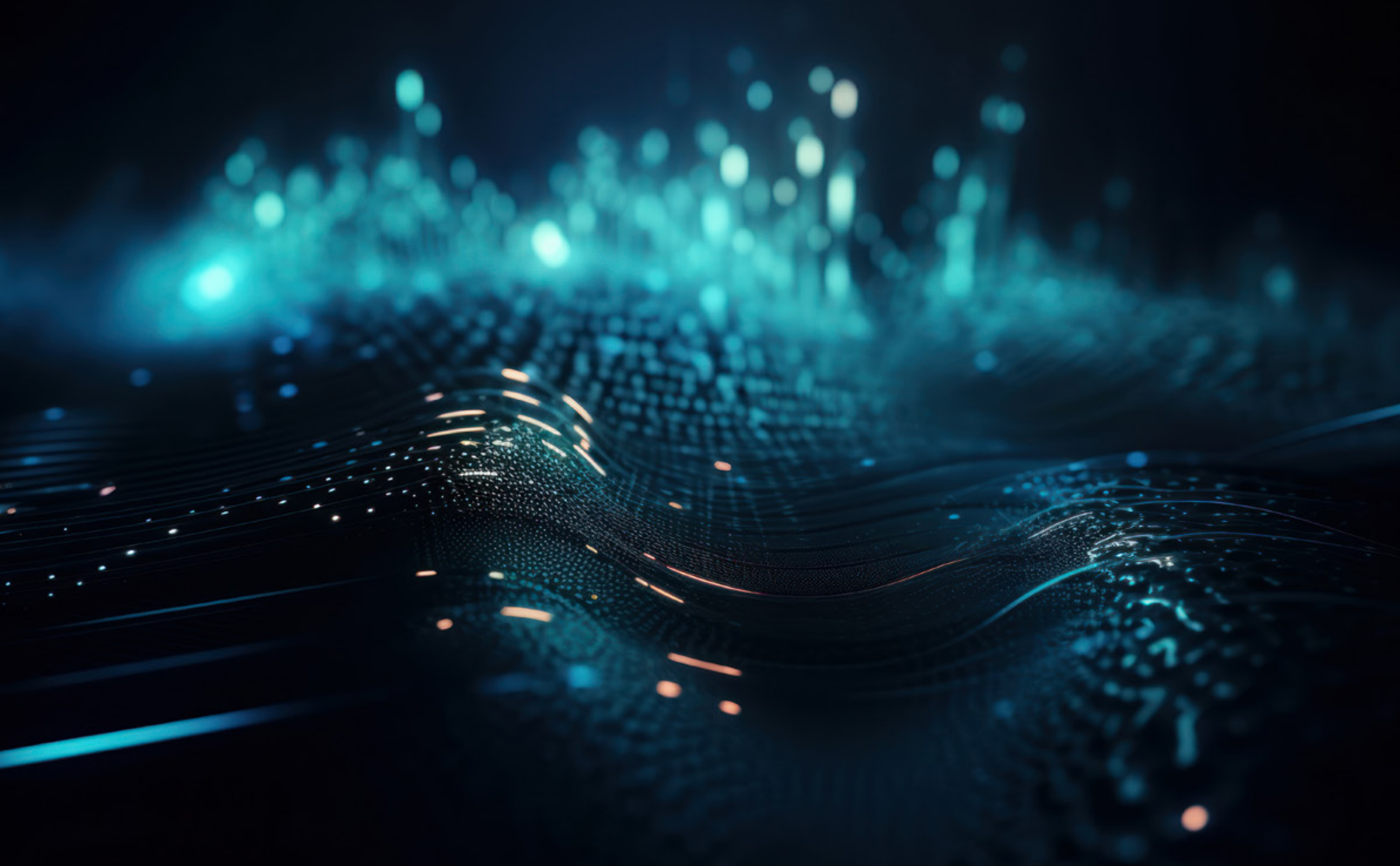
JAYWING

The AI Risk Modelling Maturity Model

Unlocking AI's potential



Unlock AI's potential

Traditional risk modelling approaches—including credit scoring, fraud detection, and regulatory models like IFRS 9 and IRB, while foundational, are increasingly strained. Nowadays, the complexity of financial markets, along with the growing volume of data, present both opportunities and challenges for credit risk teams.

While AI offers more sophisticated and predictive approaches, regulatory scrutiny around model explainability and fairness has intensified. Additionally, evolving market conditions are highlighting the importance of managing model risk and addressing concerns like bias and the 'black box' issue.

Sophisticated use of AI modelling can address these challenges, offering enhanced predictive power, while maintaining transparency and fairness. However, the adoption of AI in risk management varies across industries and departments.

According to a 2022 Bank of England survey*, the use of machine learning in UK financial services is rapidly growing, with 72% of firms using or developing ML applications. However, despite this progress, according to Accenture**, there is still significant room for improvement.

Legal and risk teams, in particular, are often at the earliest stages of AI implementation. Yet, for those leading the way, the returns are promising—42% reported that their AI initiatives exceeded expectations, while only 1% said the return didn't meet expectations.

With these successes building confidence, this ebook aims to provide a roadmap for firms at any stage of their AI journey, from those still relying on traditional methods to those already starting to integrate AI into risk management.

63%

of firms are still testing the AI waters.

12%

of firms have advanced their AI maturity enough to achieve superior performance.

Throughout this ebook, we will:

- Explore the four stages of AI maturity.
- Discuss the key dimensions that define each stage of maturity.
- Provide insights into the challenges and opportunities of each stage of the journey.
- Offer practical guidance to assess your current maturity level and how to accelerate your roadmap.

*Bank of England, Machine learning in UK financial services, 2022.
**Accenture Art of AI Maturity 2024.

Introducing the AI Risk Modelling Maturity Model

Organisations often find it difficult to define what their journey to risk modelling excellence should look like. Without a clear framework risk teams may find it challenging to focus on the right areas for their organisation.

Jaywing's AI Risk Modelling Maturity Model provides this framework, offering a structured approach to understanding and advancing AI integration in risk management. Fittingly, this framework was developed by risk modelling experts.

"The path to risk excellence is partly defined by an organisation's current level of risk modelling maturity. Jaywing has created a four-stage risk modelling maturity framework against which risk leaders can measure their firm's baseline, and then develop a clear, long-term vision."

—Ben O'Brien, MD, Jaywing

Overview of the four maturity stages

1. **Traditional risk modelling**:

At this stage, firms rely on traditional methods and linear models. While long-established, these approaches are increasingly outdated. Newer AI-driven techniques offer enhanced predictive power, speed, and efficiency, exposing the limitations of traditional methods.

2. **Black box AI implementation**:

At this stage, firms begin to implement AI in their risk modelling processes, but often in an uncontrolled or 'black box' manner. While this stage offers improved predictive capabilities and efficiency, uncontrolled AI models often lack transparency and interpretability, posing challenges for regulatory compliance and stakeholder trust.

3. **Advanced AI risk modelling and governed generative AI use**:

This stage is characterised by significant improvements in model stability and explainability. AI models at this stage offer high performance while maintaining transparency and interpretability, addressing the 'black box' issue.

4. **AI-enhanced risk management ecosystem**:

The final stage represents a state where AI initiatives, encompassing both machine learning (ML) modelling work and the use of generative AI applications, have been successfully delivered and integrated across the organisation. At this stage, the use of AI components has become business as usual, seamlessly woven into the fabric of risk management operations and decision-making processes.

The AI Risk Modelling Maturity Model

1
Traditional risk modelling

- No AI implementation.
- Reliance on traditional outdated methods.
- Limited predictive capabilities.
- Manual processes and interventions.
- Model performance limited by traditional methods.

2
Black box AI implementation

- Initial integration of AI techniques in specific risk areas.
- Improved model performance compared to traditional methods.
- Casual and general use of generative AI desktop tools (like ChatGPT or Copilot).
- Potential governance concerns with uncontrolled use of generative AI tools.
- Challenges with model explainability and the 'black box' issue.
- Potential regulatory and governance concerns.
- Difficulty in identifying and mitigating AI-induced biases.
- Increased efficiency, but with limited control.

3
Advanced AI risk modelling and governed generative AI use

- Use of advanced techniques like deep neural networks (e.g. Archetype).
- Improved explainability of complex AI models.
- Structured integration of generative AI tools in risk management processes.
- Alignment with regulatory requirements.
- Significant improvements in model accuracy and predictability.
- Comprehensive risk coverage across multiple risk types.
- Integration of human risk model expertise within development and validation processes.
- Development of an AI roadmap for controlled generative AI applications.
- Implementation of organisation-wide AI education and guidance.

4
AI-driven risk management ecosystem

- AI initiatives successfully delivered across modelling work, generative AI, and operational efficiency projects.
- Use of AI components such as NLP is fully integrated into ongoing technical development projects.
- Leveraging both machine learning modelling and generative AI technologies.
- Appropriate governance and control standards are in place for AI developments.
- Optimal balance between advanced AI capabilities and human expertise.
- Provision of powerful and reliable AI tools that significantly enhance human effectiveness and productivity in risk management.

Stage 1

Traditional risk modelling

This stage represents established methodologies and practices that have been used for decades across various industries. While these traditional risk modelling approaches—often characterised by linear regression modelling and retrospective analysis of past events—are still widely used, they are increasingly viewed as dated compared to newer AI-driven approaches.

Key characteristics

1. AI integration

- No AI implementation.
- Reliance on traditional techniques such as logistic regression, decision trees, and time series analysis.
- Models are typically built and maintained using traditional techniques.

2. Explainability

- Full transparency with traditional statistical methods.
- Models are generally easy to interpret and explain to stakeholders.
- Clear understanding of variable importance and impact on risk assessments.

3. Regulatory compliance

- Models understood by regulators.
- Meets traditional regulatory requirements.

4. Model performance

- Limited by traditional methods.
- Predictive power constrained by the inability to capture complex non-linear patterns.

5. Use cases

- Focused on core risks.
- Better suited to primary risk types such as credit risk.
- May have limited capability to model complex business challenges.

6. Data management

- Structured data, limited sources.
- Relies primarily on internal, structured data sources.
- Limited ability to incorporate unstructured or external data.

7. Governance

- Traditional risk management frameworks.
- Well-defined governance structures for model development and validation.
- Lacks specific provisions for more advanced analytical techniques.

8. Talent and skills

- Statistical and financial risk expertise.
- Team comprised mainly of traditional risk analysts and statisticians.
- Limited expertise in advanced data science or machine learning techniques.

9. Generative AI use

- No or limited use of Gen AI.

Stage 1 (continued)

Strengths:

- Well-understood methodologies with a long track record in the industry.
- High level of model interpretability and explainability.
- Established processes for regulatory compliance and model governance.
- Strong foundation in statistical theory and financial risk principles.

Limitations:

- Limited ability to handle large volumes of diverse data.
- May struggle to capture complex, non-linear relationships in data.
- Time-consuming model development and update processes.
- Difficulty in adapting to rapidly changing risk landscapes.
- Limited predictive power compared to more advanced techniques.

Organisations at this stage have a solid foundation in risk modelling but may find themselves increasingly challenged by the complexity of modern financial markets. The growing volume of data, the emergence of new risk types, and the need for more dynamic risk assessments are pushing the boundaries of what traditional methods can effectively handle.

Moving forward, organisations at this stage should consider:

1. Exploring pilot projects to introduce AI techniques.
2. Investing in data infrastructure to support more advanced model development.
3. Upskilling existing talent in AI and machine learning technologies.
4. Exploring partnerships with AI experts to understand their potential applications in credit and fraud risk.

By understanding the strengths and limitations of traditional risk modelling, organisations can better appreciate the potential benefits of advancing along the AI Risk Modelling Maturity Model and begin to move towards more sophisticated, AI-enhanced risk management practices.

Stage 2

Black box AI implementation

This stage represents a leap forward from traditional methods, as organisations begin to test the waters with AI in risk modelling. However, this early implementation often results in "black box" models, where the decision-making process is not fully transparent or easily explainable.

Key characteristics

1. AI integration

- Initial deployment of AI techniques in specific risk areas.
- Introduction of more complex AI models such as Gradient Boosted Models, neural networks, or ensemble methods.
- AI models are designed to maximise predictive power, often at the expense of interpretability.

2. Explainability

- Models are difficult to interpret, leading to potential for spurious predictions.
- Challenges in providing clear explanations of model decisions to stakeholders.
- Increased "black box" concerns due to lack of transparency in model operations.

3. Regulatory compliance

- Significant challenges in meeting regulatory requirements for model transparency and explainability.
- Difficulty in demonstrating model logic and decision-making processes to regulators.
- May face restrictions in use for certain applications due to explainability issues.

4. Model performance

- Improvements in accuracy and predictive power compared to traditional methods. Enhanced ability to capture complex, non-linear relationships in data.
- Faster model development and deployment processes for certain tasks.

5. Use cases

- Scenarios where explainability is non-critical.
- Applications might include operational efficiency, fraud, and pre-screening.
- Proof of concept analysis.

6. Data management

- Increased use of diverse data sources.
- Enhanced data processing capabilities.
- Exploration of real-time data integration, though not fully implemented.

7. Governance

- Challenges in establishing effective governance for black box AI models.
- Struggle to adapt traditional model risk management frameworks to AI models.

8. Talent and skills

- Growing team of data scientists and AI specialists.
- Increasing gap between technical AI experts and traditional risk managers.
- Need for extensive training to bridge knowledge gaps within teams.

9. Generative AI use

- Individual staff members use desktop generative AI tools on their own initiative.
- Lack of clear guidance on data security or best practices for generative AI use.
- Results of generative AI tools aren't routinely monitored or assessed.
- Risk of sub-optimal use or potential data breaches due to uncontrolled adoption.
- Limited understanding of the implications of generative AI in risk management processes.

Stage 2 (continued)

Strengths:

- Improved predictive power compared to traditional methods.
- Faster model development and deployment for certain applications.
- Enhanced ability to capture non-linear relationships in data.

Limitations:

- Significant challenges with explainability and biases
- Limited ability to leverage unstructured data or real-time data streams.
- Potential for increased model complexity, requiring more sophisticated validation processes.

Organisations at this stage are taking their first steps into AI-enhanced risk modelling, experiencing gains in predictive power but often at the cost of interpretability and control. The improved model performance comes with the need to develop new strategies for understanding and validating these complex AI models.

Moving forward, organisations at this stage should consider:

1. Investing in research and development of explainable AI techniques.
2. Developing strategies to address regulatory challenges related to model explainability.
3. Enhancing model validation processes to scrutinise black box models effectively.
4. Building cross-functional teams that blend AI expertise with domain knowledge in risk management.
5. Exploring partnerships with firms specialising in AI model explainability and compliance.

As organisations grapple with the challenges of black box AI models, they should focus on developing more transparent and explainable AI techniques, paving the way for the next stage of AI maturity in risk modelling.

Stage 3

Advanced AI risk modelling and governed generative AI use

The advanced AI risk modelling stage represents a significant leap forward in the application of AI to risk management. At this stage, organisations implement comprehensive AI techniques across risk management functions, achieving a high level of sophistication and performance with full transparency and explainability.

Key characteristics

1. AI integration

- Comprehensive AI implementation across risk management.
- Widespread use of advanced techniques like deep neural networks (e.g. Archetype).
- AI models integrated into core risk management processes and decision-making.

2. Explainability

- High level of explainability achieved.
- Advanced techniques (like Archetype's approach) provide clear insights into model decisions.
- Ability to break down complex AI models into interpretable components, including availability of case-level reason codes to support underwriter review.

3. Regulatory compliance

- Full alignment with certain existing regulatory frameworks.
- Models designed to meet stringent explainability requirements of current regulations.
- Clear documentation and reporting processes to demonstrate compliance when required.

4. Model performance

- Significant improvements in model accuracy.
- Substantial enhancements in predictive power across various risk types.
- Ability to capture complex, non-linear relationships in data.

5. Use cases

- Extended risk coverage across multiple risk types.
- AI models addressing a wide range of risk categories, including emerging risks.
- Focus on models with a higher barrier for explainability.
- Seamless integration with wider business processing.

6. Data management

- Sophisticated handling of structured and unstructured data.
- Integration of diverse data sources, including alternative data.
- Advanced data processing capabilities, including real-time data analysis.

7. Governance

- Comprehensive policies and procedures for AI model development, validation, and monitoring that align with current regulatory expectations.
- Regular reviews to ensure AI models continue to meet explainability and interpretability standards required by existing frameworks.
- Framework and guidance established for effective and responsible use of generative AI tools.

8. Talent and skills

- Strong team of AI and risk experts, continuous learning culture.
- Multidisciplinary teams combining expertise in AI, risk management, and domain knowledge.
- Ongoing investment in skill development and knowledge sharing.

9. Generative AI use

- Widespread adoption of generative AI tools for recommended purposes.
- Clear guidance and policies for appropriate use of generative AI.
- Managed risk approach to mitigate potential reputation loss or data breaches from misuse. Regular monitoring & assessment of generative AI outputs and usage patterns.
- Integration of generative AI into specific risk management workflows with oversight.

Stage 3 (continued)

Strengths:

- Highly accurate and robust risk models capable of being deployed in complex scenarios.
- Ability to generate decisions that are transparent to the business and end-user.
- Enhanced ability to identify and manage emerging risks.
- Efficient model development and deployment processes.
- Strong alignment with regulatory expectations for advanced analytics in risk management.

Challenges:

- Maintaining the right balance between AI automation and human oversight.
- Keeping pace with rapidly evolving AI technologies.
- Ensuring ethical use of AI in risk management decisions.

Organisations at this stage are leveraging the potential of AI in risk modelling while maintaining a strong focus on governance, explainability, and regulatory compliance. The integration of advanced AI techniques allows for more accurate, timely, and comprehensive risk assessments.

Moving forward, organisations at this stage should consider:

1. Continuously assessing and refining AI models to improve performance and adapt to changes.
2. Investing in advanced explainable AI techniques to maintain transparency and trust.
3. Close collaboration between AI experts, risk managers, and business stakeholders.
4. Implementing robust model monitoring and validation processes to ensure ongoing model optimality.

As organisations mature in their advanced AI risk modelling capabilities, they can begin to explore even more sophisticated applications of AI, paving the way for an AI-enhanced risk management ecosystem.

Introducing Archetype:

Archetype, uses explainable and controllable AI to generate models with greater accuracy, speed and precision than ever before. Fundamental to credit risk, fraud, pricing and marketing, Archetype's predictive models deliver model performance uplifts of up to 18%, compared to traditionally built models (using the same data). Show me how.

Stage 4

AI-enhanced risk management ecosystem

At this stage, AI is not just a tool but a fundamental component of the organisation's risk management strategy and operations.

Key characteristics

1. AI integration

- AI fully embedded within risk strategy and decision-making.
- AI used to streamline, monitoring, and reporting processes.
- Use of Gen AI to automate manual operational tasks and processes.

2. Explainability

- Fully explainable AI techniques used throughout.
- Consistent, clear explanations of AI-driven decisions across all risk models.
- Ability to provide granular insights into model decisions for all stakeholders.

3. Regulatory compliance

- Alignment with prevailing regulatory frameworks maximised. Proactive approach to demonstrating model transparency and interpretability to regulators.
- Ability to rapidly adapt risk models to evolving regulatory interpretations.

4. Model performance

- Optimised performance through regular refinement.
- Frequent cycles of model refinement and validation to ensure peak performance.
- Model updates are subject to rigorous testing and validation before implementation.

5. Use cases

- Holistic risk management across business functions.
- Comprehensive coverage of known and emerging risk types.
- Dynamic risk assessment capabilities adapting to new threats and opportunities.
- Use of AI to improve operational efficiency and customer engagement.

6. Data management

- Real-time data integration and analysis.
- Advanced capabilities in processing and analysing diverse data sources in real-time.
- Comprehensive data governance ensuring quality, security, and ethical use of data.

7. Governance

- Enhanced governance and oversight integrated into existing frameworks.
- Sophisticated processes for managing AI models throughout their lifecycle.

8. Talent and skills

- Leading expertise in AI risk modelling, attracting top talent.
- Multidisciplinary teams with deep expertise in AI and risk management.
- Continuous learning and development programs to stay at the forefront of AI and risk management.

9. Generative AI use

- Clear guidance on optimal use of generative AI tools.
- Knowledge bank shares best practices in Gen AI application.
- Tech teams can design applications using NLP technologies to deliver safe and powerful outputs.
- Unlocking Gen AI potential, such as extracting useful variables from unstructured text/conversations.
- Seamless integration of Gen AI into risk workflows, enhancing efficiency and insight.
- Continuous improvement of generative AI applications.

Stage 4 (continued)

Strengths:

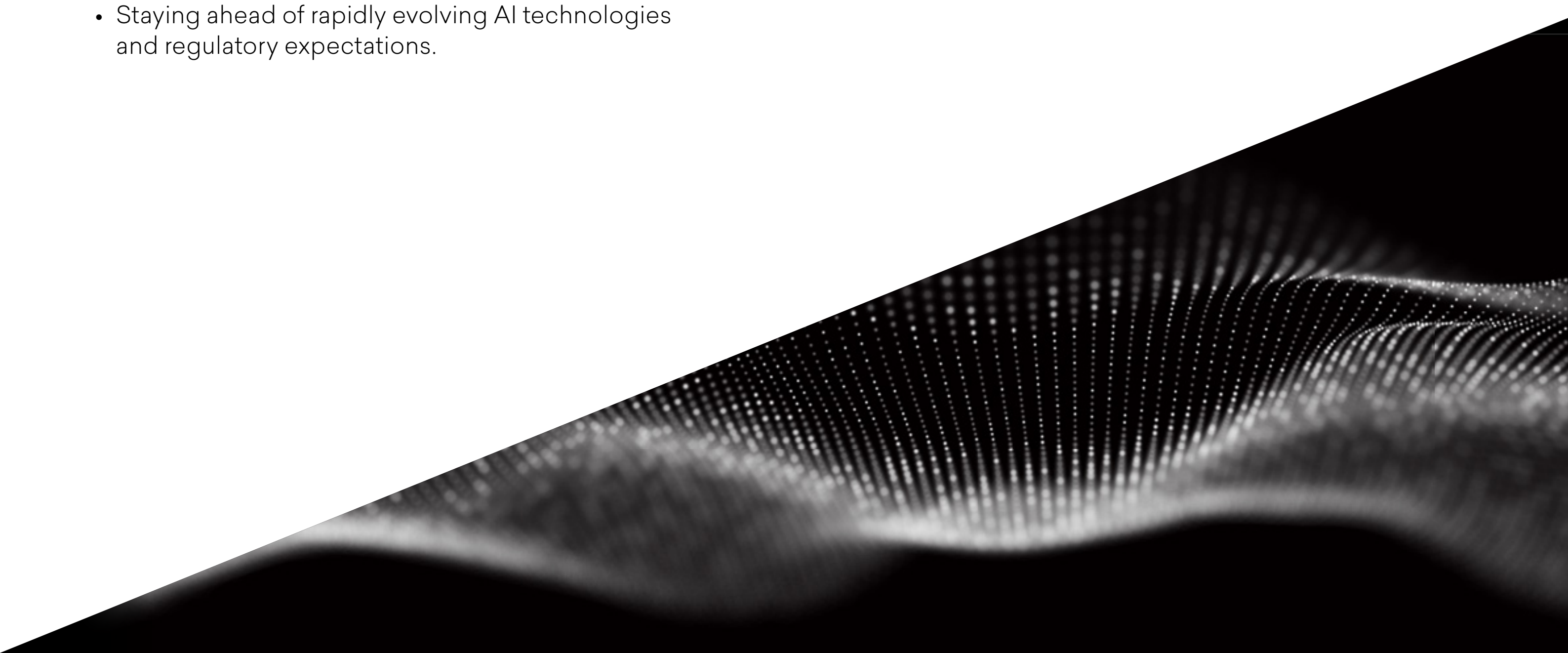
- Highly sophisticated and accurate risk management capabilities.
- Agile response to changing risk and business environments.
- Enhanced strategic decision-making informed by AI-driven insights.
- Robust governance ensures responsible and ethical use of AI in risk management.

Challenges:

- Maintaining the right balance between AI automation and human judgement.
- Ensuring consistency and coherence across a complex ecosystem of AI models.
- Managing the ethical implications of AI-driven decision-making in risk management.
- Staying ahead of rapidly evolving AI technologies and regulatory expectations.

Similar to the advanced AI stage, organisations at this stage are at the forefront of AI in risk management, balancing advanced capabilities with human expertise. AI drives decision support, predictive risk management, and comprehensive risk coverage, all within robust governance frameworks.

This stage differentiates between using AI for business risk management and managing the risks of AI models themselves. While AI informs strategic decisions and real-time risk assessments, stringent processes ensure AI model accuracy and mitigate potential biases. Continuous model improvement is implemented cautiously, with updates subject to rigorous testing, validation, and human oversight. The focus is on enhancing performance and alignment with business needs, while adhering to regulatory requirements.



Gain support throughout the entire risk maturity framework:

Our consultants understand the complexities of deploying AI models and systems and can provide expertise on industry best practices and regulatory considerations throughout the AI maturity framework. Talk to us.

Real-life example:

Challenger bank achieves time-tested optimal AL models with Archetype

Background

Jaywing has a long-standing relationship with a challenger bank, dating back to 2013, supporting regulatory risk management before developing and deploying linear models, and ultimately transitioning to AI and machine learning models with Archetype in 2018, well ahead of industry peers.

The real-world impact of Archetype is undeniable. Over 30 lenders, including Hitachi Capital, Newcastle Building Society, Nationwide, and Virgin Money, have experienced significant uplifts in results using the software. Testimonials attest to the power of Archetype as a “powerful alternative in building traditional credit scores,” typically delivering relative uplifts in Gini coefficient ranging of 10% to 15% over linear models developed on the same data.

Challenges and Objectives

Created in 2018, Archetype’s browser-based interface empowers analysts with full control over model content, data grouping, constraints, and treatments. The AI-powered solution solves the ‘black box’ problem, ensuring explainable and controllable models that comply with regulatory standards. Within a short time span, Archetype completes the modelling process, generating explainable models with detailed charts and graphs, instilling confidence in the bank’s analysts.

No competitors offer the exact same functionality; while a few providers offer AI-based modelling software, none of them can guarantee explainable, controllable models that exhibits intuitive behaviour whilst continuing to offer performance improvements.

Results

Utilising Archetype on their motor and point of sale retail finance models, the bank significantly enhances their credit assessments. Precise identification of high-risk applicants enables the bank to reduce unnecessary rejections, increasing the likelihood of acceptance on appropriate terms. Additionally, borrowers who may not be suitable for further lending are identified more accurately, preventing them from taking on debts they cannot manage. With Archetype’s explainability, the challenger bank has the transparency they need to be able to explain their decisions to customers, regulators and internal credit policy functions, if needed.

Unlike traditional credit scoring models that may lose their effectiveness over time, the AI and machine learning models have proven their resilience and consistency over a **five-year period**. The models dramatically and consistently outperform flagship scores provided by the CRAs, **with the model serving the niche asset finance portfolio achieving almost twice the discriminatory strength as one of the market leading CRA scores**. Uplifts from the asset finance portfolio deliver a 20-point uplift in discrimination*, with a 15-point improvement within the more mainstream retail book.

Amidst dynamic market changes, Archetype’s adaptability means the models are continuously optimised, allowing the challenger bank to reduce credit losses, foster responsible lending practices and provide superior customer experiences.

*Uplifts measured by the Gini statistic

Where do you sit on the AI risk modelling maturity curve?

To help organisations assess their current maturity level and identify areas for improvement, we've developed an AI Maturity Scorecard. This covers the eight key dimensions of AI maturity in risk modelling. Rate your organisation on a scale of 1-4 for each dimension, where 1 represents Stage 1 (No AI), 2 represents Stage 2 (black box AI), 3 represents stage 3 (advanced explainable AI) and 4 represents Stage 4 (AI-Enhanced Ecosystem).

Criteria	Question	1	2	3	4
1. AI integration	How extensively is AI implemented in your risk modelling processes?				
2. Explainability	How well can you explain and interpret your AI model decisions?				
3. Regulatory compliance	How aligned are your AI models with the regulator's higher bar?				
4. Model performance	How accurate and efficient are your risk models?				
5. Use cases	How comprehensive is your AI-driven risk coverage?				
6. Data management	How sophisticated is your handling of diverse data sources?				
7. Governance	How well does your AI fit into governance frameworks?				
8. Talent and skills	How strong is your team's expertise in AI risk modelling?				
9. Generative AI	How far have you got in understanding how to harness the power of generative AI?				

Scoring:

9-13: Stage 1: Traditional Risk Modelling
14-22: Stage 2: Rule-Based AI Modelling
23-31: Stage 3: Advanced AI Risk Modelling
32-high: Stage 4: AI-Enhanced Risk Management Ecosystem

While this scorecard offers a general guide, every organisation's AI journey is unique. Jaywing provides free, in-depth consultations to accurately assess your AI maturity stage, offer tailored advice, and develop a customised roadmap for advancing your risk management capabilities.

Contact us today to transform your AI strategy.

AI risk modelling maturity, accelerated.

The race towards risk modelling excellence is on, and the frontrunners are reaping substantial rewards. Across industries, high-performing organisations have rapidly progressed beyond traditional modelling to achieve robust AI-powered modelling and strategic control.

At the heart of this acceleration is cutting-edge technology. Solutions like Archetype harness the power of cloud computing to dramatically speed up the journey through the maturity stages.

These tools offer:

- Better performing models with a relative uplift in Gini coefficient likely to be in the range of 10-15%
- Redevelop manual and complex models frequently, and before they deteriorate
- Leverage explainable AI to create high-performing, transparent and intuitive predictive risk models.

All of this is achieved while maintaining complete control and explainability.

By leveraging solutions like Archetype, organisations can leapfrog multiple maturity stages, setting new benchmarks for high performance as they evolve. This technology-driven approach transforms a traditionally slow process into a dynamic, strategic advantage.

Ready to accelerate your risk modelling maturity?
Discover how Jaywing can propel your organisation to the forefront of risk management excellence.

Talk to us.

Find out more about our AI roadmap service **here**.

Meet the authors

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About Jaywing

We have a wealth of experience in the financial services sector, working within both consumer and commercial portfolios, creating pragmatic solutions that are easily understood, implemented, and executed.

Our expertise encompasses banking regulations such as IFRS 9, Stress Testing, ICAAP, ILAAP, Risk Appetite, Basel Regulations, Fraud prevention and IRB. We also help organisations align their risk strategy, pricing, and collections optimisation to help increase profitability.

Jaywing is full of the right blend of specialists – senior people with the skills and credentials you won't find elsewhere. We set the bar high for recruitment to ensure we hire the finest financial services minds and have unrivalled retention rates due to putting our people at the heart of the business.

20+ years of unrivalled expertise

Founded in 1999, Jaywing's heritage is in risk consulting, delivering data analysis skills to the financial services industry for over 20 years. Our experienced team of specialists is more than 50 strong, with a depth of expertise unrivalled by any other provider.

50+ specialists

We have supported most of the UK's leading lenders to increase profitability, gain regulatory compliance, or improve the way they use data to make decisions.

Supporting the UK's leading lenders

Through our expertise in data and analytics, we build models and deliver insight for both large and small organisations. Our collaborative approach ensures our projects deliver true value for our clients.