include traditional models like loan approval systems based on logistic regression or decision trees. This variation reflects the lack of consensus even among AI researchers.

In this context, the definition of an "AI system" provided by the EU AI Act, which has recently been adopted by the OECD, proves to be useful. An "AI System" is described as a "*machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments*" (REGULATION (EU) 2024/1689, 2024, Article 3).

The definition of an AI system is relatively recent. Before the EU AI Act introduced a legal definition aimed at addressing the accountability of automated machine systems using some form of inference, researchers typically worked with two AI categories: Narrow and General. These definitions were less precise than those provided by the EU AI Act and the OECD due to challenges in defining "intelligence". The following are IBM's definitions of Narrow and General AI.

Definition of AI [1]

Narrow AI (also known as Weak AI) refers to systems designed to perform specific tasks or solve problems, often with a high level of proficiency. This type of AI can mimic or automatically perform certain tasks that humans do, but it does not possess a genuine human-like understanding of those tasks. This broad definition often applies to what many consider AI (voice assistants, recommendation algorithms, face recognition, generative AIs).

General AI (also referred to as Strong AI or Artificial General Intelligence, i.e. AGI) represents the concept of machines possessing the ability to understand, learn, and apply intelligence across a wide range of tasks, much like a human. This is a more theoretical concept that currently remains beyond our technological capabilities.

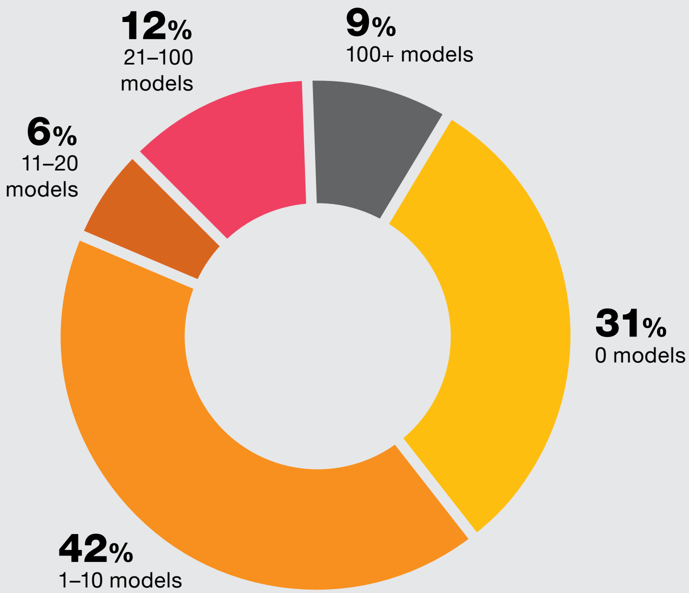
[1] www.ibm.com/think/topics/artificial-intelligence

Use of AI in the financial industry

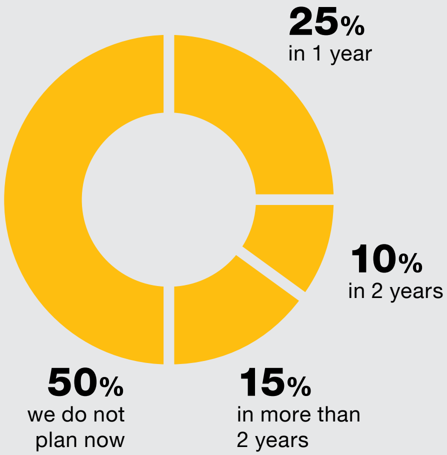
The survey shows that AI is becoming a common tool in business processes within financial institutions. Almost **70%** of respondents reported using AI-driven models and specified their areas of implementation. Among respondents who stated that their institution does not currently use AI, one half indicated plans to implement it in the future.

Credit management, including underwriting (recorded by **51%** of respondents), and compliance, such as fraud detection (recorded by **42%** of respondents), are among the most common applications of AI in financial institutions. These areas have traditionally relied on machine learning models. The benefits of AI in such areas are clear: the ability to process vast amounts of both structured and unstructured data, reduce manual oversight, minimize human error, and enhance efficiency in credit assessment and compliance processes.

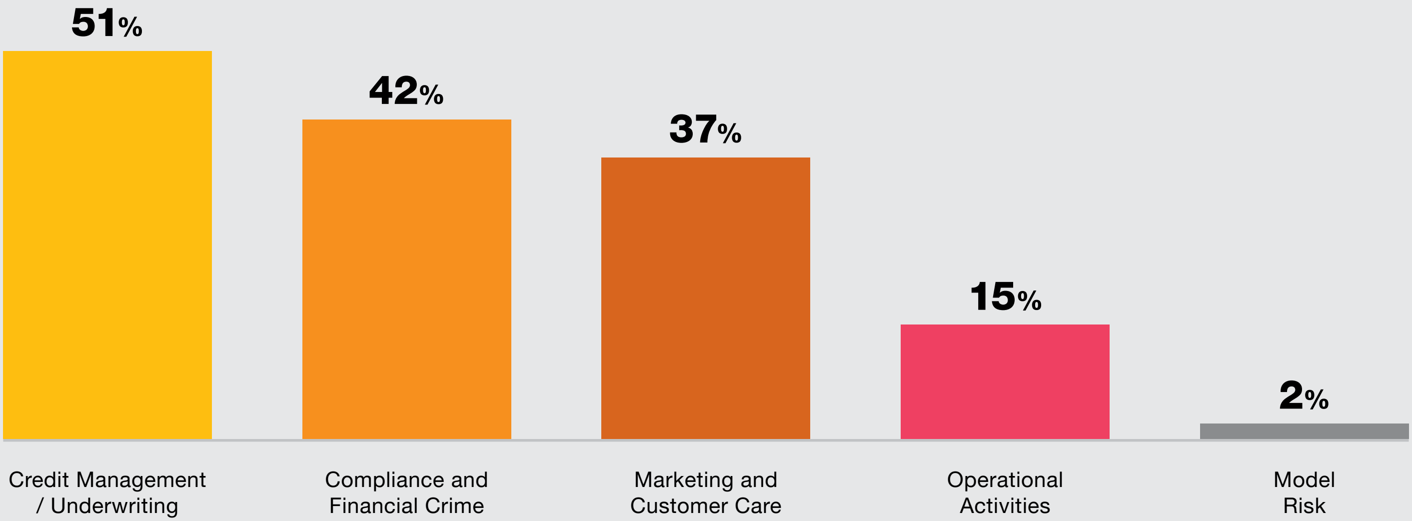
How many models that make use of any sort of AI do you have in your organization?



If you currently do not use models that utilize any sort of AI, are you considering implementing such models in the future?



In which areas and for which pupose do you use models that utilize any sort of Artificial Intelligence?



- **Credit Management / Underwriting:** Many respondents emphasized AI's crucial role in underwriting, where it automates parts of the approval process and applies more objective criteria than human decision-makers. Beyond underwriting, AI is frequently used to enhance loan monitoring by generating periodic reports and flagging loans that require attention. It can also play a key role in collections, automating client communications (e.g., message notifications, call centres) and processing data for claims and disputes.

- **Compliance and Financial Crime:** Respondents frequently emphasized AI's efficiency in compliance tasks. Financial institutions use AI to detect transaction patterns, flag suspicious activities, and automate AML reporting. Other applications include automating passport/ID verification for KYC, detecting fraud, using virtual assistants to collect required documents from customers, and extracting energy labels.

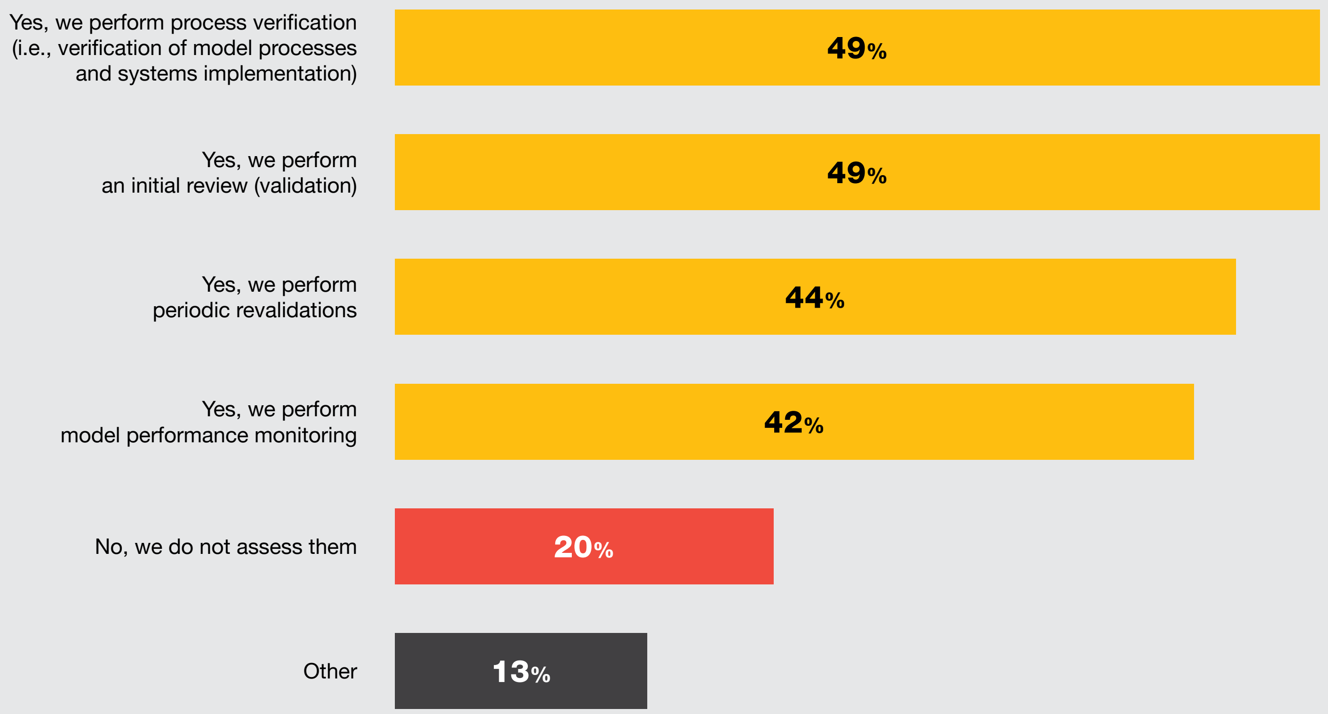
- **Marketing and Customer Care:** Financial institutions use AI-driven facial recognition to enhance customer convenience in mobile banking apps, while chatbots handle common inquiries. Some respondents also noted AI-driven automation in call centres. In marketing, AI recommends products based on a customer's purchasing history and other available data.

- **Operational activities:** AI also streamlines internal processes, such as matching candidates to job profiles or verifying employees' expenses.

Managing model risk in AI

Approximately half of the respondents manage model risk associated with AI systems through various activities using existing frameworks. **49%** of respondents indicate performing initial validation and process verification. Periodic revalidations are reported by **44%** of respondents and model performance monitoring by **42%** of respondents. However, most acknowledge the absence of a specific framework designed to address more complex and non-interpretable models.

Do you have a specific MRM framework for models that utilize AI?



Note:
Percentage out of 45 respondents using AI-driven models.

Large language models in the financial industry

When it comes to large language models (LLMs) like ChatGPT, Generative AI focused on text data, few respondents reported using them in their organizations. Only 13 respondents (**20%**) indicated that they use LLMs in their businesses, with large variety of applications. Most commonly, LLMs assist with program coding and drafting of documentation related for example to model development. Some respondents use them to explain model outcomes, process results, and provide commentary, while others leverage LLMs for validation activities, answering specific questions, or feature extraction.

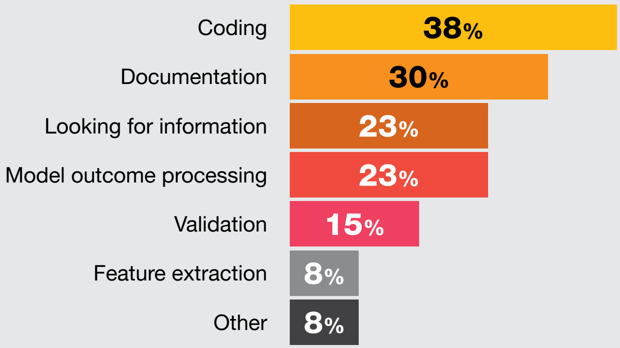
Why aren't more organizations using LLMs?
The primary reason cited is the lack of established frameworks, policies, or training to manage risks such as privacy concerns, misinformation, and unchecked decision-making. Many organizations have completely restricted the use of LLMs due to these unresolved risks, acknowledging that while the technology has the potential to enhance certain processes, improper usage can be detrimental. Nevertheless, several respondents expect that these limitations will be addressed over time. A few respondents mentioned that they are developing their own LLMs to mitigate risks like data privacy issues and hallucinations. Additionally, some respondents stated that they do not plan to use LLMs in the future, as they see no need or application for these models within their institutions.

Do you leverage ChatGPT (or other LLM) in Model Risk Management?

20% YES

↓

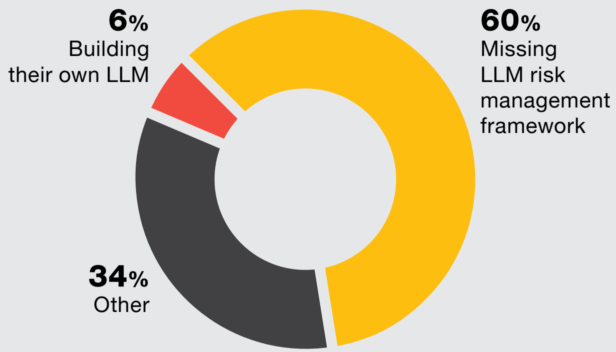
Please describe how and for which purpose you use ChatGPT (or other LLM) in Model Risk Management?



80% NO

↓

If you do not leverage ChatGPT (or other LLM) in Model Risk Management, why not?



Model Risk Tiering

Model risk tiering is a framework used to categorize models based on their potential impact and risk to the organization. The approach typically involves assessing dimensions or factors such as model complexity, use, data quality, and regulatory requirements to determine the appropriate level of oversight and validation. In the market, it's common to assign higher tier models (such as those impacting capital, trading, or regulatory compliance) more frequent and rigorous monitoring, while lower tier models are subject to lighter oversight. The majority of respondents (**82%**) implemented risk tiering in their MRM framework. To assess model risk tiers, decision tree method is heavily used (**70%** of respondents). **26%** of respondents that implemented risk tiering are using scorecards and **4%** are using matrix approach.

> **Model Tiering**
>
> Risk-based model tiering should be used to prioritise validation activities and other risk controls through the model lifecycle, and to identify and classify those models that pose most risk to a firm's business activities, and/or firm safety and soundness.
>
> **(PRA SS1/23, 2023, Principle 1.3)**

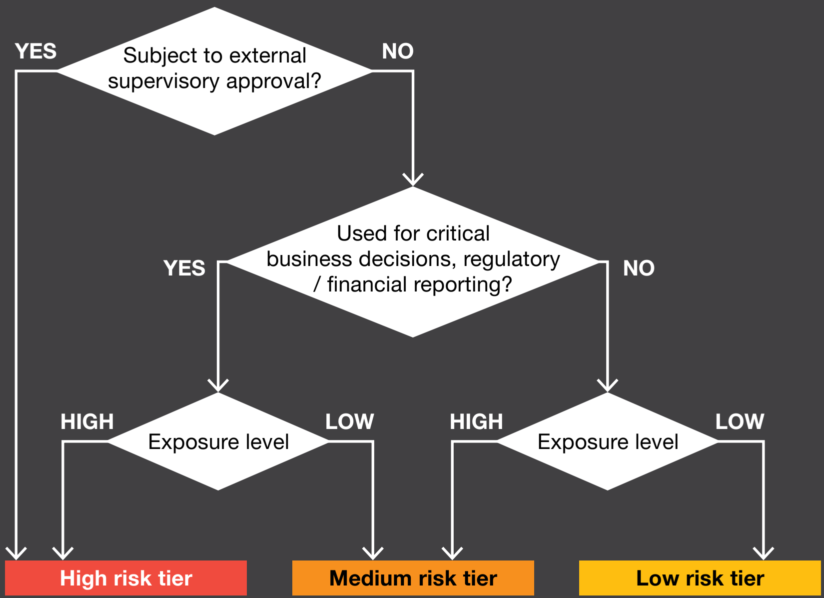
Note:
Percentage out of 53 respondents that use model risk tiering.

Do you consider model risk tiering in the Model Risk Management framework in your organization?

Which methodological approach do you use for model risk tiering?

Different risk tiering methods (illustrative examples)

Decision tree



Scorecard

Factors	Value range	Weight	Model 1
Model use		**40%**	
Regulatory or financial reporting	0 or 1	100%	1
Model materiality		**30%**	
Exposure level	1 or 2 or 3	100%	3
Model complexity		**30%**	
Complex mathematical formulations	0 or 1	50%	1
Model dependency (Upstream / Downstream)	0 or 1	30%	1
AI usage	0 or 1	20%	0
		Total score	**1.54**
		Risk tier	**High**

Combined approach

Model use

Is the model subject to external approval (e.g. auditors, central bank)?

NO

Materiality level: Low	Medium	High	Sub-category risk
Medium risk tier	High risk tier	High risk tier	High
Medium risk tier	Medium risk tier	High risk tier	Medium
Low risk tier	Low risk tier	Low risk tier	Low

YES

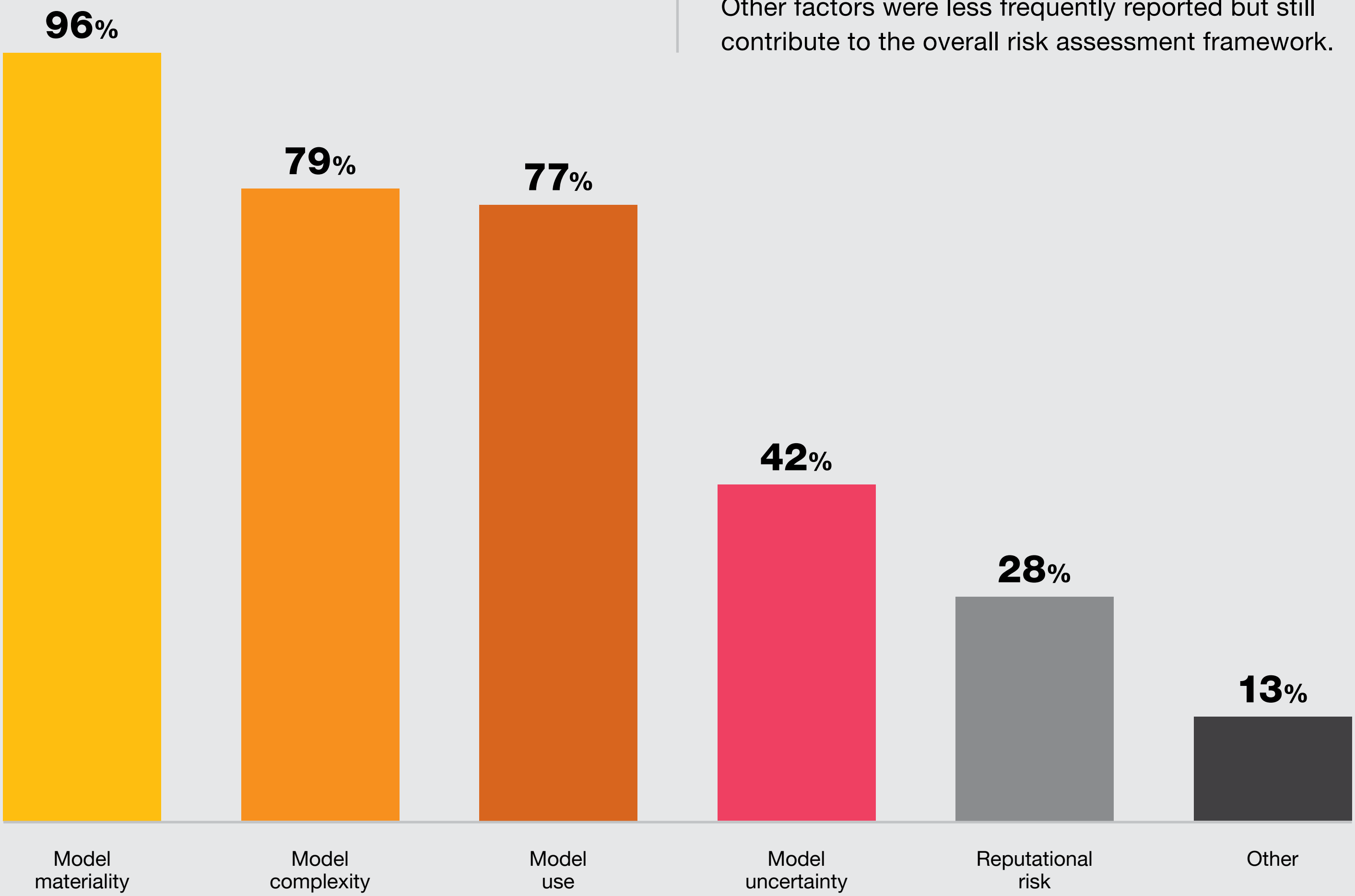
Materiality level: Low	Medium	High
Medium risk tier	High risk tier	High risk tier

Matrix approach

Materiality level: Low	Medium	High	Sub-category risk
Medium risk tier	High risk tier	High risk tier	High
Medium risk tier	Medium risk tier	High risk tier	Medium
Low risk tier	Low risk tier	Low risk tier	Low

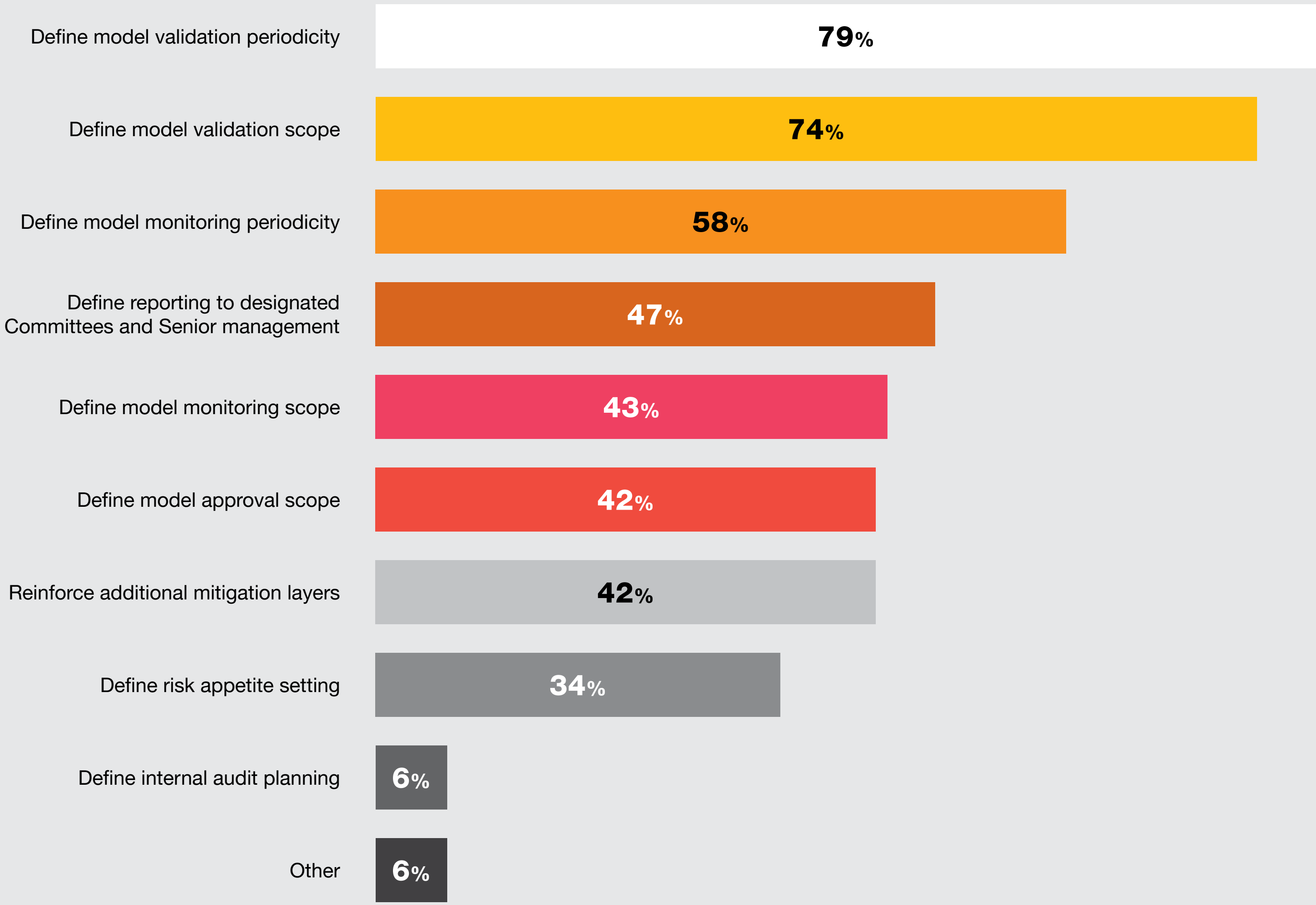
Which dimensions / factors do you consider in assessing risk tiering?

When assessing risk tiering, it is essential to consider various factors, such as model materiality, complexity, use, uncertainty and others, as highlighted in Principle 1.3 of PRA's SS1/23. In our survey, **96%** of respondents highlighted model materiality, indicating a great emphasis on material models. Model complexity is listed by **79%** of respondents. **77%** of respondents indicate model use among the answers and **42%** of respondents report model uncertainty. Additionally, reputational risk was also added as a key consideration in the survey and was indicated by **28%** of respondents. Other factors were less frequently reported but still contribute to the overall risk assessment framework.



What is the purpose of model risk tiering?

Our survey found that most institutions use risk tiering to define model validation approach, with **74%** of respondents covering validation scope and **79%** covering its periodicity. The definition of model monitoring is also widely listed among the answers, with **43%** of respondents mentioning model monitoring scope and **58%** its periodicity. Additionally, **47%** of respondents use risk tiering to define reporting to designated committees and senior management. **42%** of respondents indicate its use to define model approval scope and to reinforce mitigation layers such as documentation, data quality controls, and corrective actions on model design. **34%** of respondents use risk tiering to define risk appetite setting.



Summary

As financial institutions continue to expand their use of models, the demand for streamlined processes, strong governance, and automation remains critical. Our latest survey reaffirms the overall maturity of MRM functions. However, a key challenge has emerged: AI. The challenge starts with definitions when many institutions prefer to adhere to regulatory guidelines rather than establish their own definitions, highlighting the growing influence of regulations in shaping model governance.

While the adoption of technological solutions for MRM is increasing, a significant number of institutions have yet to integrate dedicated tools. Even among those with MRM frameworks that are already mature, many are still not using dedicated technological solutions. As institutions seek to strengthen their MRM strategies, leveraging AI and advanced risk tiering remains a crucial driver for innovation and robust risk oversight.

At PwC, we possess the expertise, knowledge, and solutions to improve your MRM function level to catch up with the industry standards, and, even more importantly, to keep its maturity level in line with complexity and thus the risk your already implemented models can bring. Let us accompany you on this transformative journey.

Yours sincerely,

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