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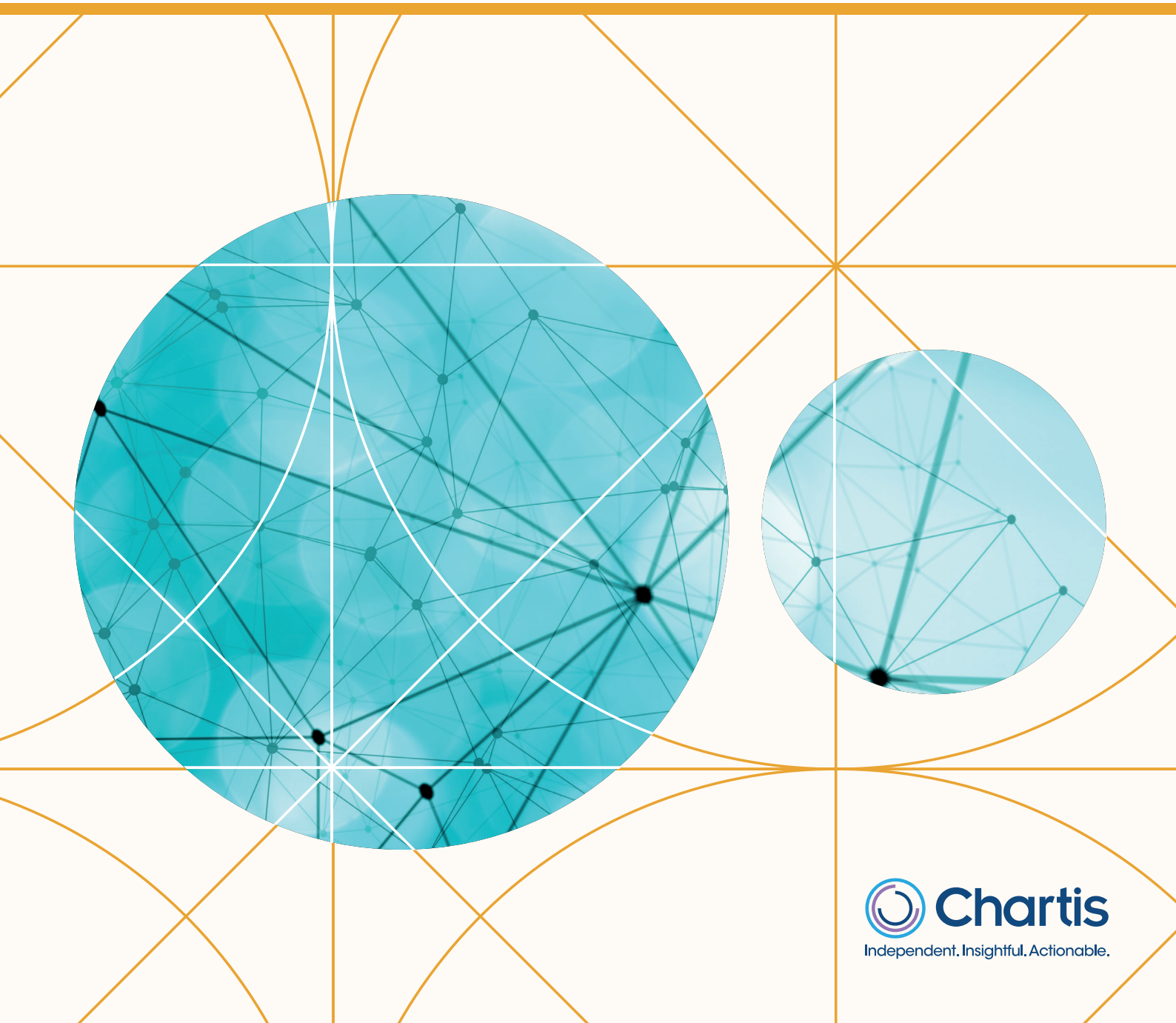
Thought Leadership

The State of AI in Risk Management

Developing an AI roadmap for risk and compliance in the finance industry

This collaborative report explores the level of adoption of AI in risk management in banks, insurance companies and financial organizations, and the challenges and successes encountered on the AI journey. It also analyzes successful AI strategies and areas of implementation.



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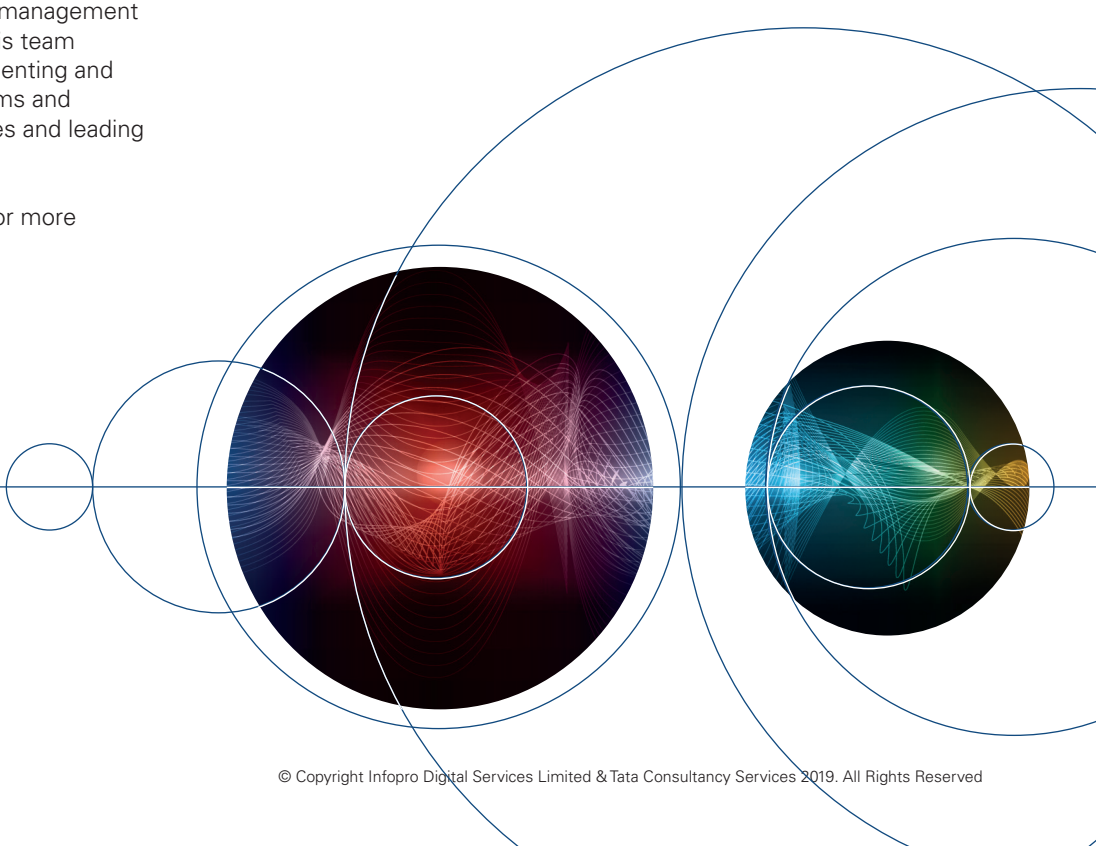

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1. Executive summary

Among financial institutions (FIs), the term 'artificial intelligence' (AI) is no longer just a buzzword. AI has become an important tool with use cases in a variety of financial-services contexts. In this report, we explore the current state of AI in risk and compliance, examining several key themes:

- The overall maturity of AI tools.
- How AI maturity looks in different contexts (e.g., across different types of institution).
- The ways in which AI tools are used across the risk and compliance value chain.

In this report we argue that the level of maturity of AI use varies considerably across FIs, both by type and at business-line level. With few exceptions, we find that the financial industry is still playing 'catch up' in AI terms. For many firms, the experimental AI phase is ongoing, with practical use cases still emerging. Even in the many larger institutions with more experience of AI, today's projects are likely to be the first in which AI is being deployed at *scale*, and in a broad range of use cases across organizational silos.

The application of AI tools also varies considerably by use case. For example, AI is relatively widespread in the area of data management, where specific tools (such as machine learning [ML], natural language processing [NLP], and graph analytics [GA]) have proved particularly suited to certain applications. To leverage data-driven projects effectively, however, institutions must have access to the right sources of data and the right expertise to manage it.

FIs in all market segments are making effective use of third-party AI applications; for example:

- Exploiting alt-data in capital markets and investment management to map the terms of loans and bonds into structured databases.
- Exploiting alt-data and media data (both traditional and social media) to drive credit risk review triggers and remedial actions.
- Leveraging a variety of external data (alt-data, vendor enriched data sets, social media data, etc.) for client screening in financial crime risk management.
- Leveraging historical data for regulatory risk analytics.
- Using neural networks in the preparation of data to leverage credit scoring models, or using supply chain, social media and other alt-data in credit analysis.
- Embedding the AI used to map and classify customer and counterparty behavior for behavioral analytics modeling. In areas such as credit scoring, there are regulatory challenges in the direct usage of customer profiling and behavioral analytics. However, more indirect uses – for example, in areas such as financial crime controls, behavioral analytics for asset and liability management (ALM) and balance sheet management, or the embedding of behavioral models in securities pricing and trading – have not seen comparable challenges or issues.

Indeed, segmentation and behavioral analytics are emerging as some of the strongest candidates for the practical, real-world application of AI in risk management – both are data-intensive, and both carry a relatively low risk of failure. A key theme emerging from our research has been that, in situations where analytics require highly dimensional, multi-parameter classification mapping or optimization against fuzzy or highly non-linear variables, AI applications work well. This is also especially true when they are used for internal analysis rather than for regulatory compliance or reporting purposes. And, when AI is applied to internal analysis, we found that the level of depth and maturity of its usage is typically higher.

At this stage in the development cycle of AI, we believe that the popularity of certain applications is dictated by two key factors:

- What the application can do.
- The level of regulatory incidence.[1]

We believe it is likely that both drivers will provide the foundations for a broader and more complex set of applications in the future.

[1] *'Regulatory incidence' – refers to the prevalence of regulatory oversight and sanctions.*

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To explore some of these issues in more detail, Chartis Research and Tata Consultancy Services (TCS) undertook a joint research project on adoption trends in the use of AI in risk management and regulatory compliance. This unique project has enabled us to develop an AI adoption roadmap for risk management, highlighting key approaches for the future success of AI projects.

Our study consisted of a quantitative survey of 101 industry participants, together with 65 targeted interviews with senior risk and compliance decision makers operating in this space. This body of research sheds new light on the adoption journey that many FIs are taking with AI, and the pitfalls and successes they are encountering along the way. Our research also includes a detailed view of successful AI strategies and areas of implementation, which readers will find in Section 5 of this report.

1.1 Research highlights

Our research uncovered several important themes and conclusions.

1.1.1 Maturity findings

- **There is no single, fixed definition of AI maturity that works in all contexts**. It is important to consider any assessment of maturity in the context in which maturity is defined. Maturity metrics in different lines of business (LOBs) and geographies can be gleaned from the characteristics of AI projects, including diffusion, deployment and standardization.

- **Maturity varies most by industry and geography**. In particular, we found that the maturity of AI applications varies by institutional type and geographical location. The ways in which AI is used across the risk and compliance value chain, for example, are most impacted by type of institution.

- **However, it is possible to measure maturity at a high level**. Certain core criteria can be used to measure maturity at a higher level. These include the diffusion, deployment and standardization metrics used to measure maturity at LOB level, together with an assessment of the methodological certainty and clarity of quants and data science teams across an organization, as well as the proportion of processes not requiring any form of regulatory approval.

- **In financial services (FS), institutions still have a relatively low level of AI maturity**. Using our maturity criteria (diffusion, deployment and standardization metrics), we found only a small number of institutions that were considered 'highly mature' in terms of their use of AI techniques. And, even within these most mature institutions, levels of adoption still varied according to LOB.

1.1.2 Usage findings

- **AI is favored for data management**. Compared to other applications, the use of AI in data management is relatively widespread. However, while AI is used extensively in data-intensive services in capital markets and wholesale banking, for example, currently it is only rarely used in decision making and regulatory-focused analytics. In contrast, in both retail banking and consumer finance, we find AI being used in a much broader set of contexts.

- **The impact of alt-data**. To accommodate the increasing amounts of unstructured data they need to handle, firms require a powerful new set of analytical methods. This, we believe, is a key factor driving virtually all institutions to increasingly (and in some cases aggressively) leverage AI in their risk and compliance processes.

- **Blend with traditional techniques to get the best results**. Our research found that, as a set of analytical and mathematical tools, AI should be unified with traditional quantitative techniques and risk management practices to achieve the best results.

- **Broad AI use cases**. Many areas of the industry are experimenting heavily with AI routines as alternatives to traditional tools, especially in retail banking and financial crime prevention. For example:

    - AI tools are being used across a broad swathe of the *retail banking* value chain, especially in areas such as retail credit scoring, behavioral analysis and customer segmentation.

    - AI is also being used extensively in modeling and production systems, proving its worth in *fraud/anti-money laundering (AML) detection* and behavioral modeling for retail banks.

    - From a governance, risk management and compliance (GRC) perspective, we see AI tools being used to set up and define controls,

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harmonize controls, and automate control testing.

- Data management in GRC is another area where AI is expected to deliver value through streamlined taxonomy management.

- AI tools are also being used in the management of early warning capabilities in both financial and non-financial risk management. For example, they are being implemented in the generation of early warning signals for client credit risk profiles (especially for small and midsize enterprise [SME] and corporate clients).

- In the areas of *equity and credit research*, social media and customer data are being leveraged to build a better understanding of performance, through the processing of unstructured data to reveal previously unseen patterns and correlations.

- In the area of *commodities trading optimization*, models that employ ML and evolutionary programming (EP) are being used to manage complex pipelines.

- In the area of *regulatory compliance*, we see AI tools and techniques being leveraged principally in data-oriented contexts such as parsing, classification, structuring and search-oriented capabilities.

- From a GRC perspective, we see AI tools being used to set up and define controls, as well as for the management of those controls.

- **ML and segmentation analytics rule**. The most heavily used tools across all areas of FS are ML and segmentation analytics. Nevertheless, segmentation and behavioral analytics emerged as the strongest candidates for practical, real-world applications in risk management use cases.

- **Challenges to overcome**. Despite the undeniable importance of AI, many FIs still have very significant skills-based, data and structural challenges to overcome. When it comes to AI maturity, the institutional response matters – how banks organize themselves, and the nature of the teams they put together, directly influence their maturity levels, and their success in AI projects.

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2. Background and methodology

2.1 Background

This report explores the adoption of AI in risk management. The research is organized along several core themes concerning the impact of AI and the quantification methods that now exist along the risk management and compliance value chain. We also examine non-financial as well as financial risk, considering standard AI use cases across different business areas. In writing this report, our aim has been to dig beneath the AI 'hype' to investigate the practical, underlying application of a range of AI tools in risk management use cases, and to establish reliable benchmarks for their use in FIs.

2.2 Methodology

To examine these themes, we surveyed 166 relevant risk and technology professionals in total, through a deep quantitative survey (n=101) and qualitative interviews with senior risk decision makers across Tier-1 and Tier-2 institutions (n=65). Respondents included senior risk and compliance stakeholders such as CROs, CTOs, CIOs, CCOs and Heads of Risk IT, sourced from a large variety of institutional types, including retail and commercial banks, capital markets institutions, and insurance and wealth management firms. The 65 interviews we conducted were detailed 'deep dives', exploring a range of relevant themes, including where institutions are using AI tools, their organizational structures, and the extent to which those structures either helped or hindered the rollout of AI projects.

Other areas explored across both streams of research activity include:

- The extent to which different AI tools impact the risk management and compliance value chain.
- The impact AI has had across different business lines.
- How changes are influencing the CRO's office.
- The challenges and difficulties institutions are facing across different AI use cases.
- Where institutions are now in their adoption of AI.
- Where they are likely to go next, and how they plan to ensure success.

2.2.1 Defining AI

AI is such a broad category of technology that it defies simple classification. However, the term AI typically refers to a suite of statistical techniques that bring together some combination of the following:

- Large data sets.
- Non-traditional data (i.e., changing and unstructured).
- Complex relationships between variables, resulting in opaque, so-called 'black box' models.
- Models with rapidly varying timeline structures.

Used properly, AI can supply FIs with previously unknown insights, better targeted mapping and more efficient categorizations. One example is the application of clustering algorithms, deep neural networks, and sentiment analysis in customer segmentation, fraud detection, price optimization, compliance monitoring and loss forecasting.

Broadly speaking then, AI tools such as ML, EP, topological data analysis and NLP can be seen as an *extension* of traditional statistical and optimization methods for specific use cases where there is a requirement to adjust for complex patterns, or to detect highly non-linear trends.

Most of the AI techniques currently in use fall into a technical, largely statistical category, with strong supporting mathematical formalisms behind them. For the purposes of this report, and for readability, we do not describe these mathematical structures and formalisms in great depth.[2]

[2] *Readers wishing to dig deeper may look at our previous reports in this space, though, including 'Artificial Intelligence in Financial Services: Demand-Side Analysis' (published in February 2019).*

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3. Key themes emerging from our research

3.1 Overview and key takeaways

A core objective of our research has been to examine the maturity dynamics of AI adoption. This section provides a high-level view of our results. We present a broad view of the maturity of different AI tools, institution types and LOBs. In Section 4 we go on to consider in further detail context-driven cases of AI tool implementation. In terms of challenges to adoption, we found that – even with the right amount and type of data – adoption is not always straightforward. The robustness of existing processes and the level of regulatory incidence can prevent the widespread adoption of certain AI projects. In contrast, we also present AI candidate projects and their common characteristics. These common characteristics inform our maturity benchmarks, which we also expand on in Section 5.

Key takeaways

- ML, NLP and segmentation analytics have the broadest application and underlying capabilities.
- ML and NLP have the broadest applicability across a range of use cases, including retail banking and financial crime.

Interview quotes

- *'AI techniques are providing a new window into the analytics for non-financial risks'*
  CRO, large US investment bank
- *'The biggest bang for one's buck is in the conversion of unstructured data to structured data. The use cases are ubiquitous.'*
  CRO, European universal bank

Our research highlighted several key findings around the specific AI tools FIs are using in risk and compliance. In general, however, the most heavily used tools are ML and segmentation analytics (see Figure 1[3]).

Predictably, the use of ML is relatively high. ML comprises a range of techniques built on 'conventional' neural networks and more complex deep learning approaches. These techniques have been in use for some time and institutions are more familiar with them, leading them to become largely mainstream. Elsewhere, segmentation analytics tools – the foundations of behavioral analytics – also enjoy relatively high levels of use. An extension and generalization of clustering models, segmentation analysis uses a broad range of underlying mathematical approaches to implement classification and clustering.

[3] *Note that rounding factors mean that some chart data may not appear to add up precisely to 100%.*

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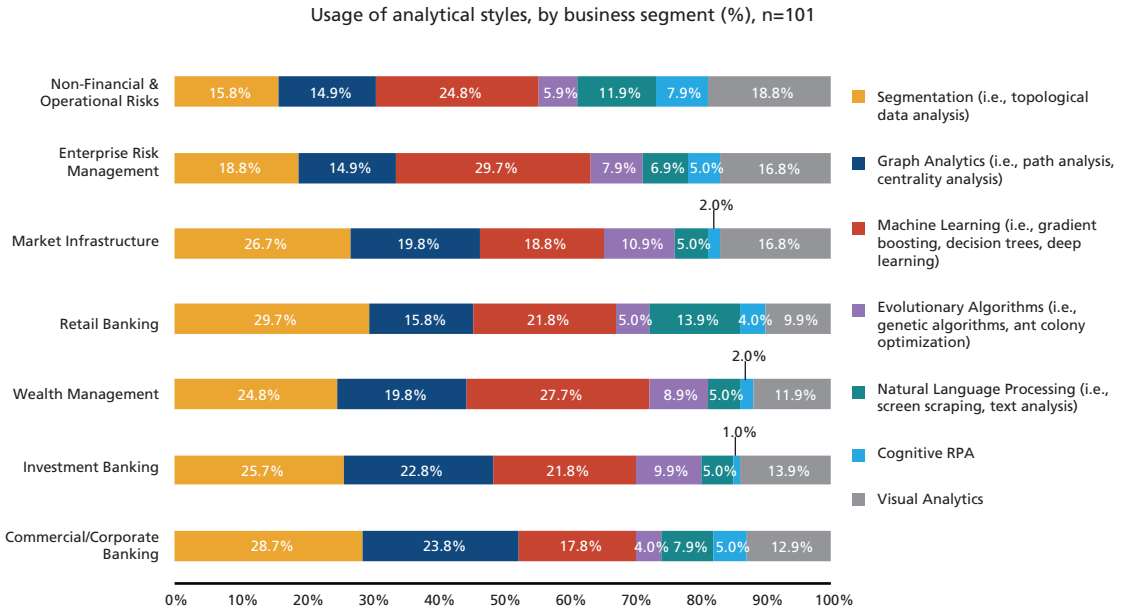
Figure 1: Segmentation, ML and graph analytics are the most widely used analytical techniques, used in half to two-thirds of projects across business segments



Question 22: Please mark the most extensively used analytical style for every business segment. (For every row, please mark one analytical style)
Source: Chartis Research and TCS

3.2 AI tools usage

3.2.1 AI tools are being used across business lines in a range of contexts

- AI is present across the retail banking value chain (see Figure 2), and especially in retail credit scoring (as a component of processes), as well as in behavioral analysis and customer segmentation. The use of AI-based models, and the formal leveraging of AI in production systems, is also seen in retail banking, as well as in financial crime contexts.
    - AI tools are also being used in the compliance management value chain in the areas of regulatory intelligence, impact management, compliance testing and regulatory adherence.
    - AI tools are also used extensively in the GRC spaces around controls management.
    - AI tools are also used to introduce cognitive/analytical interventions in financial crime risk – client screening, case analytics and automations (sanctions, transaction monitoring cases, etc.).
- While AI is used extensively for data-intensive services in the areas of capital markets and wholesale banking, it is rarely used in decision making and regulatory-focused analytics.
- Many LOBs are experimenting with AI routines as alternatives to traditional research. In equity and credit research, for example, social media and customer data are being leveraged to provide a deeper understanding of how target companies are performing.
- In commodities trading, optimization models leveraging ML and EP are being used to manage complex pipelines.
- AI tools are also being used across the entire wealth management value chain, especially in portfolio optimization for mid-market clients.

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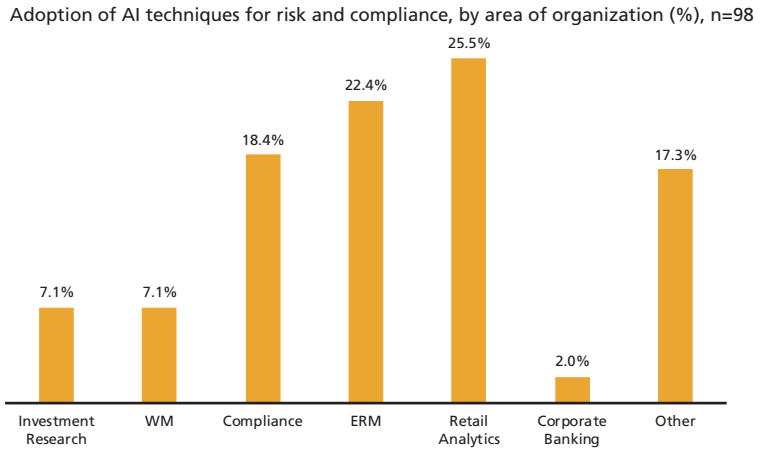
Figure 2: Adoption of AI tools, by industry area



Question 7: Which area of your organization do you believe has been the most effective adopter of AI techniques for risk and compliance purposes? (Select one option)
ERM = enterprise risk management; WM = wealth management
Source: Chartis Research and TCS

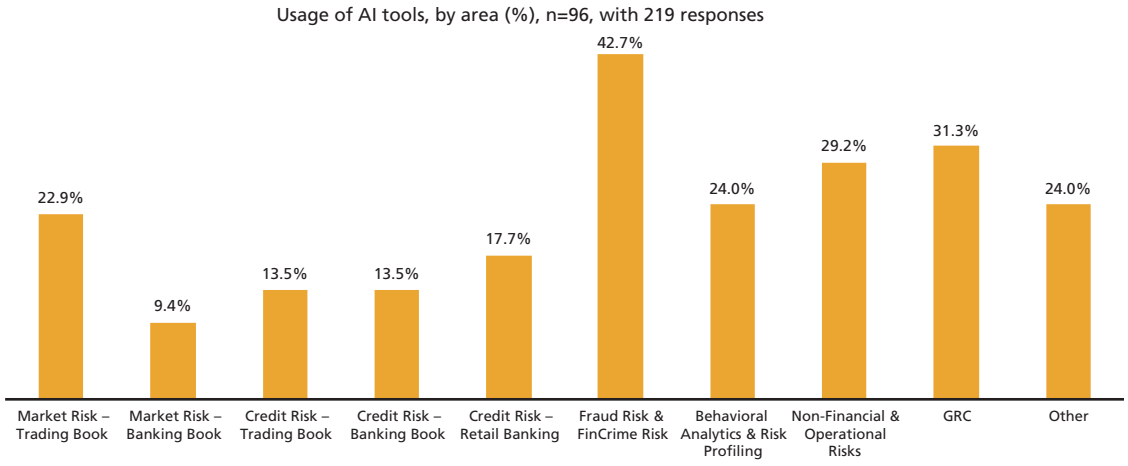
3.2.2 A small number of institutions are highly mature in their use of AI tools

Generally, we found AI maturity to vary considerably across institutions (see Figure 3). Indeed, even within the small number of highly mature institutions we surveyed, that maturity varied across LOBs. Only a very small number of institutions were using AI techniques across the board, incorporating them as foundational components of their business.

The way we define maturity in different dimensions drives a degree of variation. Some interviewees' institutions were mature in their use of alt-data, for example (e.g., extracting terms and conditions from loan and bond documentation for risk and trading analytics), but did not consider themselves as 'users' of AI, since the third-party provider of their alt-data source handled the processing for them.

Hence, reaching a reliable definition of maturity is a highly nuanced endeavor.

Figure 3: Use of AI tools to address a range of risk management challenges



Question 6: In which of the following areas of risk management and compliance are you using AI tools? (Select all that apply)
Source: Chartis Research and TCS

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3.2.3 Which AI tools are being used?

As mentioned above, ML and segmentation analytics are the main AI tools being used by institutions today. However, there are a range of other tools in use, including NLP, EP and topological data analysis. However, we believe ML, NLP and segmentation analytics have the broadest range of applications and underlying capabilities (see Figure 4).

Figure 4: ML and NLP have the broadest applicability across a range of use cases

Problem category	EP	SEG	ML	GA	NLP
Regulatory reporting			✓		✓
Real-time fraud analytics		✓	✓	✓	
Credit analytics	✓	✓	✓	✓	✓
Market risk	✓	✓	✓		✓
Data quality			✓		✓
T&Cs extraction			✓		✓
xVA	✓		✓		
Customer engagement/conduct risk		✓	✓	✓	✓
AML		✓	✓	✓	✓
Real-time risk		✓	✓		✓
Trade surveillance	✓	✓	✓	✓	✓

EP: Evolutionary Programming SEG: Segmentation Analytics ML: Machine Learning GA: Graph Analytics NLP: Natural Language Processing

Source: Chartis Research

The broad underlying capabilities of segmentation analytics enable the categorization, clustering and bucketing of a set of variables. It can also leverage ML, topological data analysis, EP, Markovian models[4] and other methods as its underlying computational architecture. In contrast, NLP – a multi-model technique – has been used extensively in a wide variety of data-centric applications across multiple areas and business lines. Both, though, are flexible and adaptable, capable of being leveraged across a range of use cases.

3.3 AI candidate projects

Key takeaways

- Fraud analytics operate on multivariate data, making them strong candidates for AI.
- Digitalization in the industry has transformed the availability of data in many areas.
- Critical to AI adoption is how close a process is to the regulatory compliance or reporting parts of the business.

The compatibility of application areas with AI projects is dictated by the availability and types of data, and the level of regulatory incidence associated with a particular area. Fraud and financial crime are areas well suited to AI applications because of the nature of the data involved. Fraud analytics, for example, operate on multivariate data (i.e., large amounts of varied, often unstructured data), and the incidence/propensity for fraud is linked back to a client's characteristics in a highly non-linear way, making it a strong candidate for AI.

[4] *A Markovian model is a type of stochastic model used in assessing the probability of randomly changing processes. Core to its operation is the principle that only the current state – rather than future states – depends on past events.*

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Non-financial operational risks (e.g., operational resilience and IT, cyber and process risk) are also strong candidates for AI projects, having traditionally struggled with the paucity of available data, and the prevalence of highly non-linear and unstructured data.

3.3.1 Digitalization has transformed the availability of data in many areas

Digitalization has provided a digital 'footprint' for every process and virtually all states of the network, which can (through AI) be monitored in real time. However, these vast, sprawling, complex and near unmanageable datasets can be very difficult to analyze using conventional techniques, making AI a virtual necessity.

However, while these techniques are clearly delivering value for users across a range of scenarios, their uptake can be impacted by the robustness of existing processes as well as regulatory incidence. In the latter case, how close a process is to the regulatory compliance or reporting parts of the business is an important factor determining uptake. In the context of **equity option pricing**, for example, the estimation of whether a volatility surface[5] is fair and accurate from a pre-trade analytics perspective is far removed from regulatory compliance. In contrast, market risk reporting under Basel 3 is much closer to regulatory compliance, since the details and exact frameworks are either mandated by the regulator, or may require regulatory approval, making it a much less appealing use case.

3.4 Relative levels of maturity across the market: key findings

Key takeaways

- Definitions of maturity vary across the market.
- Maturity benchmarks include:
  - Diffusion and deployment.
  - Standardization and progression into production.
  - Methodological certainty and clarity.
  - Regulatory approval and certainty.
- AI in risk is still an emerging area and is yet to become a core part of banks' infrastructure.
- Data management projects are relatively widespread.

3.4.1 Defining maturity at a higher level

As mentioned already, definitions of AI maturity differ across LOBs and geographies, making a unified definition difficult to frame. Nevertheless, certain core criteria can be used to measure maturity at a higher level. These are:

- The diffusion and deployment of AI projects throughout the institution.
- The level of project standardization, and how far projects have moved into production.
- The extent to which quant/data science teams have assimilated AI techniques and approaches (i.e., methodological certainty and clarity).

[5] *The volatility of an option is used in pricing and it is not constant. A 'volatility surface' is a method of calculating a stock option's implied volatility.*

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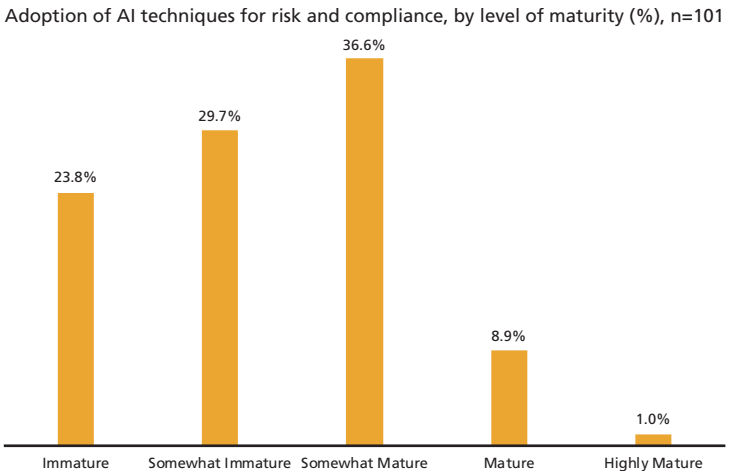
- The proportion of processes that do not require any form of regulatory approval (i.e., regulatory approval and certainty).

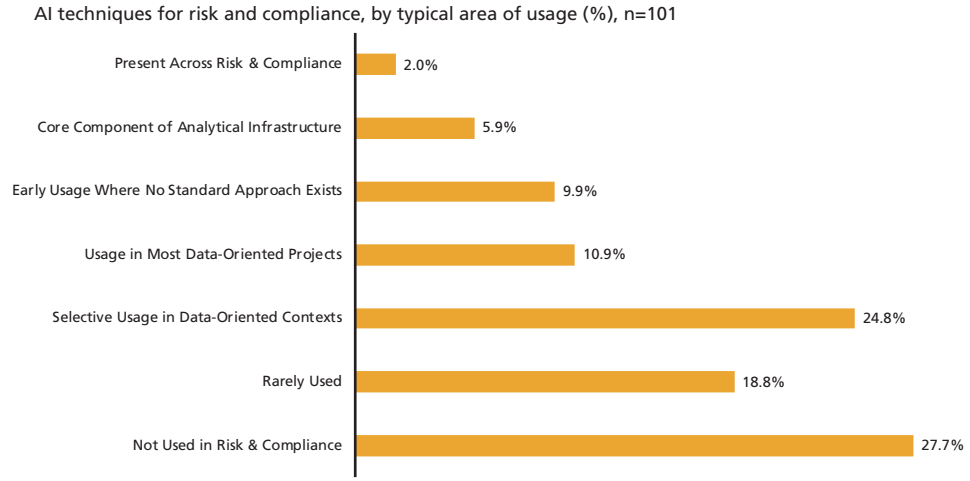
Figure 5: Adoption of AI tools, by maturity level



Question 8: In the context of risk and compliance, how would you describe the level of maturity of your organization in relation to its adoption of AI techniques? (Select one option)

Source: Chartis Research and TCS

Figure 6: Usage of AI techniques, by area



Question 9: In what contexts does your organization typically use AI techniques for risk and compliance? (Select one option)
Source: Chartis Research and TCS

Figures 5 and 6 are consistent with our general observation that AI in risk is an emerging, rather than a core, area of banks' infrastructure. Nevertheless, adoption is relatively widespread in areas such as data management, and all senior risk decision makers interviewed for this study had implemented some form of data-centric AI application.

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3.5 The challenges to maturity

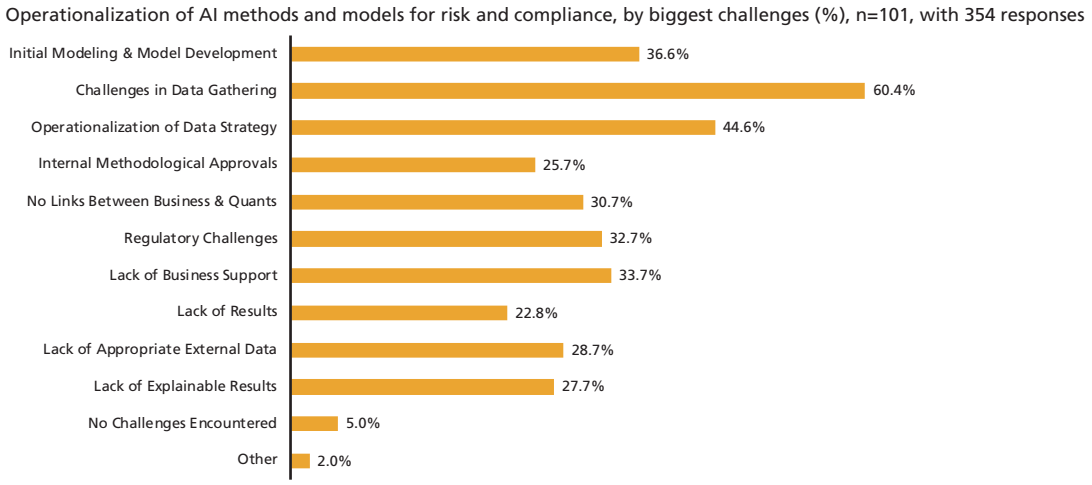
Key takeaways

- Access to the right data, and the expertise to handle it, are key success factors for AI projects.
- However, the consistency and quality of data will both vary across use cases.

3.5.1 The challenge of operationalizing AI

Although data-driven projects are widespread, a key challenge that institutions face when implementing AI tools is in accessing data that is appropriate to the task and tool at hand (see Figure 7). Unfortunately, FIs often find themselves coping with inconsistent data of variable quality. In the case of asset pricing, for example, most time series data (except only for the most liquid assets) will feature significant 'jumps', or use evaluated or interpolated prices that can themselves create significant challenges for the analytics.

Figure 7: Challenges in operationalizing AI



Question 10: Where do you see the biggest challenges in operationalizing AI methods and models for risk and compliance? (Select all that apply)
Source: Chartis Research and TCS

3.5.2 The challenge of driving deeper engagement

Another key challenge to achieving mature adoption is the lack of awareness of AI tools and their potential use cases. As Figure 8 shows, a significant number of survey respondents claimed to be unaware of a range of AI techniques. This includes 24% who claim not to have heard of ML, and about 30% who express ignorance of NLP and segmentation. Between them, these three comprise the most well-used AI techniques in the financial sector, underscoring a lack of awareness that constitutes a significant drag on adoption and overarching maturity.

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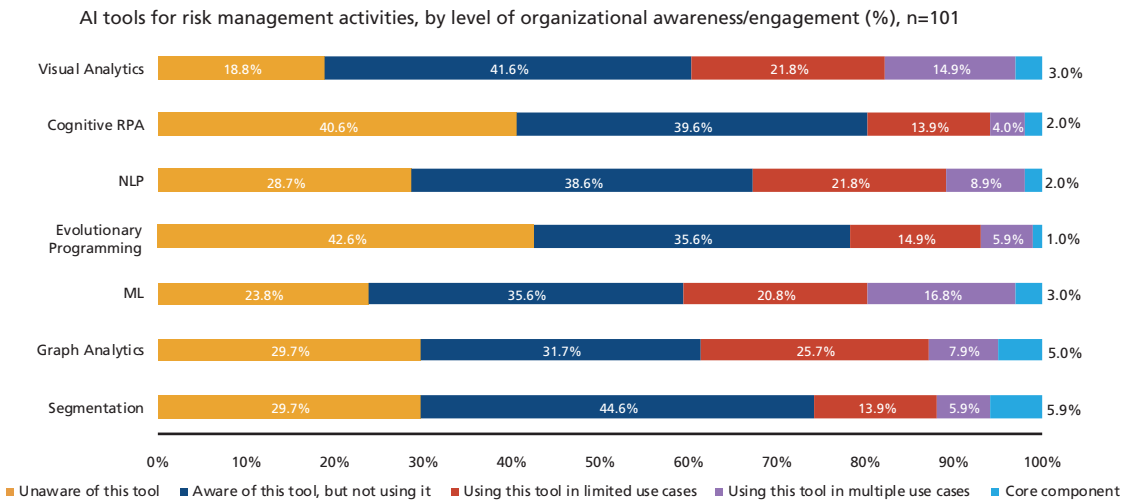
Figure 8: Level of engagement with AI tools



Question 13: To what extent is your organization engaging with the following AI tools for risk management activities? (Select one option)
Source: Chartis Research and TCS

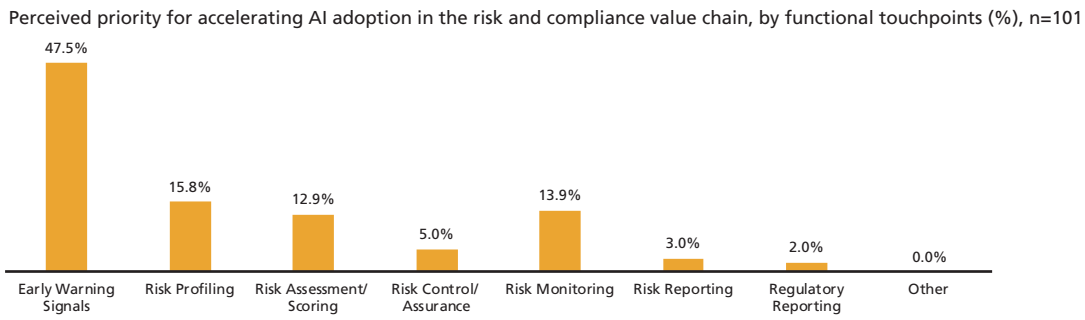
3.6 The benefits of adoption

Key takeaways

- Benefits exist across the risk and compliance value chain.
- Despite challenges, AI adoption can improve efficiency and insight.
- There is a particular focus on hard-to-spot early warning signals and, to a lesser extent, risk profiling and monitoring.

Despite these critical challenges, for those able to address them, the benefits of AI adoption are worth the pain. The key benefits to institutions are chiefly efficiency gains and deeper, more accurate insights. And, as Figure 9 shows, the ability of AI tools to generate hard-to-spot early warning signals and, to a lesser extent, work in risk profiling and monitoring use cases, is helping to accelerate adoption in FIs.

Figure 9: Perceived priority for accelerating AI adoption



Question 11: Among the different functional touchpoints in the risk and compliance value chain, where do you see the greatest priority for accelerating AI adoption? (Select one option)
Source: Chartis Research and TCS

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4. Sector-specific trends and drivers

4.1 Overview and key takeaways

The maturity and deployment of AI projects are highly idiosyncratic, depending on the specific LOB use case concerned. In this section we examine the implementation of AI tools in the wealth management, retail, enterprise risk management (ERM) and financial crime risk management (FCRM) sectors, assessing which tools are being developed and in which contexts.

In addition, we consider the significance of different drivers and challenges to adoption across different sectors and use cases. Our analysis is supported by conversations with senior decision makers as well as data from our industry survey. This section includes value chains that illustrate the way different AI tools are implemented in different contexts. We also highlight where trends in AI adoption converge and diverge across a range of scenarios. The trends we have highlighted here inform the maturity benchmarks we explore in more detail in Section 5.

This section includes two spotlights on FCRM. As a sector, FCRM has experienced relatively mature AI adoption. We consider more detailed trends in two specific areas of FCRM, those of fraud prevention and Know Your Customer (KYC). Anti-fraud is an area with a long legacy stretching across the retail banking process, forming a core part of the credit business. In contrast, while certain aspects of the KYC process overlap with other areas of the bank, these overlaps are not as broad or distinct.

Across LOBs, AI tools are being used to tackle challenges that are rooted in large non-traditional data sets. In the instance of non-financial risk, ongoing digitalization has contributed to the widespread availability of non-traditional data that can now be used to leverage AI. In this section we take a closer look at the current and long-term specific benefits that users have cited resulting from AI tool implementation.

Key takeaways

- The biggest opportunities in wealth management are in portfolio optimization and conduct risk analysis.
- The standout area of benefit in retail banking is behavioral modeling, with credit risk calculation a distant second. As previously noted, behavioral models are leveraged in indirect contexts such as: ALM (i.e., aggregating the impact of the behaviors of a group of individuals); pricing and portfolio management of securities dependent on the behavior of underlying loan pools; balance sheet management; and financial crime and controls. In areas such as credit scoring, regulatory challenges have exerted a strong influence, limiting the rollout of behavioral models.
- The use of AI techniques in ERM is focused on non-regulated use cases.
- In FCRM the greatest opportunities are in anti-fraud, AML and cyber security. KYC is an area of growing interest.

Interview quotes

- *'Algorithmic trading specifically is very, very quantitative. New techniques such as AI have a high hurdle to navigate.'*
  CIO, large quant fund
- *'Optimization is the step-child of the current AI revolution. Non-linear optimization is everywhere and waiting to be solved.'*
  Asset manager, large universal financial group (including banking, funds and insurance)
- *'Behavioral analytics is both an art and a science.'*
  Asset manager, private bank

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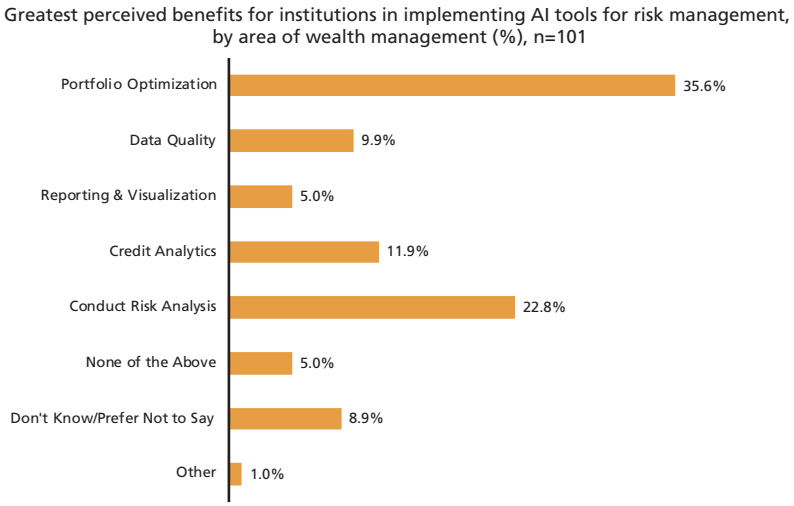
This section examines the implementation of AI tools in the wealth management, retail, ERM and FCRM sectors, with two accompanying spotlights on FCRM to illustrate some of the deeper trends at work in KYC and fraud management.

As Figures 10 to 14 show, different sub-sectors within the FS industry have different perceptions of the benefits of AI. To summarize:

- **In wealth management**… the biggest opportunities are in portfolio optimization and conduct risk (see Figure 10). Wealth management itself describes a variety of business contexts, ranging from fund management for ultra-high net worth (UHNW) individuals all the way to mass affluent services. In many categories the full application of standard portfolio optimization and analytics techniques does not make economic sense. AI-based optimization is therefore increasingly popular, and now underpins virtually all 'robo-advisors', as well as other automated or semi-automated advisory services.

Figure 10: Areas where implementing AI tools could have the biggest benefit – wealth management sector



Question 14: In which of the following areas of WEALTH MANAGEMENT do you see the greatest benefits for institutions in implementing AI tools for risk management? (Select one option)
Source: Chartis Research and TCS

- **In retail banking**… behavioral modeling is the standout area of benefit for institutions, with credit risk calculation a distant second (see Figure 11). Behavioral modeling has widespread applications and is a foundational element across all areas of the retail bank. This includes in managing fraud, checking for financial crime, managing credit and addressing the ALM and treasury needs of a retail book of assets. Equally, we note the extensive usage of NLP in data and document management. NLP and ML are also being leveraged for managing events such as triggers for risk ratings and reviews.

- NLP and ML are used for conduct risk management in the retail sales lifecycle to drive insights and minimize negative customer interactions and outcomes.

- Advancements in AI are offering promising uplifts in risk early warnings through augmented external risk factors for early warning and risk reviews.

- Elsewhere, when capital markets traders securitize retail assets – such as residential mortgage-backed securities (RMBSs) and commercial mortgage-backed securities (CMBSs) – there is a pressing need to create behavioral models. These can be highly complex, depending on a variety of financial and non-financial parameters. They may include macroeconomic data or specific customer states (e.g., the nature of the mortgage or the individual property on which it is secured) or other operational data. ML techniques provide a powerful engine to map these types of data.

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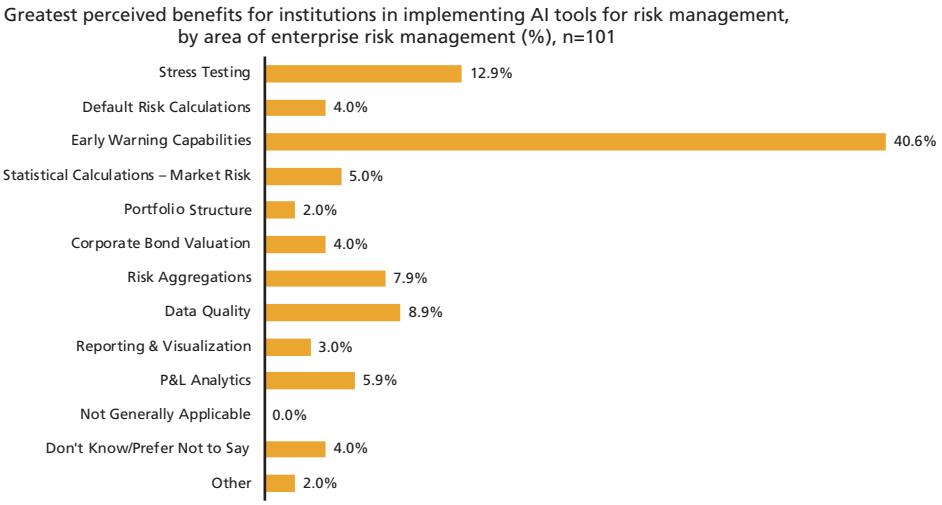
Figure 11: Areas where implementing AI tools could have the biggest benefit – retail banking

Question 15: In which of the following areas of RETAIL BANKING do you see the greatest benefits for institutions in implementing AI tools for risk management? (Select one option)
Source: Chartis Research and TCS

- **In ERM**… the use of AI techniques appears to focus on non-regulated use cases, such as the generation of early warning signs, and the analysis of 'what if?' scenarios instead of regulatory reporting projects (see Figures 12 and 13). An interviewee we spoke to from one large universal bank suggested that they used AI to construct a varied and expansive stress and scenarios library, which they could use to scan tens of thousands of benchmark results, and millions of market data points, to pinpoint potential areas of concern. For them, a combination of ML and EP (i.e., using EP components to set targets and boundaries) allowed them to systematically consider scenarios using different permutations of market benchmarks, credit curves and other market variables, which they applied across the institution.

Figure 12: Areas where implementing AI tools could have the biggest benefit – ERM



Question 16: In which of the following areas of ENTERPRISE RISK MANAGEMENT do you see the greatest benefits for institutions in implementing AI tools for risk management? (Select one option)
Source: Chartis Research and TCS

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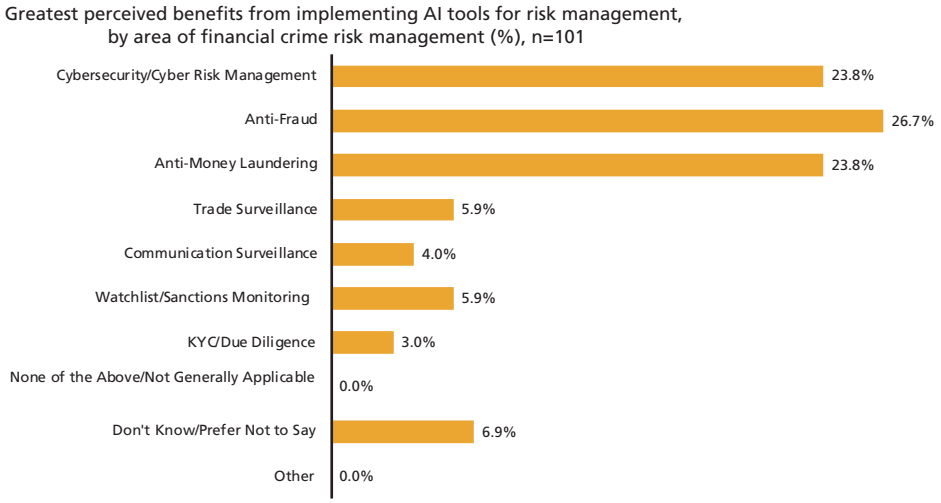
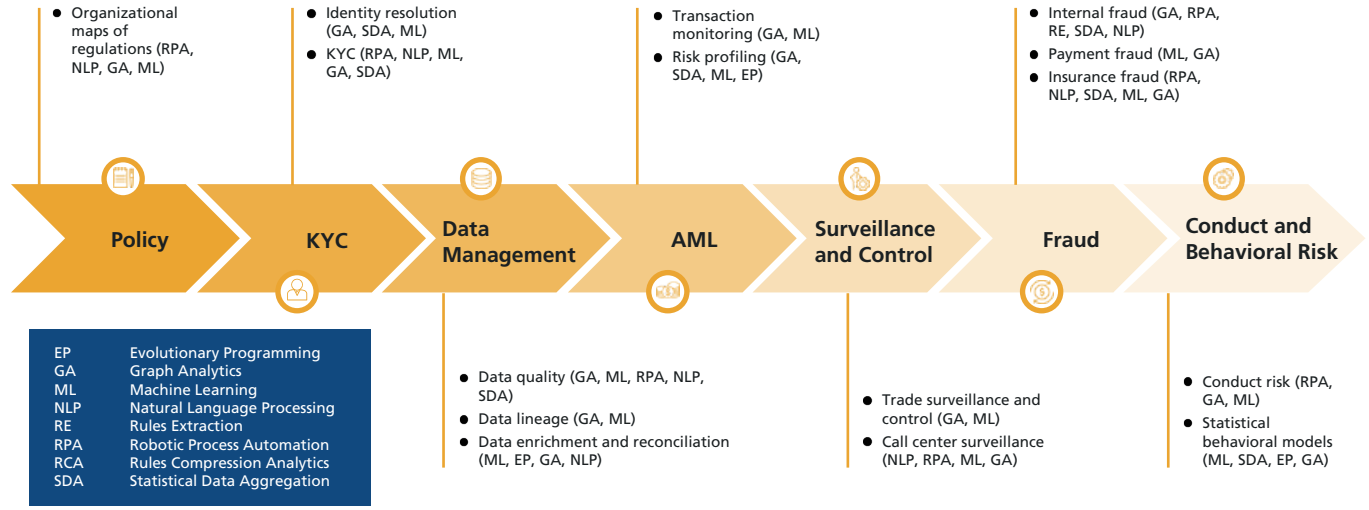
Figure 13: Areas where implementing AI tools could have the biggest benefit – FCRM



Question 17: In which of the following areas of FINANCIAL CRIME RISK MANAGEMENT do you see the greatest benefits for institutions in implementing AI tools for risk management? (Select one option)
Source: Chartis Research and TCS

Figure 14: Areas where implementing AI tools could have the biggest benefit – financial crime and compliance



Source: Chartis Research

- **In FCRM**… respondents see the greatest benefits in anti-fraud, AML and cybersecurity applications, with KYC an area of growing interest (see Figures 13 and 14). Client screening using external risk factors and alert prioritization frameworks for sanctions screening and transaction monitoring are providing greater resiliency in the management of financial crime signals. In the following section we focus on the use of AI in both KYC and anti-fraud contexts.

4.1.1 FCRM Spotlight 1: Leveraging AI in KYC – ID management, risk profiling and graph analytics

Crucially, for most banks, the analytics, processes and data used in the KYC and AML areas of FCRM are also used in other areas of the business (and vice versa). Figure 15 shows the areas of perceived benefit

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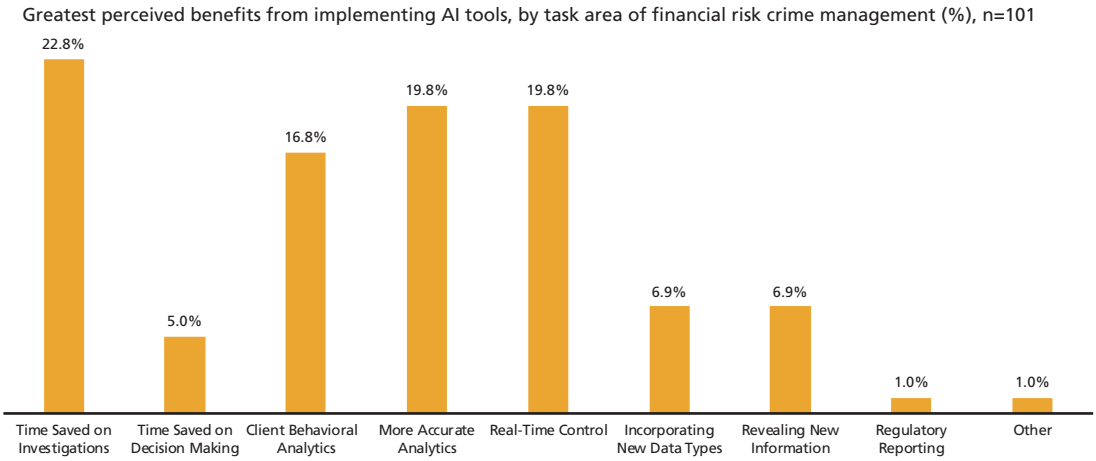
identified by our respondents, with time saving, enhanced accuracy and real-time control emerging as key drivers of adoption.

Figure 15: FCRM tasks for which implementing AI tools could have the biggest benefit



Question 18: What is the greatest area of potential benefit of implementing AI tools in a FINANCIAL CRIME RISK MANAGEMENT context? (Select one option)
Source: Chartis Research and TCS

In particular, as Table 1 outlines, certain techniques were recurring themes in our conversations with senior decision makers in this space. Our research shows that AI is now a critical component of KYC/AML systems specifically, and the overall financial crime space in general, with strong overlap into other business segments.

Table 1: Key themes in AML and KYC

Tool or technique	Overview and notes
ID management	'Defining' the customer or counterparty is absolutely central to FCRM. Whatever the underlying activity defining the customer, its bedrock processes increasingly feature a broad set of graph analytics that are leveraged to define, outline and enrich counterparty and customer profiles. In tackling payments fraud, for example, being able to link customers to specific devices is a powerful capability that relies on multi-variable time series data, creating a mapping problem that can be easily addressed using ML.
Data quality and filtering	ML and related algorithms are ideal for highlighting and remediating rapidly evolving data anomalies.
Risk profiling, risk factor analysis and optimization	Topological data analysis, cluster analysis (using embedded ML) or genetic algorithms can be used to define the smallest set of risk factors that most accurately describes a pre-specified set of customers, accounts or activities.
Graph analytics and visualization	By reformatting relationships into graphs, users can gain valuable perspectives on the interrelationships between a variety of individuals, holdings, corporate entities, devices and activities that would otherwise be invisible using standard statistical methods. Large-scale automated graph management is increasingly central to many types of financial crime analysis, including that used in payments fraud. Some firms have established components that integrate with some of the largest payment processing platforms.

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Tool or technique	Overview and notes
Alert management	ML offers greater agility in responding to screening and transaction monitoring alerts by allowing risk-based prioritization. It allows timely interventions for organizations to control and report suspicious activities.
Case investigation/ suspicious activity report (SAR) management	Case investigation is labor-intensive and can require a broad range of data sets. We note that a broad range of AI tools – such as graph analytics, NLP and ML – have been combined to provide supporting data and accelerate the process of investigation. The specific mechanics and the tools so combined differ from bank to bank, and a broad range of investigation accelerators have and are being explored.

Source: Chartis Research

4.1.2 FCRM Spotlight 2: Leveraging AI in fraud risk management

While it is often identified as a FCRM activity, in organizational terms much of the fraud analytics conducted by banks is often part of other overarching retail banking processes (see Table 2).

Table 2: Value generated from the use of AI in different fraud analytics contexts

Element of fraud analytics	Value generated
Pattern recognition and predictive modeling	Pattern recognition and predictive models link behavioral patterns to specific properties and parameters. These models can often be high-multi-parameter* in nature, and are ideally suited to ML-style approaches. Generally, ML-oriented models work better when long sequences of multi-variable data are available (one example is in device reputational analytics, which can be a component of fraud risk measures).
Segmentation analytics	Segmentation analytics can help extract and divide core data into parametrically homogenous segments to generate behavioral patterns by looking at segment-membership patterns over time.
Risk profiling and risk appetite definition	In this context, AI dynamically extracts and generates risk profiles and risk appetites for all clients (i.e., internal *and* external).

** Parameters are variables that can be estimated from the dataset, and which define a model and its conditions.*
Source: Chartis Research

4.1.3 Leveraging AI in other areas of the bank – reporting and non-financial operational risk management

Traditionally, quantifying operational risk has been extremely challenging. Standard statistical models have always struggled with the relative paucity of data and a lack of deep statistical processes. However, in our discussions with banks and other FIs, three key trends stood out.

- **Widespread digitalization has effectively solved the data paucity problem**. Digital platforms can now log every data element, so all communication between front-office personnel and clients, as well as trader communications, can be logged. Crucially, the state of every process can also be logged. These detailed logs can be mined to provide a rich and flexible view of the state of 'operations' over a period of time, with significant benefits to the institution. The issues and resolution data collected in this process, for example, provides a strong base on which to build powerful new process analytics, which can provide significant long-term business gains and optimization.

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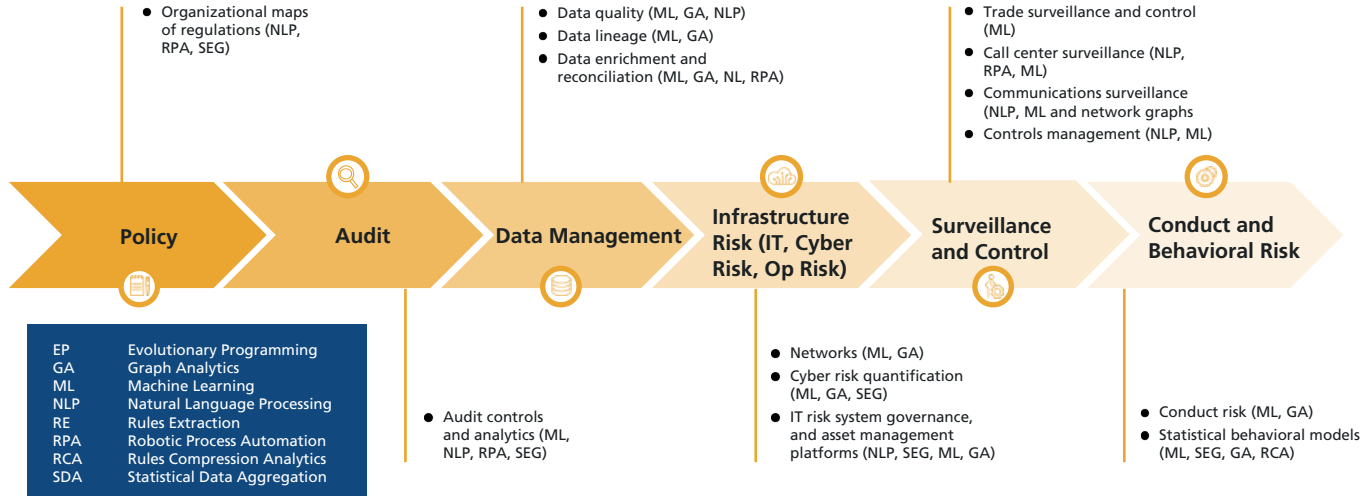
- **Equally important is the fact that external and internal networks can now be monitored in much greater detail**. This advance comprehensively addresses the data challenge that has plagued traditional models. However, it also creates a wholly new issue, since this data is not in a traditionally structured form and can instead exist as text, charts, images, voice files and other formats. As a result, firms need a powerful new set of analytical methods. This, we believe, is a key factor driving virtually all institutions to increasingly (and in some cases aggressively) leverage AI in their risk and compliance processes.

- **There are broad uses for AI in non-financial and operational risk management contexts, although one-quarter of respondents are not engaged**. Of the three-quarters of respondents in non-financial and operational risk management contexts who see uses for AI (see Figures 16 and 17), operational risk management and cybersecurity were leading use cases, closely followed by GRC and model risk management. While one in four respondents (28%) did not see uses for AI in this context, clearly – for those who do – a broad range of opportunities exists.

Figure 16: Use of AI tools in non-financial and operational risk management

Question 21: In which of the following areas are you using AI tools for non-financial and operational risk management? (Select all that apply)
Source: Chartis Research and TCS

Figure 17: AI in non-financial risk (GRC, operational risk, cyber risk…)



Source: Chartis Research

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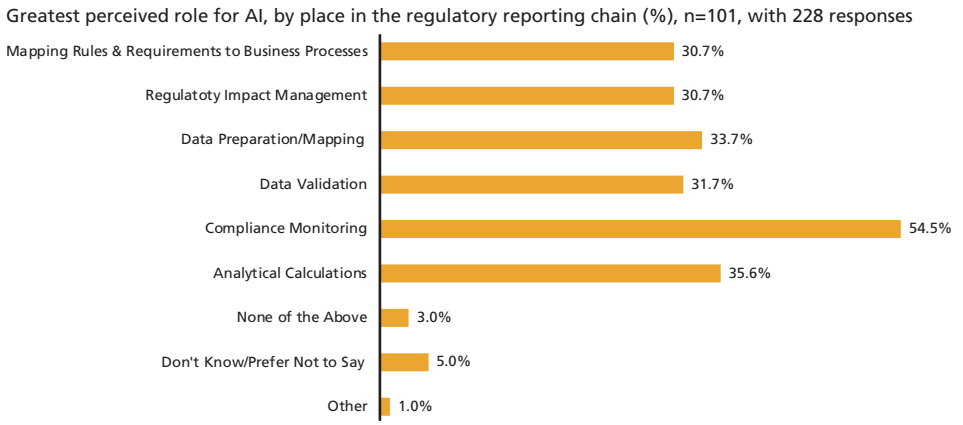
In regulatory reporting, key areas of AI use have been in managing and validating data, validating results against predetermined criteria, and monitoring overall compliance (see Figure 18). In our interviews, representatives from several large banks explained that they were now running elaborate data management and validation programs using strong ML and related analytical frameworks. This represents a significant shift and underscores the applicability of AI along the regulatory reporting value chain.

Figure 18: The role of AI in the regulatory reporting value chain



Question 20: Where in the regulatory reporting value chain do you see the greatest role for AI? (Select all that apply)
Source: Chartis Research and TCS

Relative maturity – a view across segments

Clearly AI has use cases across FS, and – as highlighted by our spotlight and exhibits above – where AI is being used, it is being applied in a targeted way. As Figure 19 shows, the majority of respondents – around two-thirds across LOBs – see use cases for AI in their businesses. Of those remaining, the majority believe it is simply 'too early to tell' whether AI is applicable in their area of the organization, again underlining the low level of maturity we are seeing across FS in general.

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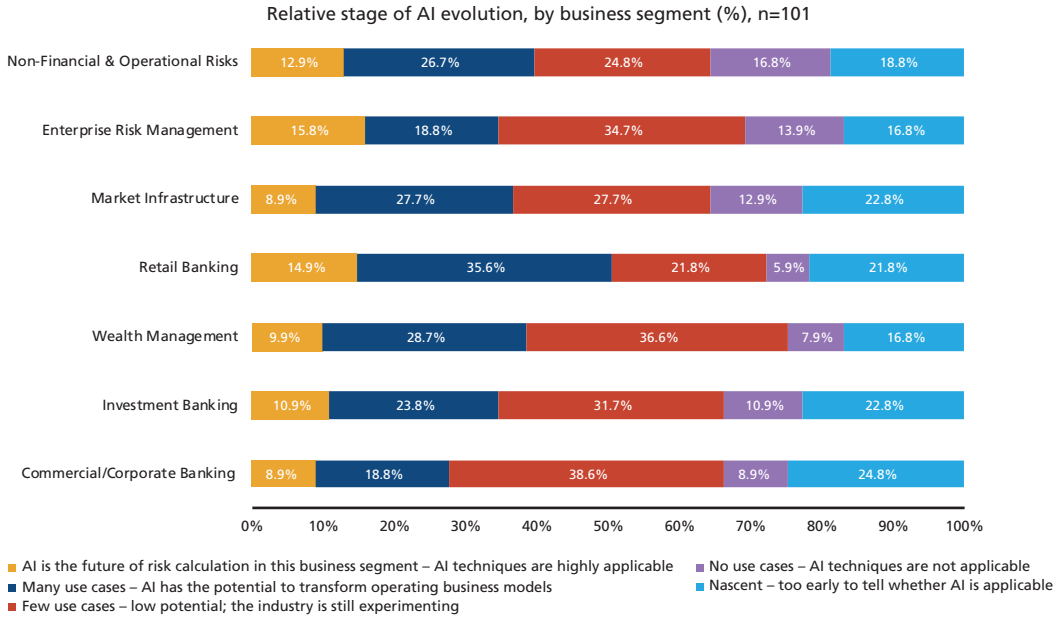
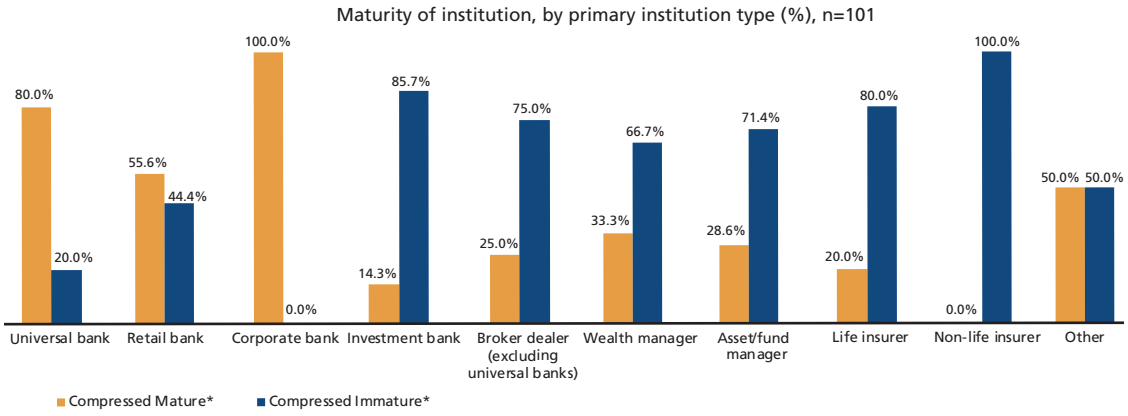
Figure 19: The evolution of AI within business segments



Question 23: Please mark the relative stage of AI evolution as it applies to each of the business segments. (In each row mark the relevant stage of AI evolution that you feel is most applicable)
Source: Chartis Research and TCS

However, when self-reporting their level of AI maturity the picture is somewhat weaker (see Figure 20). Hotspots in retail, corporate and universal banking are present, though certain industries (e.g., insurance) present themselves at a low level of adoption for risk and compliance.

Figure 20: The maturity of AI adoption by institution type



Q8. In the context of risk and compliance, how would you describe the level of maturity of your organization in relation to its adoption of AI techniques? (Select one of the following options)
** Note: for ease of analysis, sub-options within survey responses have been aggregated into two categories, 'mature' and 'immature', to show broader trends.*
Source: Chartis Research and TCS

4.2 Key sectoral dynamics

In this section, we dig into the maturity dynamics of a set of key sectors, looking at the prevailing trends and drivers in each.

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Key takeaways

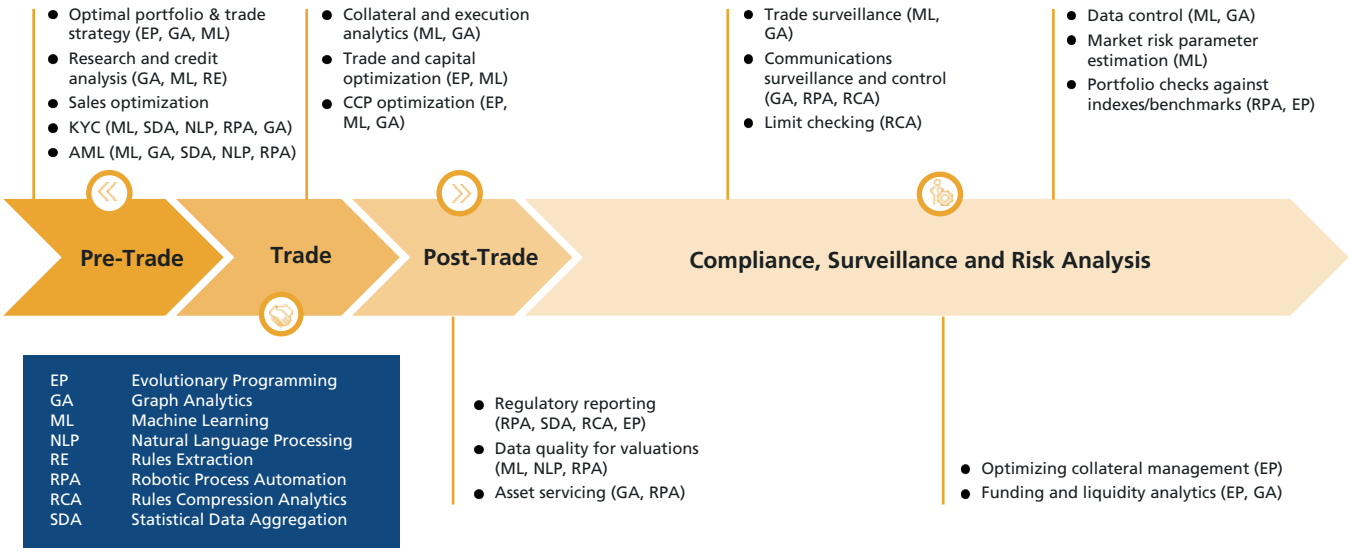
- The application of AI in retail banking has been widespread, with some structural and regulatory boundaries.
- Transformation of unstructured data to structured data has been the most successful AI use case in corporate banking.
- Use of ML has created new options in non-financial risk and analysis and control.
- AI adoption in insurance is still emerging, and some interesting use cases are being adopted.
- Application of AI in capital markets is wider than may have been anticipated. AI use tends to be more data-centric than in other areas of the FS industry.
- In the core set of traditional capital markets areas – such as forecasting, risk measurement, pricing, performance analytics, and P&L explain – the level of AI use remains relatively low.

4.2.1 Adoption and application of AI in CAPITAL MARKETS

As Figures 21 and 22 show, AI has a wider application in capital markets than some might expect, although its use tends to be more data-centric than in other areas of the financial industry. Some use cases revealed by our study include:

- NLP for corporate bonds T&C database construction.
- ML for yield curve and volatility surface anomaly detection.
- ML for yield curve construction.
- EP for portfolio construction.
- ML/EP for limit optimization.

Figure 21: AI in the capital markets value chain



Source: Chartis Research

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Figure 22: Application of different AI tools to credit models and frameworks

Credit analytics/Credit flow process	ML	GA	SE	ST	MLB
Margin analytics			✓	✓	✓
Derivatives counterparty risk	✓		✓	✓	
Credit modelling	✓	✓	✓	✓	✓
Credit portfolio management	✓	✓	✓	✓	✓
Risk-aware accounting			✓	✓	✓
Physical collateral analytics	✓	✓	✓	✓	✓
Credit trading	✓		✓	✓	
Credit-adjusted ALM and balance sheet optimization			✓	✓	✓
Retail credit scoring	✓	✓	✓	✓	✓
Behavioral analytics	✓		✓	✓	✓
Credit control and limits management	✓		✓	✓	✓

ML: Machine Learning GA: Graph Analytics SE: Simulation Engines ST: Stress Testing MLB: Market-Linked Behavioral Analytics

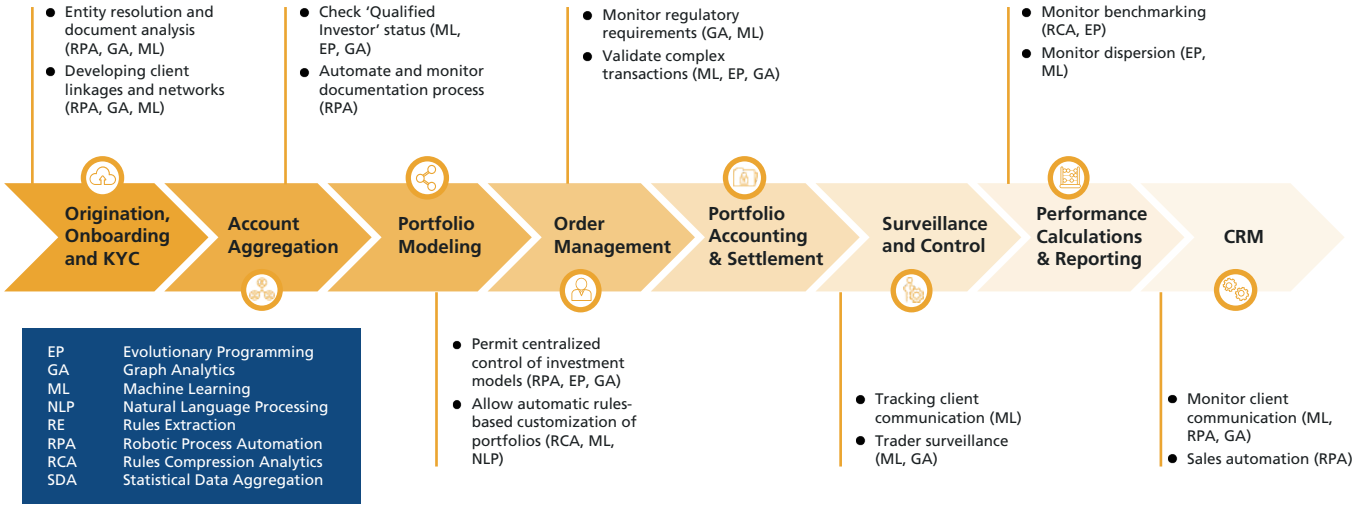
Source: Chartis Research

In the core set of traditional capital markets areas – such as forecasting, risk measurement, pricing, performance analytics, and P&L explain – the level of AI use remains relatively low. However, this seems to be largely attributable to the availability of pre-existing and well-established algorithms. We believe that the growing use of AI in algorithmic trading we have seen (as well as in the risk management of the algorithmic trading process itself) provides one example of how AI is helping to bridge this gap, easing the path for future AI adoption.

4.2.2 Adoption and application of AI in WEALTH MANAGEMENT

As mentioned before, portfolio optimization and conduct risk represent the strongest use cases for AI in wealth management. The economic case for the full application of standard portfolio optimization and analytics techniques is weak at best, opening the door for AI-based optimization, which now drives a broad range of automated and semi-automated advisory activity. As Figure 23 shows, though, AI can be embedded across the entire wealth management value chain. As maturity deepens in this area of the bank, we expect AI to expand its reach.

Figure 23: Use of AI is prevalent across the wealth management value chain



Source: Chartis Research

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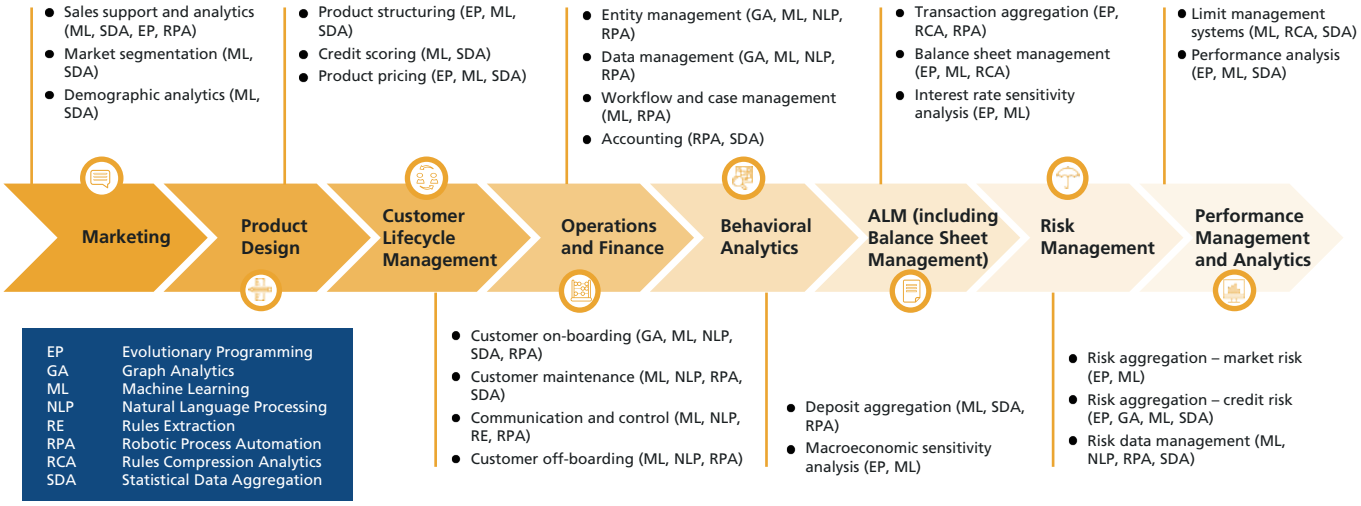
4.2.3 Adoption and application of AI in RETAIL BANKING

The application of AI in retail banking has been widespread, with some structural and regulatory boundaries (see Figure 24). Use cases we observed include:

- As a component of credit scoring.
- Client segmentation and behavioral analytics.
- Client profiling and client risk analytics.
- EP for portfolio construction.
- KYC/AML support (in segmentation and behavioral models).
- Entity resolution using a combination of graph analytics and ML.
- Customer communications management and analysis.
- Model validation, testing and scenario construction.

Figure 24: AI in the retail banking value chain



Source: Chartis Research

4.2.4 Adoption and application of AI in WHOLESALE BANKING

Unstructured data permeates the wholesale and commercial banking ecosystem, from complex contracts to varied operating processes. However, the digitalization of business processes is increasingly making the wholesale banking ecosystem amenable to AI and automation (see Figure 25). Additionally, non-traditional data is progressively playing a more central role in supporting credit analytics and other forms of risk profiling and analysis. Much of these non-traditional data sources – such as inventory data and various operating metrics/results – can then be appropriately analyzed and packaged either internally or externally (from vendor sources), using AI.

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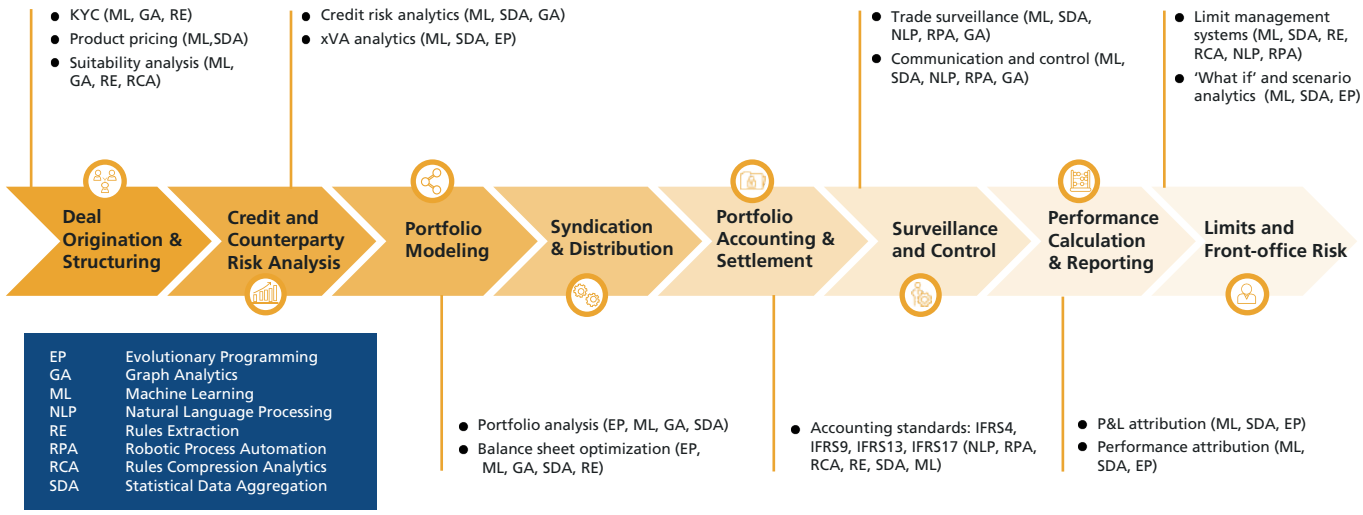
Figure 25: Use of AI is prevalent across the wholesale banking value chain

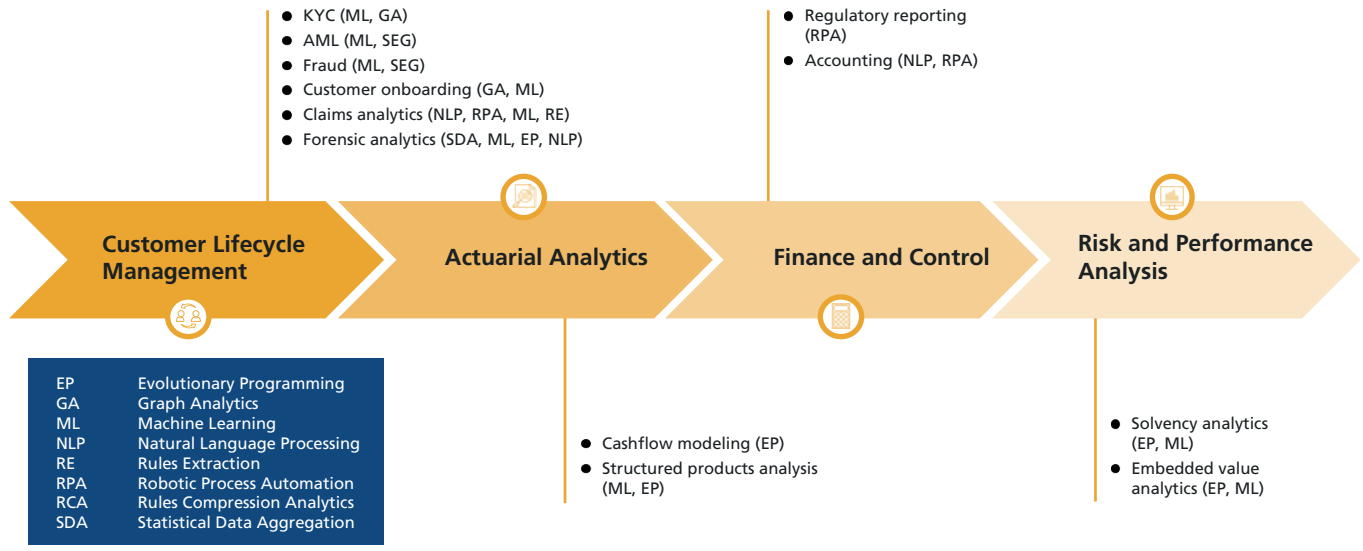


Source: Chartis Research

4.2.5 Adoption and application of AI in INSURANCE

As Figure 20 at the start of this section shows, insurance is one of the less mature segments for AI adoption in risk and compliance. The level of maturity is particularly low in the life insurance segment. In general insurance lines (i.e., property, casualty and certain classes of catastrophe, fire and marine cover), reported adoption was higher. However, the full potential of AI in data-intensive segments of the insurance industry on both sides of the insurance equation is far from being fully realized. However, despite the lagging trend, some use cases did emerge from our study (see Figures 26 and 27).

Figure 26: AI in the life insurance value chain



Source: Chartis Research

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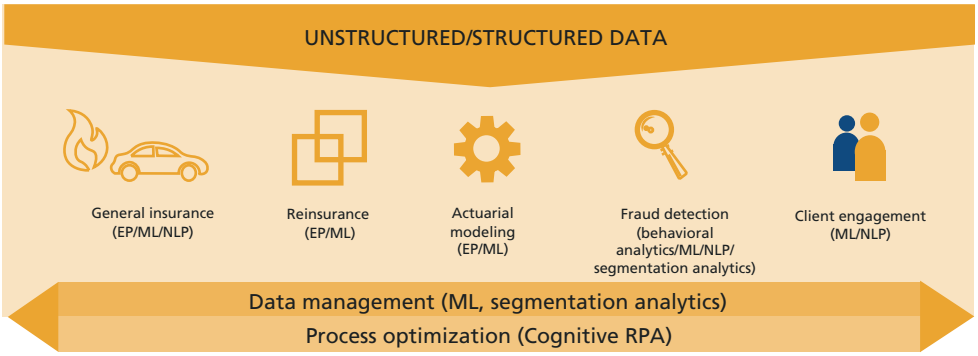
Figure 27: AI in the life insurance value chain (2)



Source: Chartis Research

- **Among life insurers, core actuarial analytics do not appear to be a significant driver for AI-based tools**. Existing statistical methods for risk modeling are already sophisticated, and AI is not a clear alternative. However, there are many potential use cases in data management, demographic analysis, multi-variable time series analysis and parameter optimization.
- **General lines are data-intensive, with operations involving many non-linear and multi-variable problems**. While several use cases already exist (such as fraud management), the full potential of this area is far from being realized, with many potential use cases to consider.
- **AI tools have had a significant impact in the area of cyber risk quantification**. Leading solutions employ AI-based risk-scoring engines. Many data vendors that provide critical pieces of the insurance analytics environment (e.g., geology, property, satellite imaging and weather data) already implement and execute a large number of AI-driven processes.

4.3 Stress testing and behavioral models: illustration of best practices in AI usage

To demonstrate best practice in action, the following section considers how ML techniques are being used to generate stress testing and scenario analysis constructs (and where they are being used). We will also investigate the wide range of use cases for behavioral modeling across FS.

Stress testing and behavioral modeling both present strong AI candidate projects and are currently experiencing success. The scope and the size of data entailed in stress testing and scenario management mean that traditional quantitative techniques have gaps and are labor- and resource-intensive. Similarly, behavioral modeling is a multi-dimensional and complex issue that is difficult to tackle with traditional quantitative techniques.

However, behavioral modeling projects can fall foul of the level of regulatory incidence that would make them low-risk projects. Consequently, current behavioral modeling projects are used to inform decision making or risk quantification, especially in ALM in retail banking. They are not leveraged in areas of direct interaction with the regulator or used as the decisive factor in a decision-making process. As candidate AI projects then, both stress testing and behavioral modeling can be used to illustrate best practices.

4.3.1 Stress testing and ML

Stress testing and scenario management are multi-dimensional and multi-variable processes. The core data management area of stress testing (i.e., setting up time series, managing and storing scenarios, replaying scenarios, etc.) is, from a methodological standpoint at least, the most stable. However, for

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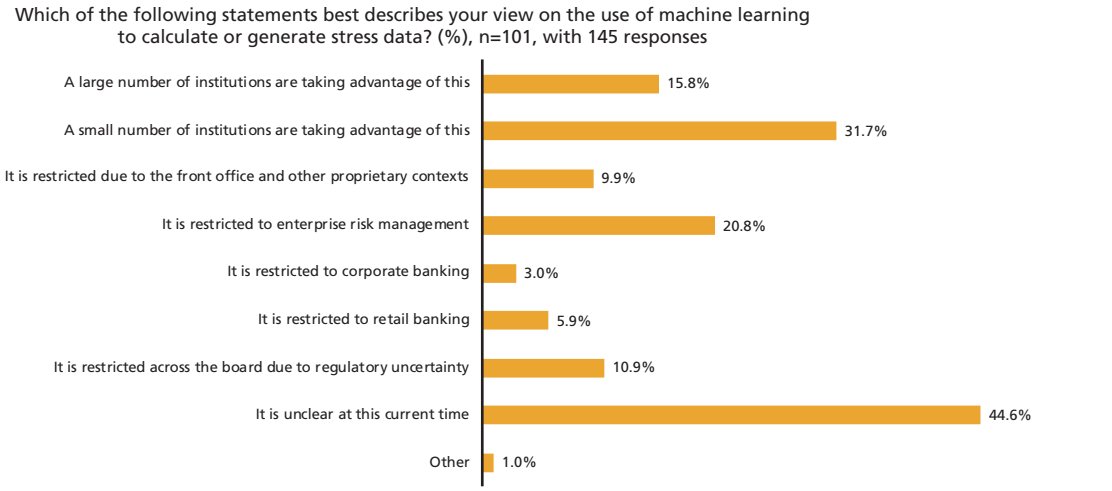
almost half of respondents to our survey (about 45%) the uses of ML for generating stress data remain 'unclear' (see Figure 28).

Figure 28: Calculating stress data using ML is an emerging area



Question 19: Which of the following statements best describes your view on the use of machine learning to calculate and/or generate stress data? (Select all that apply)
Source: Chartis Research and TCS

However, the correlation of risk factors, indices and benchmarks, and the construction of specific scenarios, are far less methodologically stable and are highly context-specific, depending on whether a scenario is stress testing for a retail environment, or for wholesale over the counter (OTC) derivatives trading. Figures 29 and 30 show some of the most powerful ways in which AI can be used to enrich the stress-testing process.

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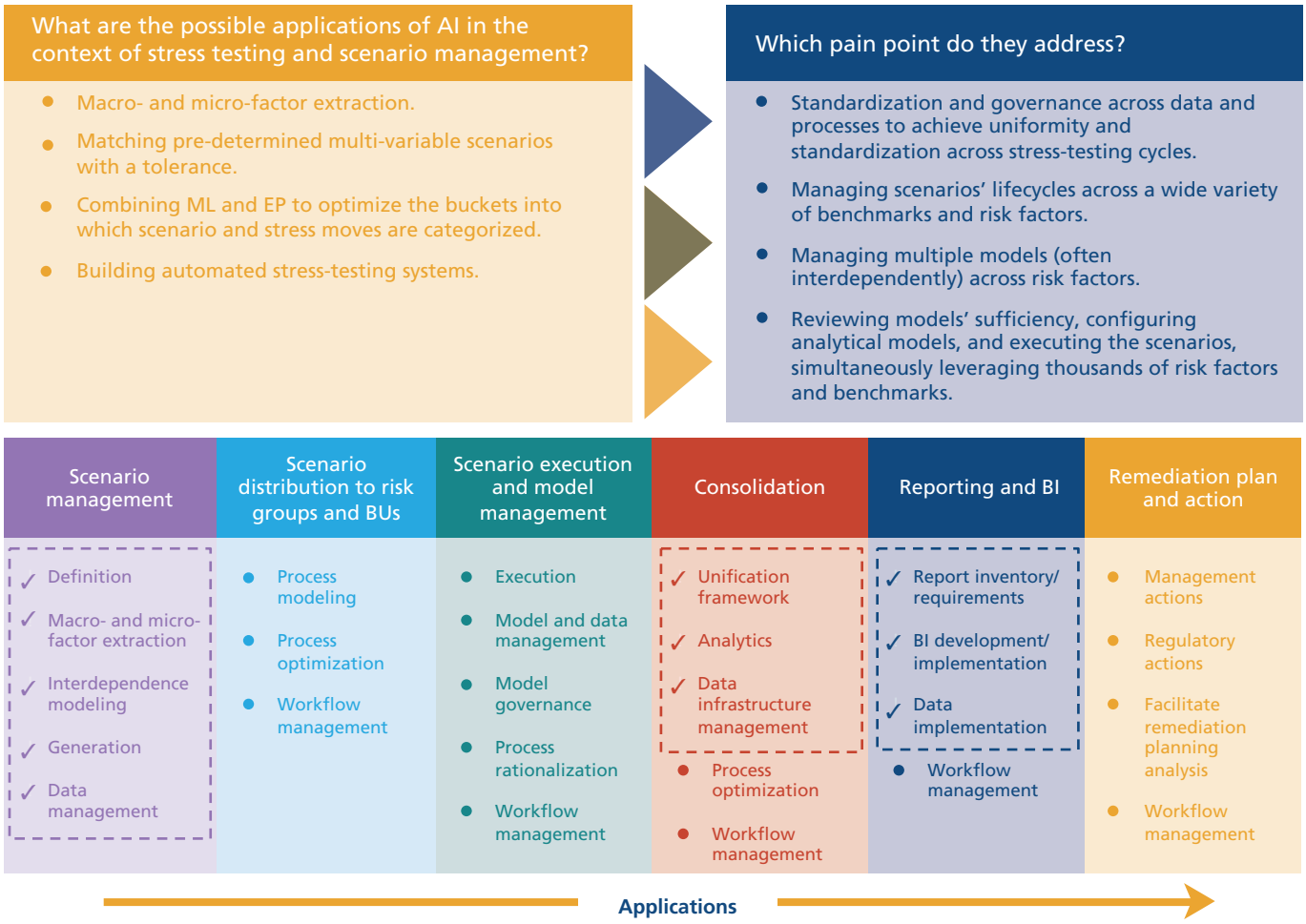
Figure 29: Core areas of potential AI usage in stress testing and scenario management



Source: Chartis Research

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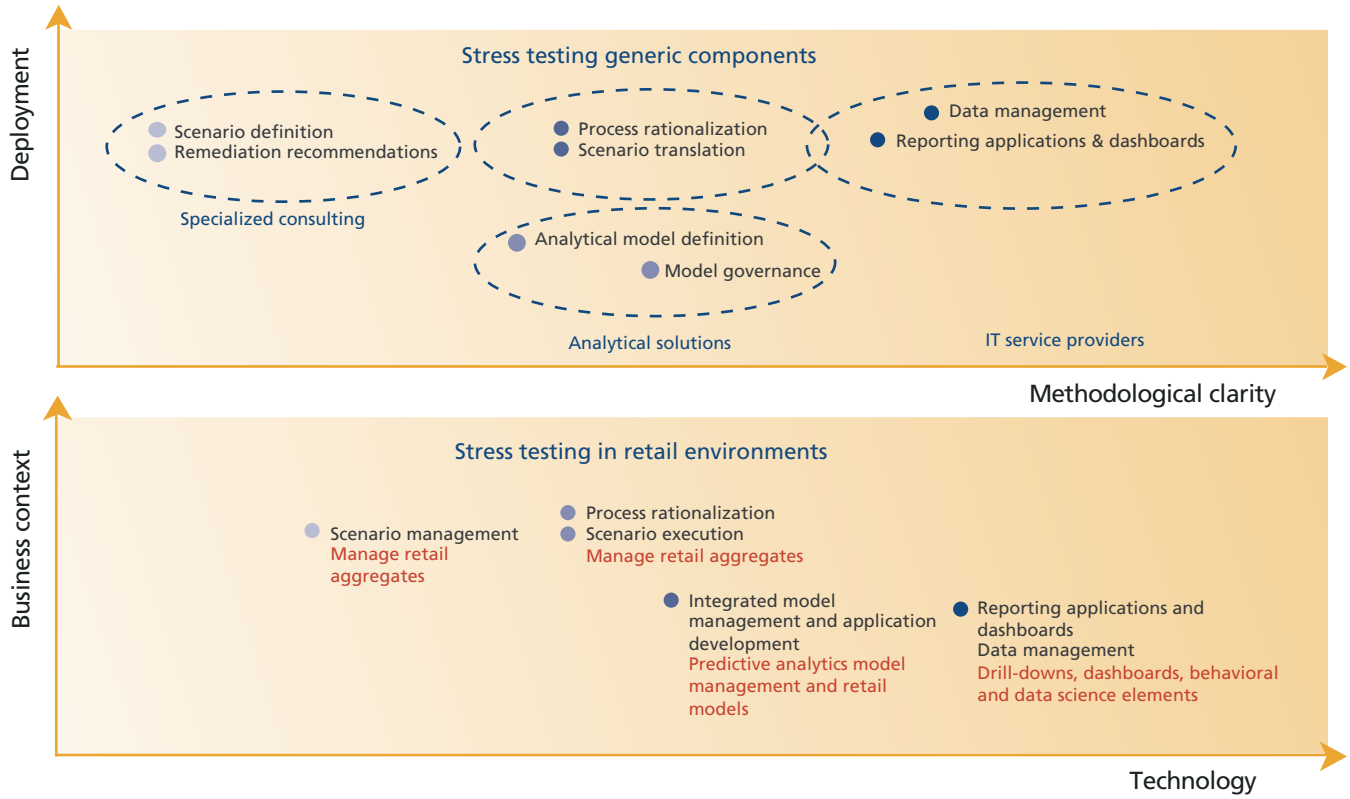
Figure 30: Stress testing and scenario management are multi-dimensional and multivariable processes



Source: Chartis Research

4.3.2 Behavioral models

FIs also need to model and analyze the behavior of customers and counterparties in a wide variety of contexts. When counterparties are wholesale entities, they are generally governed by economic rationality, and this is reflected in their market behavior. This approach is often the exception, however, especially in the case of retail customers, which have to link customer behavior to a variety of variables that typically include interest rate history, credit environment and macroeconomic variables.

A good example of where AI is being used for behavioral modeling is in the banking book.

- Banking books contain numerous implicit options, such as prepayment options on mortgages, borrowing options and early withdrawal options.
- These options may be exercised in response to changes in market interest rates, and as a result they induce (non-linear) interest rate risk or 'optionality'.
- The introduction of optionality is difficult to cope with in managing the asset/liability of retail products. To contend with retail customers' wide diversity of behaviors when exercising their options, FIs must develop behavioral models, which allow them to transform data about behaviors and interest rate movements into patterns they can analyze.

Table 3 shows several AI use cases for behavioral modeling.

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Table 3: Use cases for behavioral modeling in FIs

Context	Overview
The banking book: interest rate risk management	A bank's interest rate exposure (highlighted most dramatically by retail mortgages in the US) is determined by the prospective behavior of its customers. The relationship of interest rate levels to customer behavior (such as prepayments, break deposits, currency switches or the exercise of optionality) is rarely a strict correlation.
The banking book: credit risk management	Customer behavior that affects interest rate risk also affects credit risk, as the life of assets is shortened or lengthened.
Financial crime (KYC, AML)	Banks categorize customers based on the way they behave (how long they take to execute a transaction, for example).

Source: Chartis Research

These behavioral models are essential for ALM, for several reasons. They are useful for risk managers in performing dynamic analyses of future cash flows and estimating the likely path of future net interest income according to various financial scenarios (including stress scenarios). Moreover, sound behavioral models are critical for hedging interest rate risk. From the perspective of future accounting and reporting regimes, banks need to mark-to-market their banking books for compliance. Finally, behavioral models are vital in the development of sound funds transfer pricing (FTP), to spread economic value-added commercial incentives across all business units. FTP can improve ALM, while traditional structural models are often entrenched and intractable.

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5. Developing leading practices and a future roadmap

Building on our survey findings, our interviews and our detailed view of the evolving landscape, in this section we outline the AI journey ahead. The journey is informed by the best practices we have identified, as well as our observations of the wider market and the evolution of AI in different industry contexts. We find that there are different options, choices and pathways to maturity, and this section is split into five key areas:

- Best practices.
- The path to success.
- The future of AI.
- Building optimal organizations and measuring success.
- Looking forward: what is the broad picture emerging from this study?

Interview quotes

- *'Data scientists have to become bankers quickly.'*
  COO for Risk, large global private bank and asset manager
- *'Understanding all the data and other paraphernalia surrounding our existing analytics is critical to integrating deep learning into trading systems.'*
  Head of Trading, large European universal bank
- *'Understand your data.'*
  Senior IT professional, quant hedge fund
- *'Model-free hedging and pricing is not "math" free.'*
  Retail bank quant, global universal bank
- *'There are many areas of quantitative support that need to be addressed before we get to the truly hard, and possibly impossible, questions - such as market forecasting.'*
  Asset manager across multiple investment styles (predominantly hedge funds)
- *'Success in applying AI is building on the foundations of available ideas and technologies, not an exploration into the unknown.'*
  Head of Risk IT, large European universal bank

5.1 Best practices

Our research has uncovered six leading practices for firms to consider.

- Having a data science team does not preclude the requirement for the risk management team and other existing quant teams to develop solid methodological perspectives on AI tools (specifically ML, deep learning and segmentation).
- FIs should have a strong initial focus on data-intensive projects, avoiding projects with a very strong regulatory incidence.
- They should also focus on ML/deep learning projects that lack a strong alternative tool (such as cyber risk analysis and behavioral analysis).

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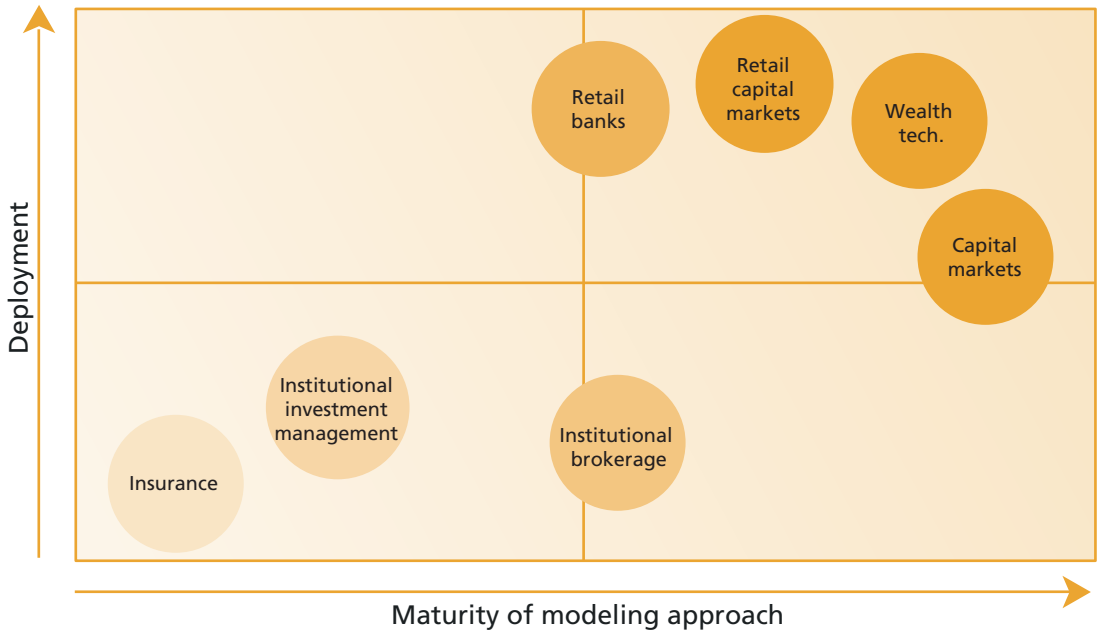
Rather than focusing on reducing full-time equivalents (FTEs), FIs should focus on efficiency gains, gaining additional insights, and initializing tasks such as credit scoring and data management for analytically intensive applications (which may in some cases result in FTE reductions).

- Organizations are leveraging risk and compliance-focused innovation labs to drive AI-led development.
- CROs are looking to leverage cross-industry best practices, especially in the areas of GRC, compliance management and conduct risk management, to maximize outcomes and accelerate the adoption of AI.
- A particularly effective approach for a CRO's office is an agile one, which includes the processing of rapid proofs of concept with clear and well-defined outputs and benchmarks. Subsequently, proofs of concept can be transformed into fully fledged implementation programs. An agile strategy ensures that the concept and approach is validated through rapid and flexible development.

Figure 31 gives a detailed overview of the maturity and use of analytics across industry sectors including retail banks, wealth managers, corporate banks, capital markets institutions and insurers.

Figure 31: Maturity of modeling approach



Source: Chartis Research

5.2 The path to success

5.2.1 Creating a unified and coherent approach

Fundamental to the successful adoption of AI is an FI's approach to using both traditional quantitative tools and AI tools. FIs already employ vast numbers of quantitative tools, some of which can be replaced by AI tools and processes. Their challenge now is to determine whether quant tools can be significantly and efficiently improved by replacing a traditional quantitative technique with an AI equivalent. For example, in cases such as applying early warning signals in the credit lifecycle of a retail bank, AI tools are implemented to *support* existing analytical methods.

Hype around AI has also propelled investment in areas across FS, and realistic practical applications are now emerging. In the race to invest, however, many FIs are taking an ad hoc approach to applying AI tools. A 'bottom-up' approach is not necessarily successful, especially in selecting the best tool for the

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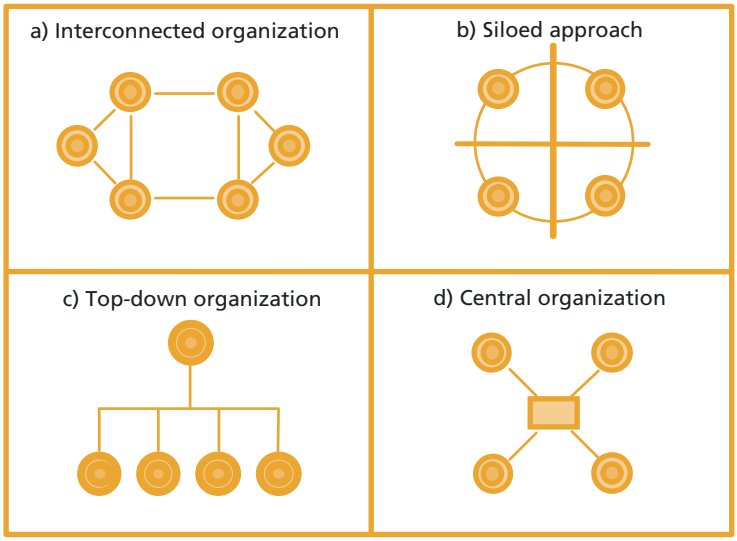
job. Rather, FIs will often opt for tried-and-tested, traditional quantitative techniques. In contrast, FIs with relatively successful AI implementations take a 'top-down' view, putting a strategy in place, and viewing the application of AI tools as a path to maturity.

One effective strategy for FIs is to begin their AI journey with low-risk applications, such as estimating whether a volatility surface is fair and accurate from a pre-trade analytics perspective. FIs can build on their increasing effectiveness and experience in these application areas. In time, they should put coherent strategies in place so they can eventually expand their AI footprints into more complex areas (such as predictive forecasting and time-series analytics).

Figure 32 illustrates the different types of organizational structure we looked at, identifying different levels of centralized development and analysis across these types of organization.

Figure 32: Organizational structure, development and analysis



Source: Chartis Research

5.3 The Future of AI

In this section we introduce a roadmap of what organizations should do, how they should develop and select projects, and what the key drivers of success are. We also highlight the evolution of AI in different business areas (such as retail banking, commercial banking and capital markets), as well as the broader evolution of AI applications overall.

Additionally, in this section, we also aggregate and expand on the CRO perspectives we have gathered as part of our analysis. In describing the current state of AI in risk management and providing an investigation into its future, considering the position of the CRO's office is vital. Its unique context, including its interactions with regulatory restrictions and its quantitative background, makes the office key in any discussions of AI in risk management. Having done this, we conclude our analysis with recommendations for *optimal* AI development strategies, and provide key takeaways.

5.3.1 The AI adoption roadmap – steps to success

Our AI Adoption Roadmap (see Figure 33) outlines the key milestones on the path to digital maturity in AI for risk and compliance, outlining the broad picture emerging from our study.

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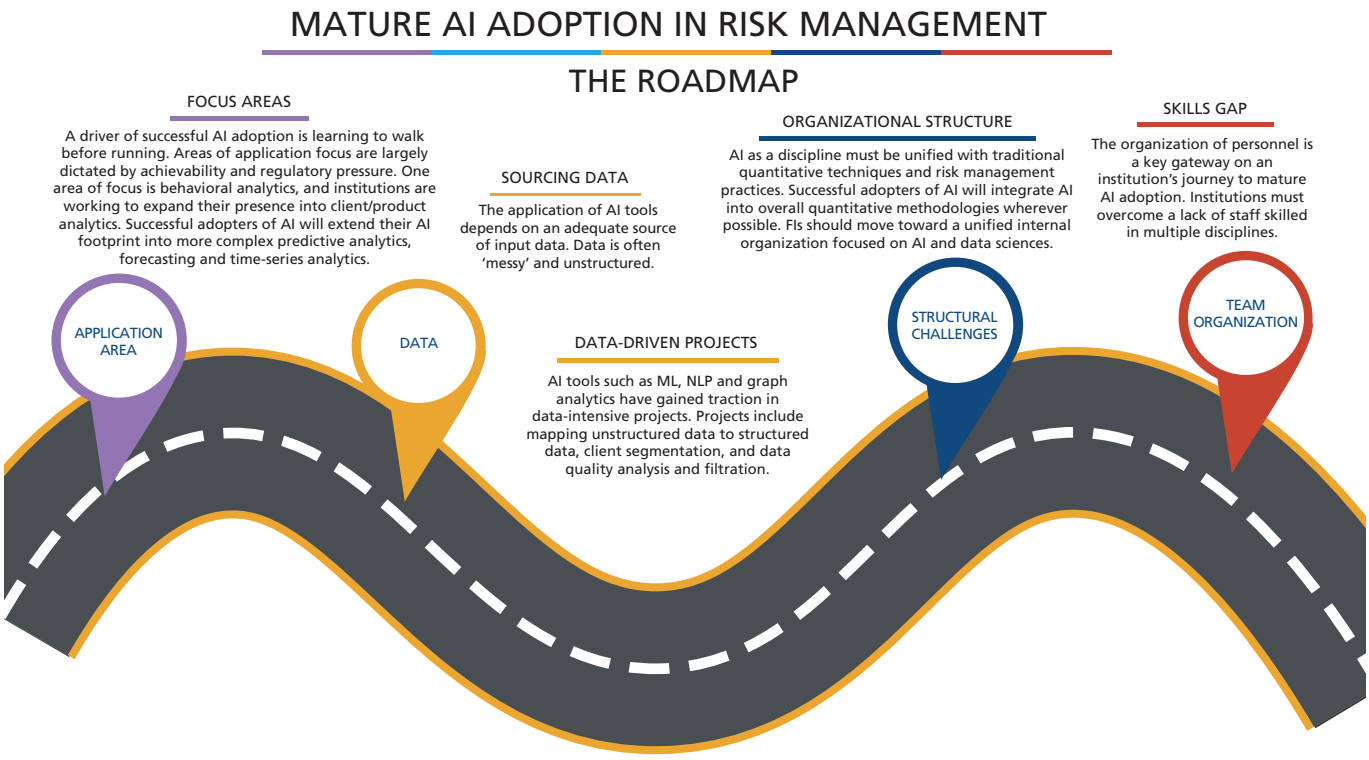
In formulating the map, we noted the following factors:

- AI tools and techniques (including ML, NLP and graph analytics) are used in data-intensive projects to map unstructured data to structured data, carry out client segmentation, and analyze and filter data. This provides a relatively solid base of initial projects with a low risk of failure, which is important, since the success of projects improves the credibility of AI techniques within an organization.

- Off the back of such successes, an FI's AI footprint can be expanded into more complex predictive analytics, forecasting and time-series analytics, with a focus on areas such as behavioral analytics and an expanded presence in client/product segmentation analytics. These areas (especially behavioral analytics) have shown significant success.

- In addition, wherever possible, AI should be integrated into an FI's overall quantitative methodology, to create a unified internal organization focused on AI and data sciences.

Figure 33: AI Adoption Roadmap



Source: Chartis Research

5.3.2 The future of AI: the CRO perspective

Our research reveals a dominant perspective among CROs around the evolution of AI applications. A broad consensus has emerged that AI adoption is an iterative, multi-dimensional and multi-disciplinary activity. During an interview, one CRO of a UK-based global bank described AI adoption as *'…simultaneously learning Japanese, juggling and solving a Rubik's Cube'*.

Most respondents identified greater theoretical clarity and terminological exactitude as the key steps in the future evolution of AI adoption in their institutions. They also broadly agreed that the early stages of AI adoption are characterized by vague conceptual projections and unrealistic formulations. Nevertheless, both traditional quant teams and data science-oriented teams have progressively developed a greater

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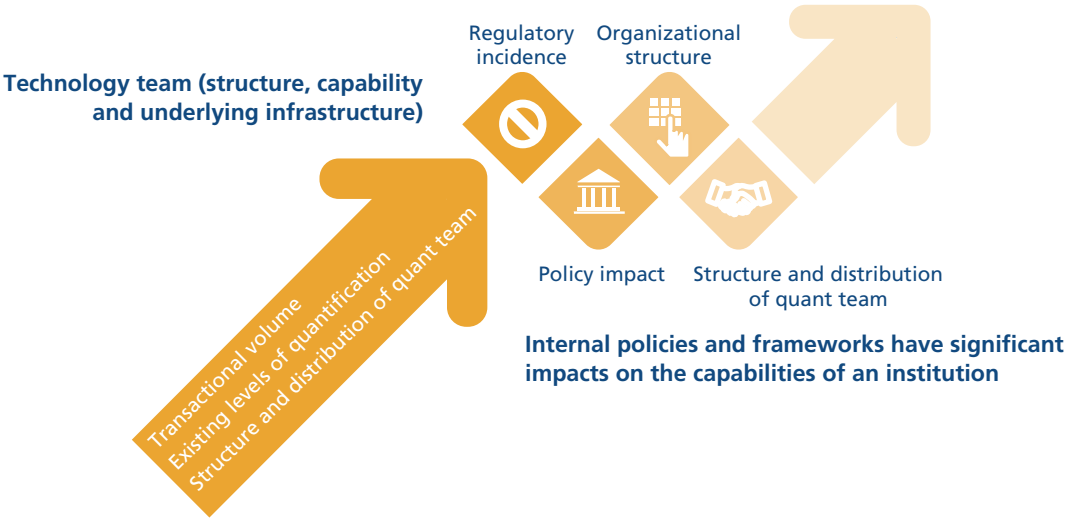
theoretical and mathematical understanding of AI terminology. Moreover, a better understanding of the theory of different ML techniques, and how they apply to specific problems, is emerging.

Improvements in knowledge are coinciding with a push to translate and standardize terminology. AI terminology often derives from its development in the pattern-recognition or image-processing industries, and it needs to be adapted to the particularities of the specific financial problems being addressed. There has been a wave of research around how deep learning techniques 'learn', and how they develop functional approximations. These are now being applied to specific areas, such as foreign exchange (FX) options pricing, collateralized debt obligation (CDO) construction, pre-payment modeling, economic scenario construction, ALM, and funds transfer pricing. Developing this 'theoretical scaffolding' is seen as one of the most powerful drivers of future AI use in areas such as enterprise risk management, capital markets and trading, and asset management.

The evolution of AI in risk management is multi-dimensional and driven by many different forces. And so, while this scaffolding (outlined in Figure 34) is still developing, there continues to be rapid growth in AI adoption for data management across the board. In specific areas such as behavioral modeling, stress testing and model validation (e.g., alternative functional approximation, extraction of macro and micro scenarios, etc.), the underlying complexity, inherent non-linearity and multi-variable nature of the core problem space has ensured that adoption continues apace, even as construction of the theoretical frameworks continues in parallel.

Figure 34: The evolution of AI in risk management is multi-dimensional and driven by many different forces



Source: Chartis Research

5.3.3 Different paths to maturity and varying evolutionary trends

As previously noted, adoption of AI depends on many variables, most of which we have discussed in this paper. These include the nature of business, specific business lines, geography, the regulatory incidence of particular activities, and organizational structure.

On geography, for example, high-maturity institutions are currently concentrated in the Western markets of Europe and North America (NA), where the majority (52% in Europe, and 68% in NA) are classed as mature (see Figure 35).

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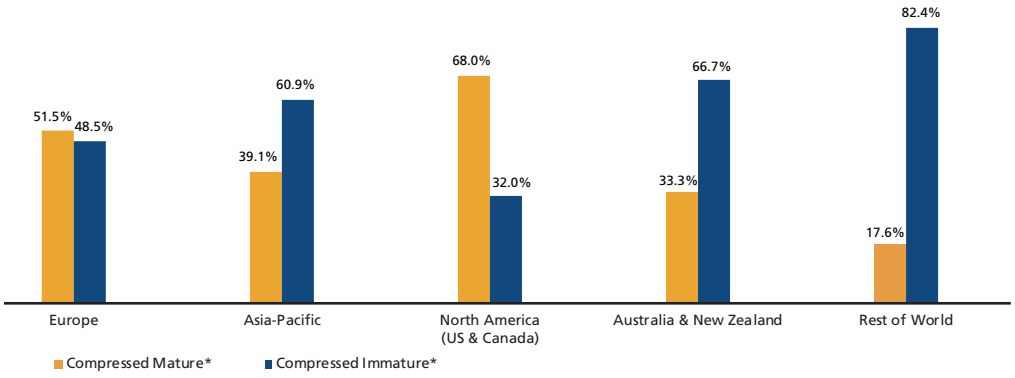
Figure 35: Maturity of AI adoption for risk and compliance, broken down by geography



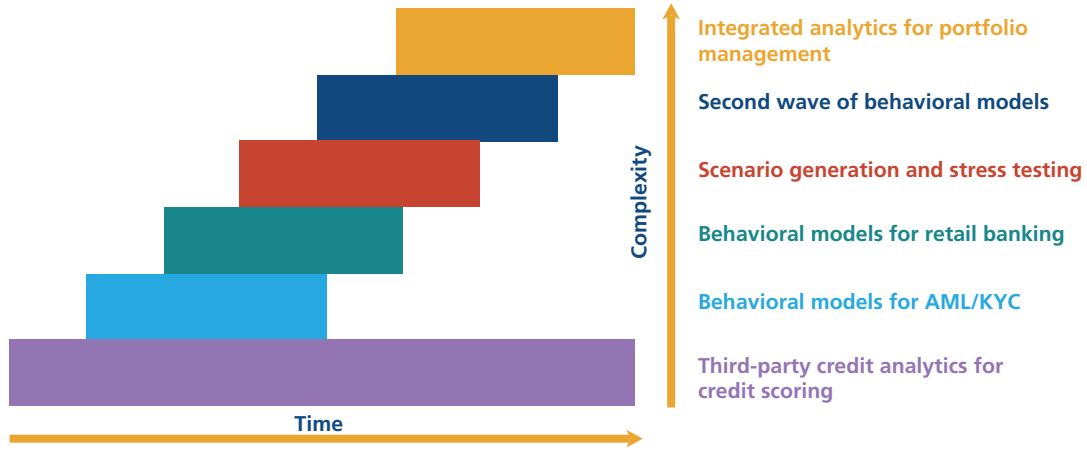
Question 8. In the context of risk and compliance, how would you describe the level of maturity of your organization in relation to its adoption of AI techniques? (Select one of the following options)
** Note: for ease of analysis, sub-options within survey responses have been aggregated into two categories, 'mature' and 'immature', to show broader trends.*
Source: Chartis Research and TCS

This multi-dimensionality makes building a single map of the future evolution of the landscape particularly hard. Below we provide a few perspectives on how AI in risk management will proceed in various dimensions (by business line and geography, for example), and how the underlying enabling technologies will evolve as a result. This underlying *enabling* technology is perhaps in many ways the most powerful reason for the growth – or rather the regrowth – of AI.

Looking at specific segments and areas of application, we see a consistent shift into more complex solutions. In the next few pages we will look at the evolutionary direction of travel for AI in capital markets and retail and commercial banking, as well as in the broader areas of analytics and technology.

- **Retail banking**. Credit scoring and other third-party analytics (e.g., leveraging neural networks and other AI techniques) have been in use by retail banks for a relatively long time (see Figure 36). We increasingly see an evolution toward behavioral models and scenario generation, with fully mature organizations looking to leverage AI in broader enterprise-wide contexts, integrating behavioral and segmentation models into portfolio optimization and product pricing.

Figure 36: Evolution of AI in retail banking



Source: Chartis Research

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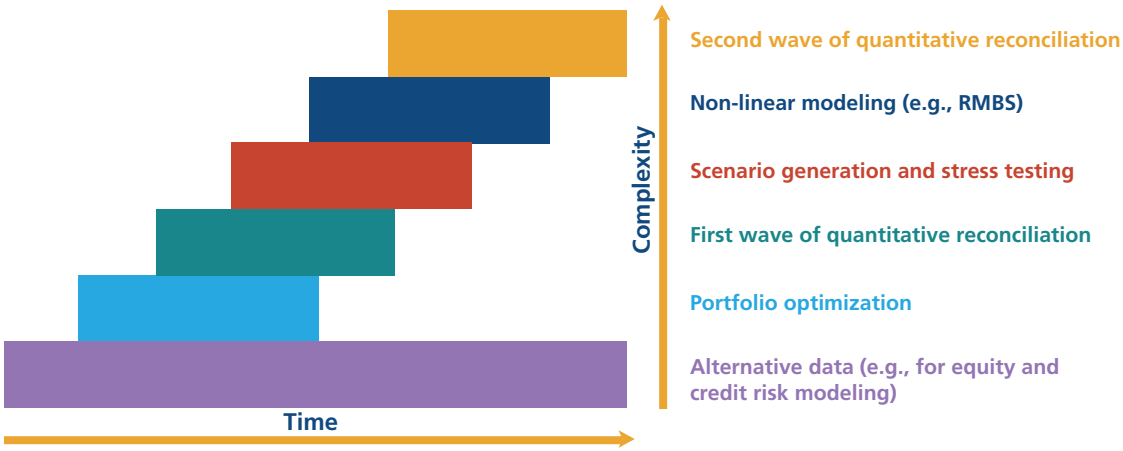
- **Capital markets**. AI is widely used in a range of capital markets contexts (such as NLP for corporate bonds T&Cs database construction; ML for yield curve and volatility surface anomaly detection and yield curve construction; EP for portfolio construction; and ML/EP for limit optimization. There are broad applications in other areas too, such as model validation, testing and scenario construction. And with maturity relatively low in this space, there is great potential to deepen and broaden it as the sector continues to evolve (see Figure 37).

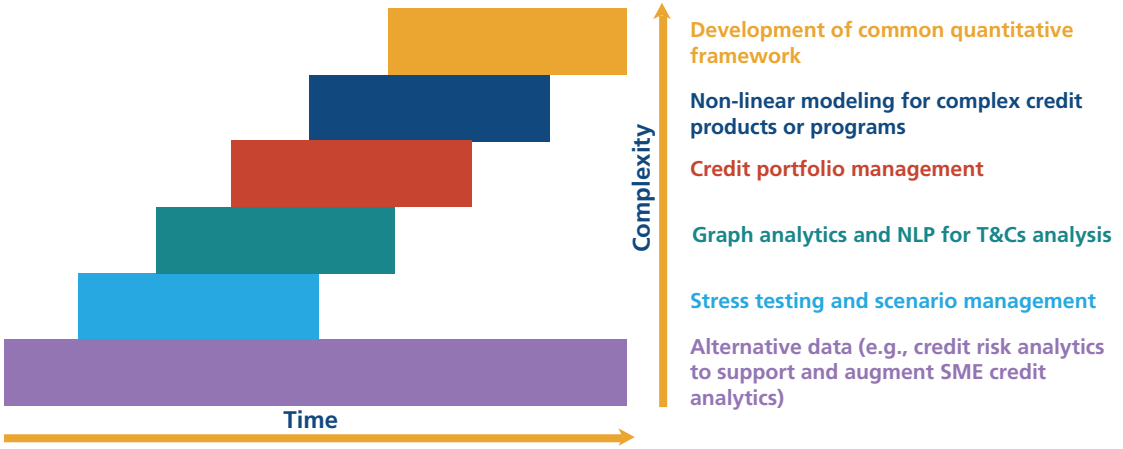
Figure 37: Evolution of AI in capital markets



Source: Chartis Research

- **Commercial banking**. The most significant challenges to AI usage in commercial banking come from its relatively less structured data management ecosystem. Much of the data used in decision making in commercial banking LOBs, is embedded in complex documents. However, these documents are now being digitalized and are becoming more accessible. Benchmarks, credit curves and related data are less well structured. However, the impact of new accounting standards in this area has been profound. Credit portfolio management practices and fees are also being transformed in a fundamental way. New passive strategies have very low fees and require high levels of automation in order to make a profit at scale. At the same time, they are far more mathematically tractable. In contrast, the more labor-intensive SME banking segment is often a target for AI-led automation. Meanwhile, applications in other areas, such as model validation, testing and scenario construction, forge ahead, although data challenges still persist (see Figure 38).

Figure 38: Evolution of AI in commercial banking



Source: Chartis Research

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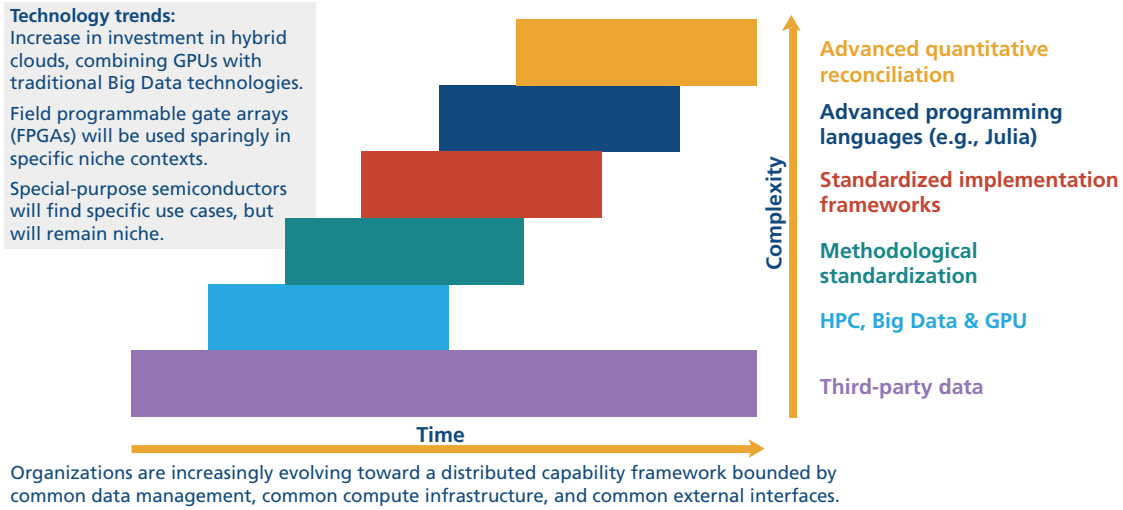
- **Analytics and technology**. Looking across analytics and technology as a whole, we see third-party data as a constant, with a steady shift toward more advanced methods (see Figure 39). One of the more standout results of our study was the investment put into 'quantitative reconciliation' to create single consistent quantitative frameworks. These combine standard pricing and analytical models in every business (e.g., derivatives pricing from the OTC derivatives/Fixed Income Clearing Corporation [FICC] group, or retail credit scoring from the retail banking group).

Figure 39: Evolution of AI in analytics and technology



Source: Chartis Research

Figures 37 and 38 highlight a key factor: the ongoing importance of alternative data in supporting core analytical functions. As previously noted, ML and other AI frameworks are used extensively for preprocessing unstructured data into structured data.

5.3.4 How do respondents (including CROs) view the evolution of AI applications?

Key takeaways

- AI will be increasingly integrated into FIs' risk management methodology and regulatory compliance, and in the long term it will become an integral tool in an FI's risk management framework.
- The rise of AI in risk management promises to provide new insights derived from behavioral analytics and segmentation.
- AI tools must be rigorously analyzed and data consistently managed, and all computational methods require a considered assessment of their validity, consistency and 'explainability'.
- No single algorithmic change will solve the explainability issue. But a deep understanding of the suitability and nature of data is vital to explainability.
- Data management will continue to be a strong area of AI use.
- There is an urgent need for a theoretical reconciliation between traditional pricing, modeling and risk analytics, and new AI-oriented statistical approaches.

AI will be increasingly integrated into an FI's risk management methodology, and in the long term it will become an integral tool in an FI's risk management framework. The rise of AI in risk management

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promises to provide new insights derived from behavioral analytics and segmentation. It will also provide automation and simplification in the areas of data management, stress testing and scenario generation, as well as a new methodology for complex, multivariable problems and non-linear optimization.

However, integrating AI into risk management brings new challenges that demand careful attention and consideration.

Tools must be rigorously analyzed and data consistently managed, and all computational methods require a considered assessment of their validity, consistency and 'explainability'. As tools are increasingly adapted for risk management, FIs must not underestimate the emerging challenges and risks in the area of governance. In the longer term there will necessarily be increased collaboration between institutions and regulators around methodology and best practices. Specifically, this will be around how to increase the explainability of AI tools, as well as the need for sound model validation techniques, and ensuring that governance and controls are applied properly.

However, there is still widespread confusion around 'explainability', which is not a 'silver bullet'. No single algorithmic change is going to make AI explainable. Indeed, as for all statistical processes, a deep understanding of the associated data, its distributions and boundaries, is essential. Certain types of AI work poorly with certain kinds of data, for example. Ensuring that there is a complete understanding of the data itself is the best starting point for *all* explainability. However, of equal importance is carefully structuring the problem so that intermediate results can be generated to provide an intuitive understanding to end users, as well as checkpoints where end users can validate their intuition.

From a capital markets perspective, there is also a broad consensus among CROs that data management (including the consumption of internal and external alt-data) will continue to be a strong area, both now and in the future. There is also a perception that, regardless of how AI is applied in other contexts, its application in data management will continue to grow and expand.

The range of unstructured and semi-structured data out there is very large and very broad. Additionally, even structured data sets (e.g., indices, credit curves, volatility surfaces, etc.) can provide an analysis space so vast that no human can conceptually handle its variety and complexity. Equally, it is obvious now that the vast majority of the instruments traded in the markets are inherently non-linear and multi-variable, with a complex mapping structure that is amenable to ML. This means that conventional models can be improved upon (e.g., in pricing options on illiquid assets in fixed-income markets).

However, conventional frameworks have great explanatory power and are embedded in the way that risk modelers think. They also form a fundamental structure for the interaction between risk and business (i.e., trading and sales). This is creating an urgent need for a theoretical reconciliation between traditional pricing, modeling and risk analytics, and new AI-oriented statistical approaches.

As Figure 36 above showed, the perception of AI's evolution in retail banking is somewhat different. The general overall view is that, in many cases, AI is already there and ubiquitous. Often these AI processes are embedded in the data and analytics that institutions acquire from external sources, leveraging AI techniques (such as third-party credit scoring). As previously noted, we found very good reasons to leverage AI in areas such as behavioral analysis, which in turn furnish the bedrock of a wide range of analytics (including portfolio analytics, fund transfer pricing and fraud analytics), fraud modeling, risk profiling, and risk-adjusted asset pricing.

Overall there is the general perception that the rollout of AI techniques in retail banks is less constrained by methodological challenges as by a shortage of resources and, to a much lesser extent, by regulatory uncertainty.

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5.4 Building optimal organizations and measuring success

5.4.1 How will organizational structures evolve?

Key takeaways

- There is a consensus that institutions should have a dedicated data science team in addition to existing quant teams. How these teams should be structured and staffed remains contentious.
- Whether they are principally technology-driven or multi-disciplinary, they should be led by a core with strong risk experience.
- There is little agreement on whether teams should be spread across the institution or driven by individual business lines.
- The overall focus on methodological reconciliation between traditional techniques will drive decentralization, as well as a sharper focus on specific areas. This in turn will also drive different technology requirements, scalability and trade-offs.

Organizational structure across banks varies widely; however, there are some powerful forces driving standardization. The answer to the question of whether institutions should have a dedicated data science team in addition to their existing quant teams is a broad 'yes' but, despite this consensus, there remains considerable disagreement about how these teams should be structured and staffed.

Some institutions believe they should be principally technology-driven, while others believe they should be highly multi-disciplinary. However, while there may not be consensus on the structure, there is a growing consensus that they should be led by a core with strong risk experience.

On the issue of whether teams should be spread across the institution or driven by individual business lines, we felt that there was no real consensus here. Much of this is driven by the nature of the institution in question, and how complex its capital markets businesses are. Where the capital markets business is very strong, there is a strong tendency to want this to be driven by the business, even if there is already a central data science team. Conversely, where the capital markets business is a relatively small part of the picture, the tendency toward centralization is stronger.

We believe that the overall focus on methodological reconciliation between traditional techniques will drive decentralization, as well as a sharper focus on specific areas. This in turn will also drive different technology requirements, scalability and trade-offs.

Meanwhile, questions of staffing remain complex. For example, should teams be staffed principally by quants from other pre-existing disciplines (such as retail banking and capital markets), or by external recruits with specialisms in data science? The answer appears to be a mix of both, although in the most successful use cases we noted that however these teams are configured, one constant is that they are led by key risk personnel (e.g., the CRO or Risk COO).

5.4.2 How do CROs view the evolution of AI applications?

Going forward, the integration of AI tools into risk management methodologies and processes will only increase, and they will become integral to the risk management framework. This evolution promises to deliver new insights (e.g., via behavioral analytics and segmentation), automation and simplification (e.g. through data management and stress testing/scenario generation), and new methodologies for complex, multivariable problems and non-linear optimization.

But this integration brings new challenges that must be managed. Analysis of tools and data must be careful and constant and include an assessment of all computational methods for validity, consistency and 'explainability'. As firms' adoption of AI increases, they should not underestimate the governance challenges and risks they will have to face.

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To effectively manage the emerging governance challenges and risks, institutions and regulators will take a necessarily collaborative approach. This will include the alignment and development of best practices for improving the 'explainability' of models, model validation, and governance and controls.

How institutions apply tools in specific contexts will differentiate their approach to AI and be a significant contributing factor to their success in using this transformative technology.

5.4.2.1 Key questions around defining and building optimal organizations

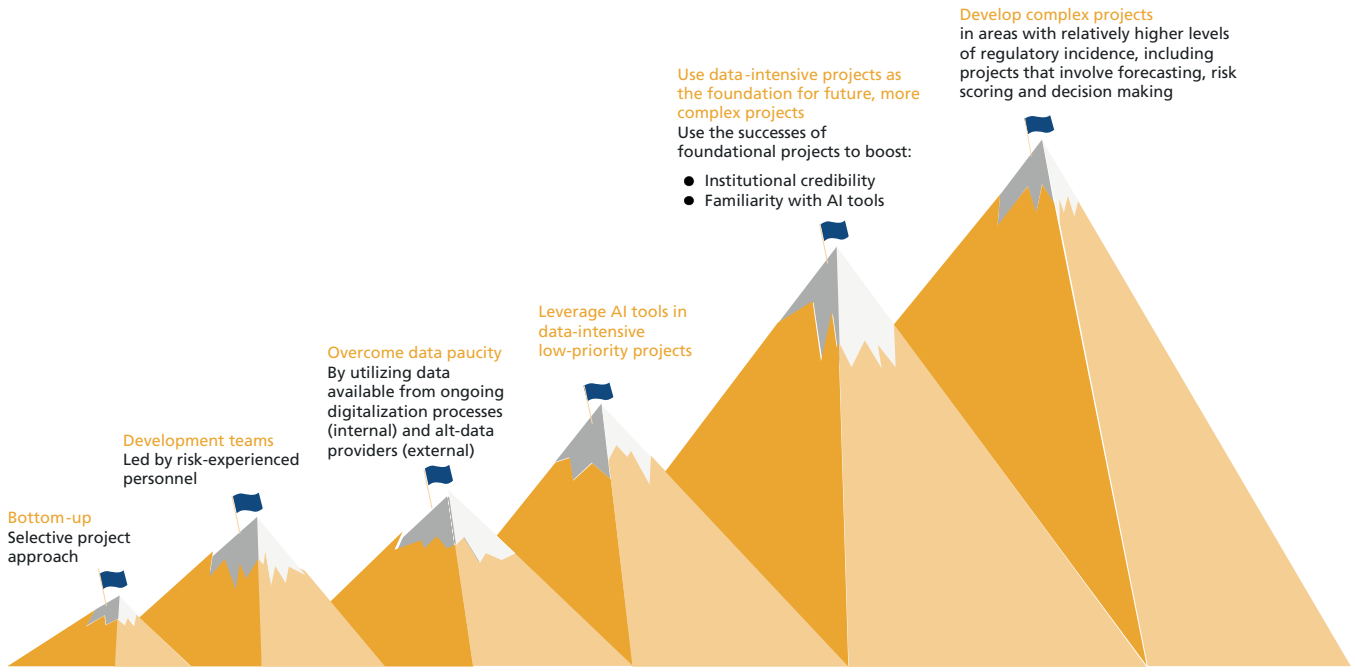
Firms benefit organizationally from strong risk leadership and a blend of disciplines across quants and data scientists for AI projects (see Figure 40). Some key questions arise:

- **Should institutions have dedicated data science teams, even in addition to existing quant teams?** Broadly the answer is 'yes', but there are considerable disagreements around how these teams should be structured and staffed.

- **Should teams be spread across the institution, or driven by individual business lines, and should they be staffed principally by quants from other disciplines (e.g., retail banking, capital markets), or contain external recruits with specialisms in data science?**
  The solution appears to be a mix of both. However, the most successful use cases we have seen indicate that, regardless of how these teams are configured, they should always be led by risk personnel (e.g., CROs and Risk COOs).

- **What should the underlying driver of AI development be?**
  Institutions are adopting a variety of approaches to this. Some are driven principally by technology, while others follow a multi-disciplinary approach. While there may not be consensus on the optimal development structure, however, firms increasingly agree that they should be led by a core team with strong risk experience.

Figure 40: Characteristics of organization maturity



Source: Chartis Research

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5.4.3 Measuring your success in AI adoption

We believe that there are six dimensions in which organizations can measure their success in adopting AI.

- **Regulatory acceptance**. A very important dimension of success. However, many types of analytics do not have any regulatory incidence.

- **Business impact**. Is there a measurable business result? Is the business more profitable? What is the size and speed of change as a result of implementing an AI solution?

- **Operationalization or availability of applications**. Should a project continue to run ad hoc, or has it achieved a high degree of standardization or industrialization? This applies to highly important (and even mission-critical) projects that depend on AI adoption within an organization, though even these can retain an ad-hoc 'flavor'. Full operationalization also implies that these models have undergone model volition and quantitative testing.

- **Quantitative reconciliation or standardization**. To what extent are AI models and tools a part of the standard quantitative infrastructure of the business? We observe that the most successful adopters in their mature phase look to embed AI models within normal quantitative frameworks. They also use similar validation and documentation requirements, reconciling AI approaches with standard analytical approaches.

- **Enhanced experience**. In discussions we often noted that CROs have innovation funds, dedicated to enhancing the risk customer experience.

- **Operational efficiency**. Achieved through reductions in manual proliferations and end-user computing

There are several potential quantitative metrics which have been useful in judging the success of sets of AI algorithms and/or AI projects.

- **Accuracy of output**. Testing the accuracy of output is especially relevant in situations where pre-existing statistical techniques are well-established. To prove effective, in comparison to traditional tools, the AI project must result in lower error (e.g., credit scoring, market price forecasts) or better and more stable segmentation (e.g., client segmentation analytics, behavioral etc.). While testing accuracy may appear a straightforward measure, it involves a variety of subtle issues, including the range, variety and structure of the test dataset, the processing and pre-test partitioning of test data, the error measures used, etc.

- **Speed and scalability**. In many projects (especially data-centric projects), success criteria are based largely around the ability to scale historically slow, ad-hoc manual process into scalable, fast and reliable activities. Therefore, AI in data anomaly detection and NLP in document analysis or document management projects must be able to perform significantly faster (typically by orders of magnitude) than the manual/pre-existing process. Generally, to be considered successful, the AI implementation in data-centric projects should be unambiguously more scalable and faster.

- **Quality and sensitivity of results**. In many areas (such as portfolio optimization and asset pricing), second-order measures (such as hedgeable risk, the stability of hedges generated, the stability of sensitivity measures, and the convergence to the existing pricing and optimization model) are critical.

- **Ease of use and low overhead model specification**. In a variety of non-linear problems the complexity of the model specification is the key operating challenge. This results in only experts being able to specify relationships or provide parameter optimization. We believe that in certain classes of problems (such as derivatives), when model-free or when AI drives pricing, model parameterization or parameter fitting-type problems can be efficiently specified and handled by neural networks - although doing so is a challenge. The first three metrics we have identified are highly quantitative measures and are straightforward to formulate; however, 'ease of use' is a relatively subjective metric.

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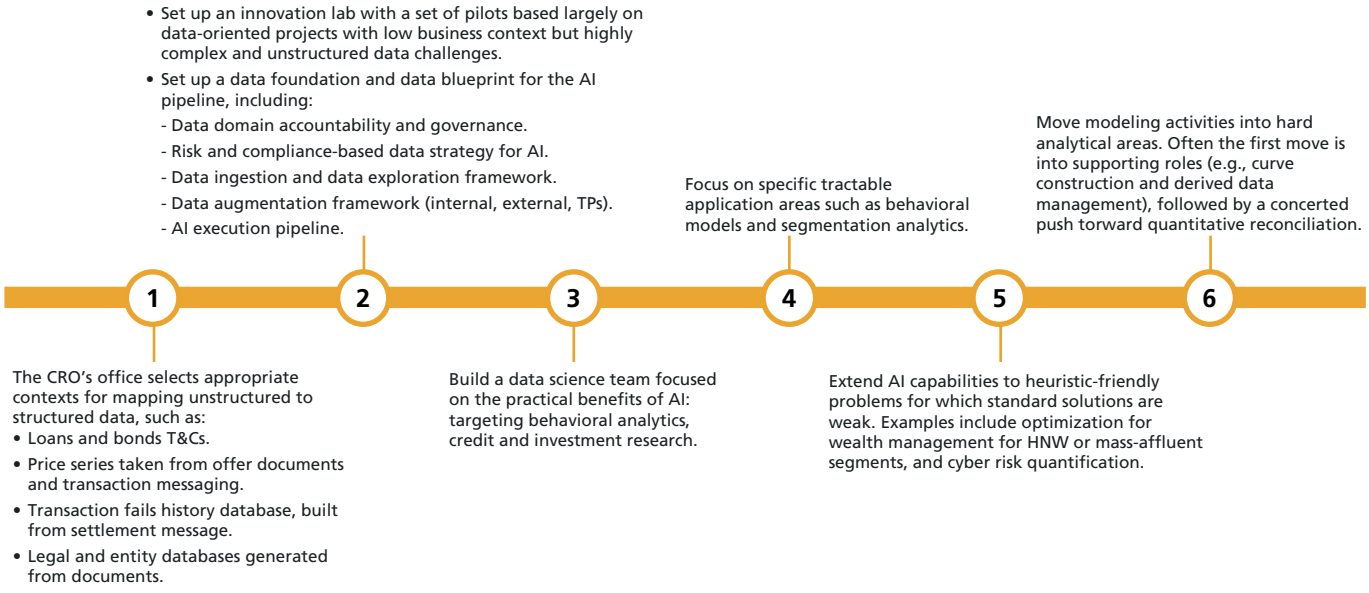
- **Practical trade-offs**. Finally, many projects require a careful trade-off of the above criteria. For instance, in the case of AI projects in financial crime (anti-fraud, KYC, AML, etc.), there needs to be the right balance between speed, scalability and accuracy. Our analysis suggests that there has been a strong drift toward accuracy at scale for fraud and AML projects in general. However, certain classes of fraud projects require that analytics have real-time performance. Therefore AI projects targeting anti-fraud solutions within a payment context will have to operate in real-time.

5.4.4 The optimal AI development strategy

The most effective and optimal observed project path consists of six steps, from model selection through to the transplantation of modeling activity into hard analytical areas. This strategy path is outlined in Figure 41.

Figure 41: The optimal AI development strategy



Source: Chartis Research

The path taken will consist of a number of implementation stages. In Figure 42, we consider what the optimal stages should be.

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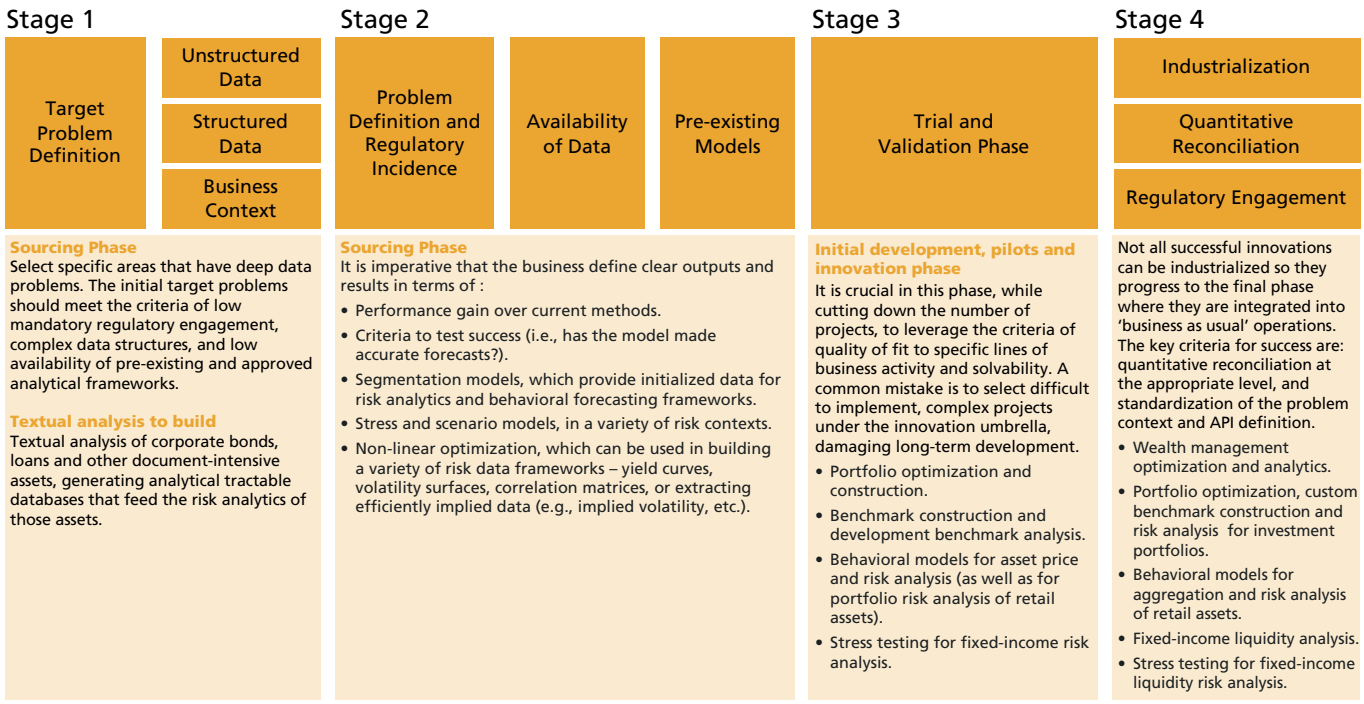
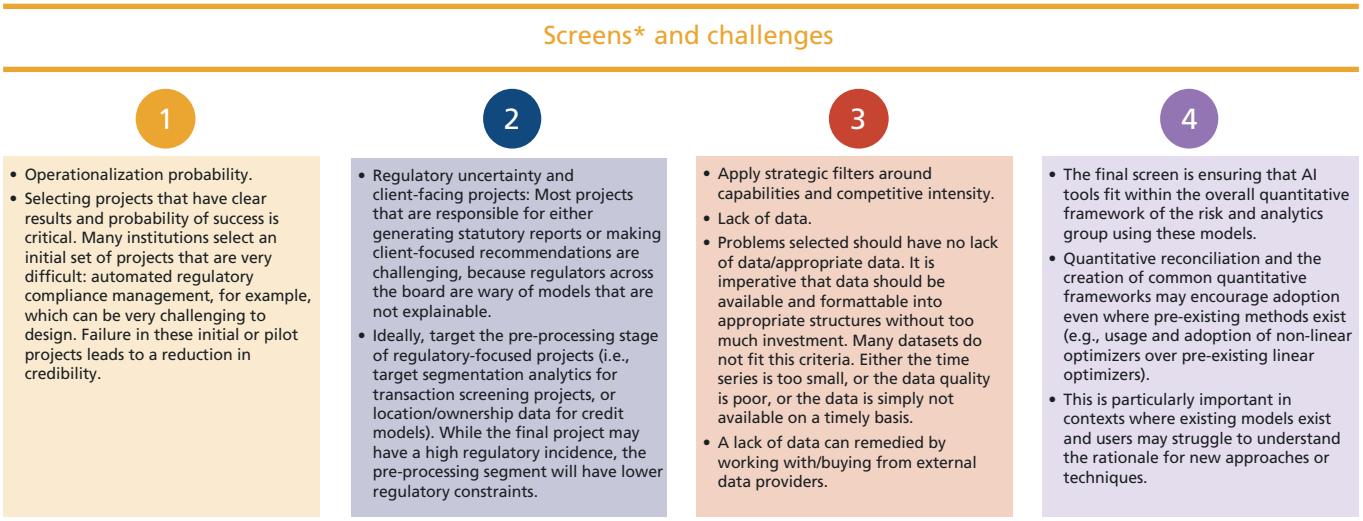
Figure 42: Implementation stages of an AI project



Source: Chartis Research

We have also discussed some of the challenges and barriers to success that organizations of different stripes have encountered. Figure 43 highlights the four most significant challenges emerging from our study that firms should consider.

Figure 43: Impediments, roadblock and possible remediation strategies



** 'Screens' implies the application of a filter or 'screen' to an idea or approach, and outlines the steps firms must take to industrialize AI processes.*
Source: Chartis Research

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5.5 Looking forward

Ultimately, the level and maturity of AI adoption seems to reside in the eye of the beholder. Adoption across business lines, institutional types and geographies is highly variable, although AI for data management is becoming ubiquitous almost everywhere. Adoption in core processes, on the other hand, seems much weaker.

The journey ahead to ensure that AI becomes a foundational element of core business processes in risk management, rather than an exotic tool used in highly restricted environments, runs through a swamp of methodological reconciliation with standard statistical processes. This issue is strongest in capital markets, where methodological rigor (as perceived by practitioners) is highest, and weakest in retail banking, where AI is well-embedded. Indeed, large universal banks proved to be among the strongest adopters of AI, with considerable investment in areas such as data management, retail banking and financial crime.

While adoption in other areas is spotty, our study suggests that AI tools will join conventional statistics and pricing models throughout the financial ecosystem, and that this will require structural changes to the mix of skills employed. Equally, the technology supporting capital markets groups specifically, and quant teams generally, will need to evolve.

Another core finding of the survey was that, while methodological differences may divide traditional quants and data scientists, there were equally strong divisions between technologists from data science and Big Data backgrounds and those with backgrounds in building scalable trading risk systems. In short, data science teams emphasize Big Data, unstructured data and Hadoop-like systems, while traditional risk and analytics proponents often emphasize traditional high-performance computing (HPC) architectures and grids.

Nevertheless, the emerging consensus is that the future will be a hybrid, with a blurring of the boundaries of HPC and Big Data. This will test the skills of the technology teams in most institutions, creating an interesting path ahead for AI adoption in risk and compliance.

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6. How to use research and services from Chartis

In addition to our flagship industry reports, Chartis offers customized information and consulting services. Our in-depth knowledge of the risk technology market and best practice allows us to provide high-quality and cost-effective advice to our clients. If you found this report informative and useful, you may be interested in the following services from Chartis.

For risk technology buyers

If you are purchasing risk management software, Chartis's vendor selection service is designed to help you find the most appropriate risk technology solution for your needs.

We monitor the market to identify the strengths and weaknesses of the different risk technology solutions, and track the post-sales performance of companies selling and implementing these systems. Our market intelligence includes key decision criteria such as TCO (total cost of ownership) comparisons and customer satisfaction ratings.

Our research and advisory services cover a range of risk and compliance management topics such as credit risk, market risk, operational risk, GRC, financial crime, liquidity risk, asset and liability management, collateral management, regulatory compliance, risk data aggregation, risk analytics and risk BI.

Our vendor selection services include:

- Buy vs. build decision support.
- Business and functional requirements gathering.
- Identification of suitable risk and compliance implementation partners.
- Review of vendor proposals.
- Assessment of vendor presentations and demonstrations.
- Definition and execution of Proof-of-Concept (PoC) projects.
- Due diligence activities.

For risk technology vendors

Strategy

Chartis can provide specific strategy advice for risk technology vendors and innovators, with a special focus on growth strategy, product direction, go-to-market plans, and more. Some of our specific offerings include:

- Market analysis, including market segmentation, market demands, buyer needs, and competitive forces.
- Strategy sessions focused on aligning product and company direction based upon analyst data, research, and market intelligence.
- Advice on go-to-market positioning, messaging, and lead generation.
- Advice on pricing strategy, alliance strategy, and licensing/pricing models.

Thought leadership

Risk technology vendors can also engage Chartis to provide thought leadership on industry trends in the form of in-person speeches and webinars, as well as custom research and thought-leadership reports. Target audiences and objectives range from internal teams to customer and user conferences. Some recent examples include:

- Participation on a 'Panel of Experts' at a global user conference for a leading Global ERM (Enterprise Risk Management) software vendor.
- Custom research and thought-leadership paper on Basel 3 and implications for risk technology.
- Webinar on Financial Crime Risk Management.
- Internal education of sales team on key regulatory and business trends and engaging C-level decision makers.

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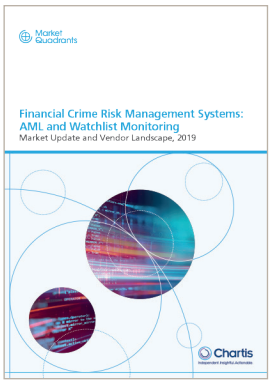
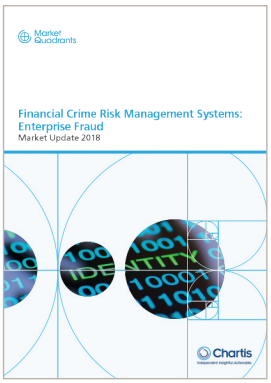
7. Further reading

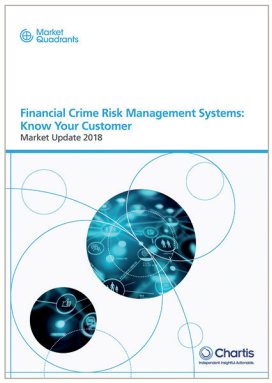
Artificial Intelligence in Financial Services, 2019: Demand-Side Analysis



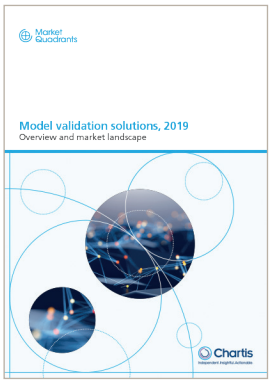
Artificial Intelligence in Financial Services, 2019: Market and Vendor Landscape



Financial Crime Risk Management Systems: Enterprise Fraud; Market Update 2018



Financial Crime Risk Management Systems: Know Your Customer; Market Update 2018



Model validation solutions, 2019: Overview and Market Landscape

RiskTech100 2019

For all these reports, see **www.chartis-research.com**

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