The ML divide in credit risk

INNOVATION GENERATING GROWTH

Welcome to Experian's 2025 credit insight report

AI is revolutionising credit risk, unlocking new possibilities, and driving innovation. The real value lies in identifying high-impact use cases that deliver measurable outcomes.

While integrating AI into established processes like credit risk can be challenging, the potential is immense. Forward-thinking businesses are already seeing impressive results. With the right strategy, others can confidently follow and reap the rewards.

This report sets out to understand how Machine Learning (ML) is transforming credit risk assessment in Financial Services and Telcos.

Our research, conducted by Forrester Consulting, investigates the impact that ML is having on those institutions that are already using it, and explores the reasons why some are yet to implement it. Along with ML, we discuss how Generative AI (GenAI) is rapidly changing data analysis and model development.

Are these technologies integral to the future of credit risk? The simple answer is yes. Our research suggests that the benefits ML provides are significant. When done right, there is no doubt that ML delivers faster, fairer, more accurate credit decisions.

It's a win-win situation for both lenders and their customers, and a step toward true financial inclusion. But to be confident in its use, trust is critical. Trust in the data, trust in the models, and trust in every decision. The rewards for establishing trust are considerable, as ML can facilitate better credit decisions than was previously possible and is a significant step towards truly equitable access to finance.

At Experian, we believe data should improve lives and that everyone deserves equal access to financial opportunity. But data alone isn't enough – you need insight. You need action. And you need the right technology to turn both into long-term growth.

We're here to help you do that.

MARIANA PINHEIRO
CEO Experian EMEA & APAC

What’s covered in this year’s report?

Before we look at the findings, it is important to clarify the definitions used in this report. The term AI has limited value as an umbrella term and will not be used. Machine Learning is defined as advanced algorithms, such as XGBoost, but not traditional scorecards based on linear or logistic regression.

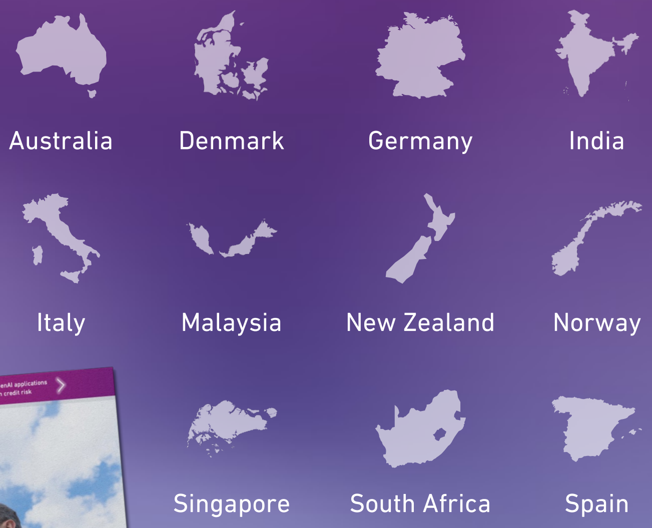
This distinction is important to make, as from a more academic technical perspective, these older algorithms can be classified as ML. However, within credit risk assessment, they are referred to as traditional static scorecards and have existed for several decades.

This is the comparison we have explored in this research – the difference between advanced ML and traditional scorecards.

To understand this landscape, we commissioned Forrester Consulting to survey 1,195 senior decision makers responsible for developing and implementing AI/ML in credit risk in Financial Services and Telcos across eleven countries: **Australia, Denmark, Germany, India, Italy, Malaysia, New Zealand, Norway, Singapore, South Africa and Spain.** We then split these respondents into two groups – those who are already using ML and those who have not adopted it.

For a full breakdown of firmographics, please refer to the final part of this report.

11 EMEA and APAC markets



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Snapshot of key findings

88%

of organisations already using ML have seen an improvement in acceptance rates for SME loans since adoption

86%

of organisations already using ML have seen an improvement in credit card bad debt rates since adoption.

83%

of respondents agree that cloud computing is an essential part of their strategy to maximise the value of data.

75%

of respondents are prioritising the move to a unified data, analytics, decisioning and fraud platform over the next 1-3 years.

73%

of respondents believe that organisations that adopt ML in credit underwriting will gain a significant long-term competitive advantage.

70%

of organisations that are already using ML plan to significantly increase investments in their ML capabilities over the next 1-3 years.

Base: 1,195 senior decision makers responsible for developing and implementing AI/ML in credit risk
Source: Experian research conducted by Forrester Consulting, July 2025

Business outlook, priorities, challenges and budgets

The last few years have been tumultuous with numerous shocks to the global financial system. Interest rate volatility has stabilised but continues to remain above pre-pandemic levels, and global growth predictions remain muted due to policy uncertainty and trade tensions.

Although these rapid economic fluctuations increase liquidity risks, financial institutions have remained resilient, with around 70% of member jurisdictions already implementing Basel III standards.

This year's research shows that 67% of respondents **expect revenue to increase over the next twelve months,** and a similar proportion **(65%) expect more investment in technology.** While this is encouraging, there is still a strong focus on cost management and reducing costs for 69%.

67% overall expect revenue to increase in the year ahead

73% Fintechs

63% Banks

Optimism levels about growth have shown a slight dip from last year's findings, but average positive sentiment remains well above the fifty percent mark at 59%.

"I am optimistic about growth this year"

Country	STRONGLY AGREE	AGREE	Total
New Zealand	50%	31%	81%
Malaysia	39%	35%	74%
Denmark	44%	24%	68%
Singapore	35%	28%	63%
Spain	33%	28%	61%
Norway	39%	20%	59%
Italy	37%	15%	52%
India	30%	20%	50%
Germany	28%	21%	49%
Australia	26%	20%	46%
South Africa	33%	12%	45%

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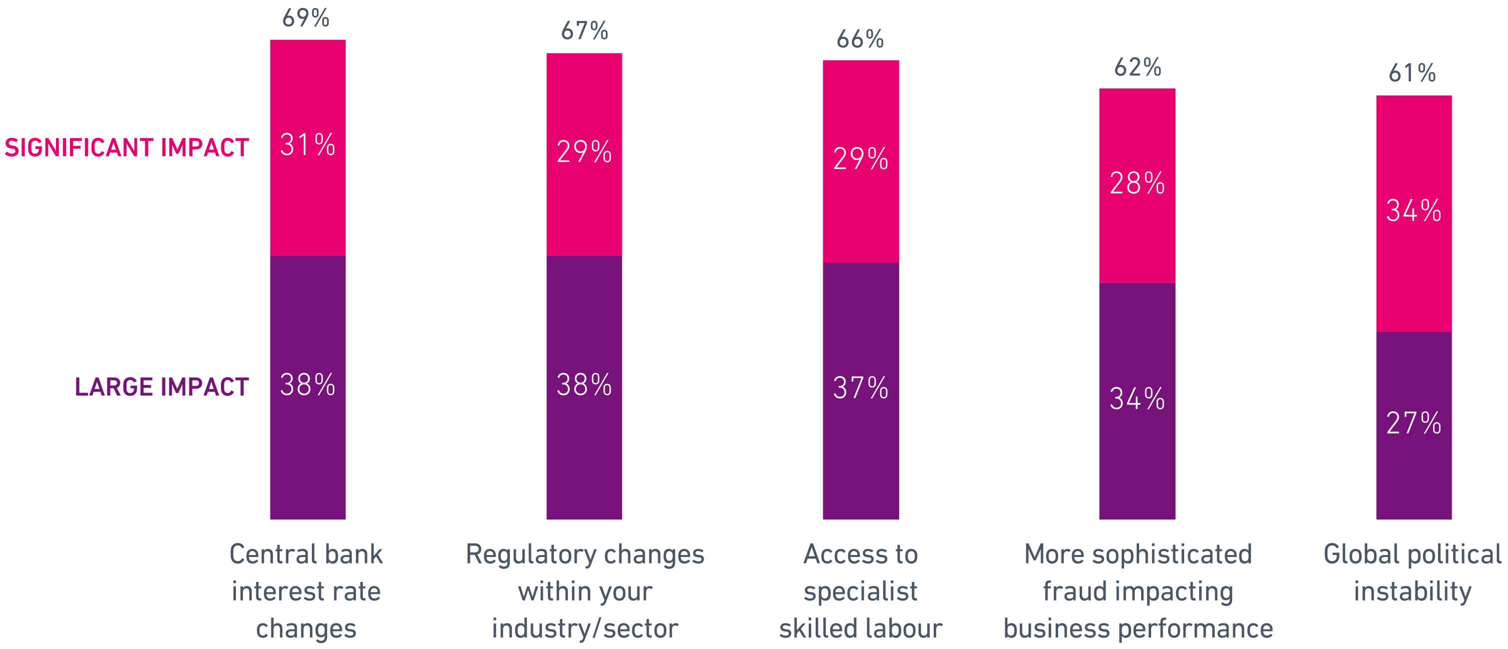
Source: Experian research conducted by Forrester Consulting, July 2025

External risk factors

Central bank interest rates are the biggest overall risk factor (69%) for the medium term, as many countries expect interest rate reductions, but uncertainty remains due to global geopolitics. Global political instability is highlighted as the most significant external factor impacting business (34%).

Interest rates, regulations and skilled labour are the biggest external risk factors for the next 1-2 years



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Priorities for the year ahead

Apart from improving profitability, the most immediate priorities are **investing to protect against fraud and adopting advanced analytics with AI/ML capabilities.**

The fraud threat has increased significantly since GenAI became publicly available, and we will explore the extent of this new threat and how businesses are responding in our upcoming fraud report.

Adopting advanced ML is a complex process that requires sufficient relevant data and the right data infrastructure to maximise the potential benefits. Considering this complexity, it's unsurprising that it came out as both the top critical priority (37%) for the next 12 months, as well as being the top strategic focus area for the next three years.

Top business priorities – short vs medium term

12 MONTHS		Rank	1-3 YEARS	
Improving profitability	76%	1	Implementation of AI/ML into risk decisions	76%
Investing to improve protection against fraud	72%	2	Move to a unified data, analytics, decisioning and fraud platform	75%
Adopting advanced analytics with AI/ML capabilities	70%	3	Improving the time to decision for customers	74%
Growth through upselling and cross-selling	68%	4	Re-evaluation of risk strategy in view of regulatory changes	71%
Growth through new customer acquisition	67%	5	= Improving the speed of model development and deployment = Investment in native and/or enabled cloud managed services	71%

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Priorities over the next three years

The results show that three-quarters (75%) of respondents are prioritising a unified data, analytics, decisioning and fraud prevention platform.

A unified platform can fast-track ML adoption, while also directly addressing the third and fifth medium-term priorities – improving time-to-decision and the speed of model development and deployment.

75%

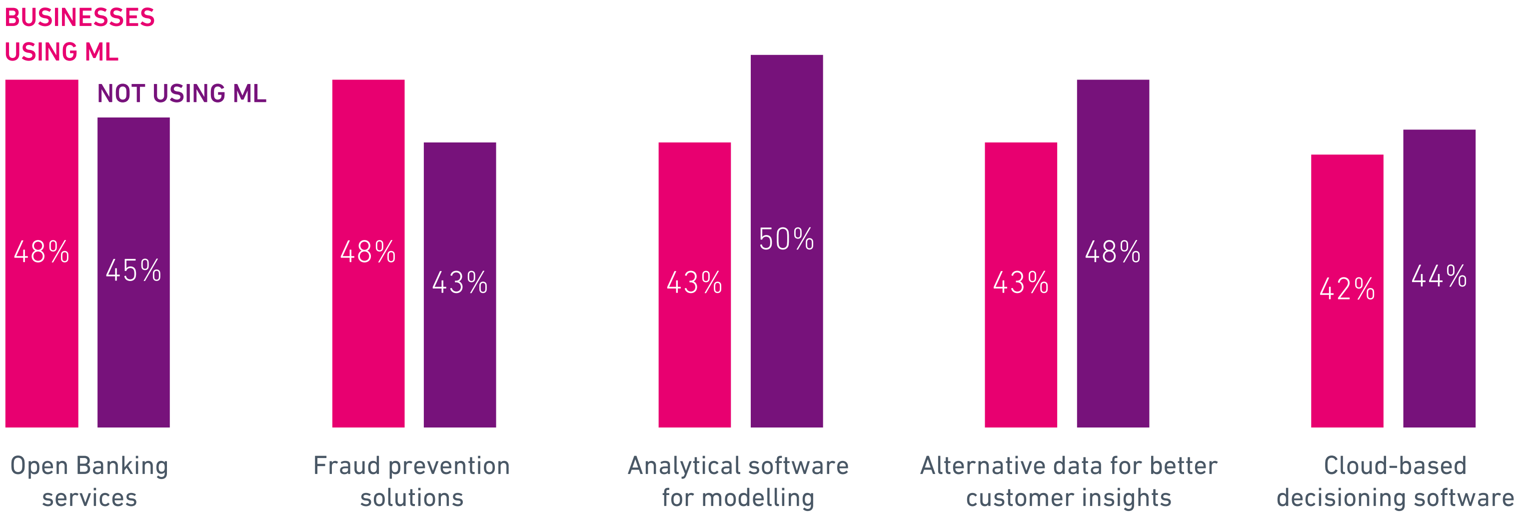
of businesses are prioritising the move to a unified platform for data, analytics, decisioning and fraud prevention in the next 1-3 years.

Year-on-year budget increases differ between ML adoption groups

For those who have already invested in ML, there is a focus on Open Banking and fraud prevention. This could be because ML-based categorisation is important to extract the most value from unstructured transaction data obtained from Open Banking, and also key to fighting complex fraud.

Both groups recognise that Open Banking is providing significant benefits, with 82% of respondents agreeing that it is helping them uncover previously hidden and underserved market segments. Future sentiment for Open Data is also extremely positive, as seen by the 84% who believe that it has the potential to make traditional credit scoring obsolete by providing individual dynamic risk profiles that are updated daily.

Budget increases for the year ahead show a focus on Open Banking and analytical software



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Alternative data for better customer insights remains a strategic investment area. Indeed, more than three-quarters of respondents (77%) agree that **access to alternative data for risk assessment models is increasingly becoming a key approach to improving the accuracy of lending decisions.**

It is interesting to note that for those who have not adopted ML, their biggest budget increase is nevertheless for analytical software for modelling, as businesses look to improve the accuracy of their analytics.

Budgets have increased for cloud-based decisioning software for 43% of respondents. As local data residency becomes more widespread and eases data sovereignty concerns, the majority (83%) agree that **cloud computing is essential to their strategy for maximising data value**.

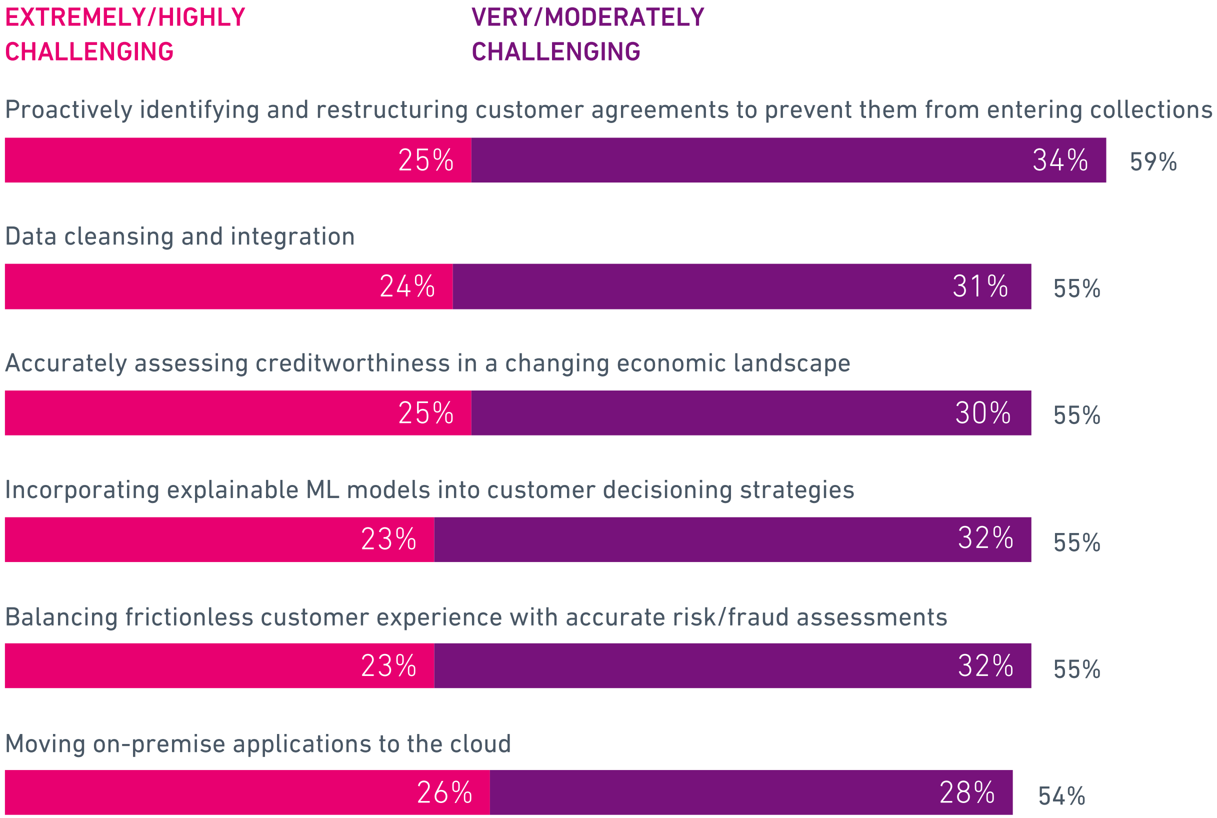
Top challenges for the next twelve months

More than half of respondents (53%) expect the volume of customers defaulting and entering collections to increase in the year ahead. This finding illustrates that the impact of consistently high interest rates and cost-of-living expenses is a real threat to ongoing profitability.

Proactive identification of vulnerable customers and restructuring of payment agreements is critical to avoid them entering collections. However, this remains a considerable challenge – in fact, the biggest for the year ahead.

Challenges around model development and deployment remain, with data cleansing (55%) and the difficulty of incorporating explainable ML models into decisioning strategies (55%) both highlighted as focus areas for the next 12 months. More than two-thirds (69%) of respondents agree that **data silos and legacy infrastructure are the biggest challenges limiting innovation in their organisations.**

Early and proactive identification of vulnerable customers is the biggest challenge for the year ahead



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Yes: How is ML impacting credit risk for adopters?

There is no doubt that those organisations that have already adopted advanced ML have seen an improvement in acceptance rates and levels of bad debt.

Our research shows that this uplift is not only due to the greater predictive accuracy of these models, but also due to the ability to analyse non-traditional data sources and better identify vulnerable customers.

ML delivers the most value when it has access to vast and varied datasets. For ML to deliver an uplift in predictive accuracy, it must be trained on sufficient data. The richer the dataset, the better the outcome. No matter how sophisticated the modelling – if the underlying data lacks complexity and volume, it will not deliver additional value.

Credit risk modelling is highly suited to ML analysis due to the scale of historical credit data that exists. When these advanced analytical tools are connected to financial records through Open Banking, the precision is compounded.

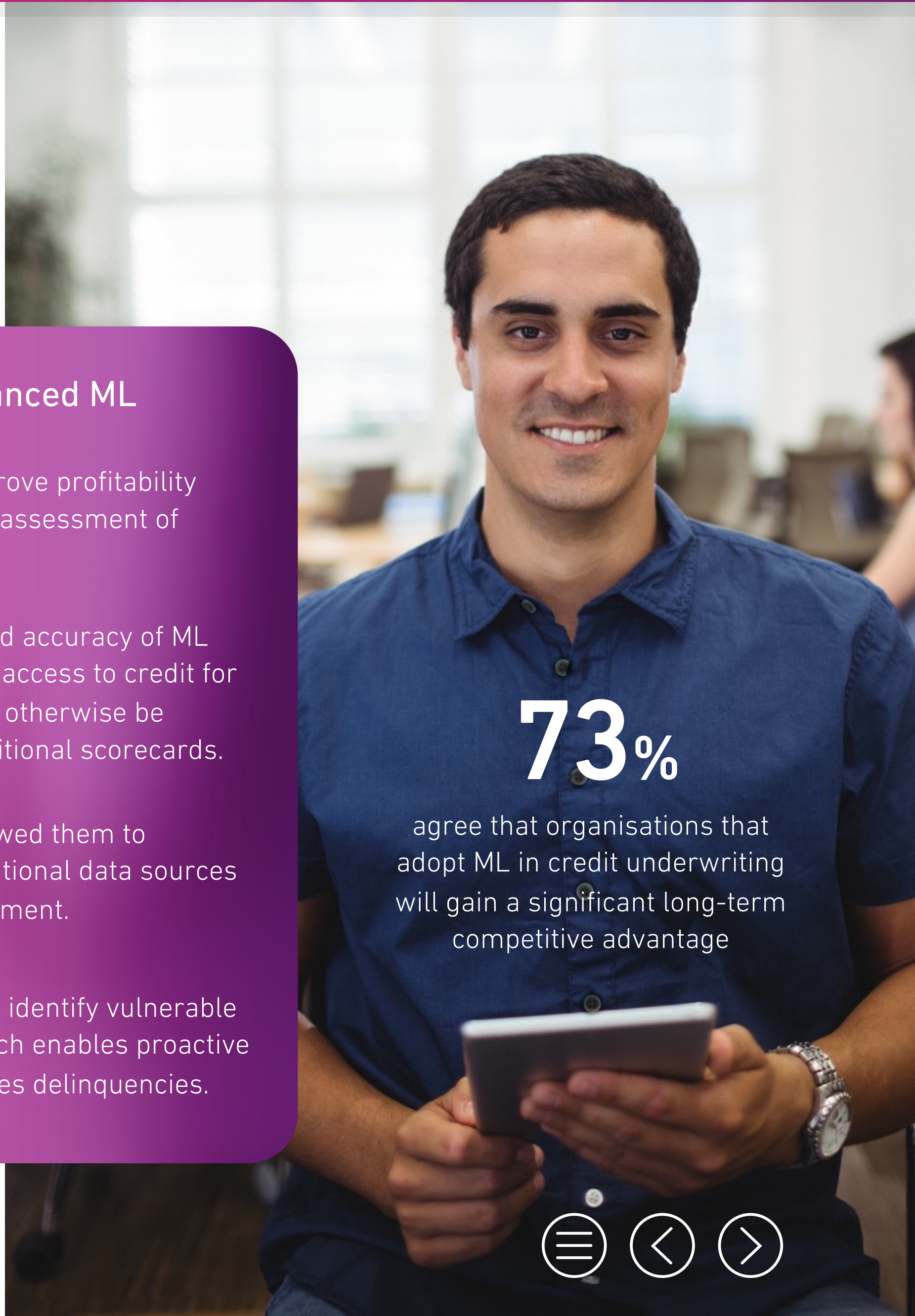
Key benefits for those who are using advanced ML

71% agree that ML can improve profitability by providing a reliable assessment of thin-file customers.

70% agree that the improved accuracy of ML means they can widen access to credit for consumers who would otherwise be denied credit with traditional scorecards.

68% agree that ML has allowed them to include more non-traditional data sources into their credit assessment.

67% agree that ML can help identify vulnerable customers earlier, which enables proactive intervention and reduces delinquencies.



73% agree that organisations that adopt ML in credit underwriting will gain a significant long-term competitive advantage

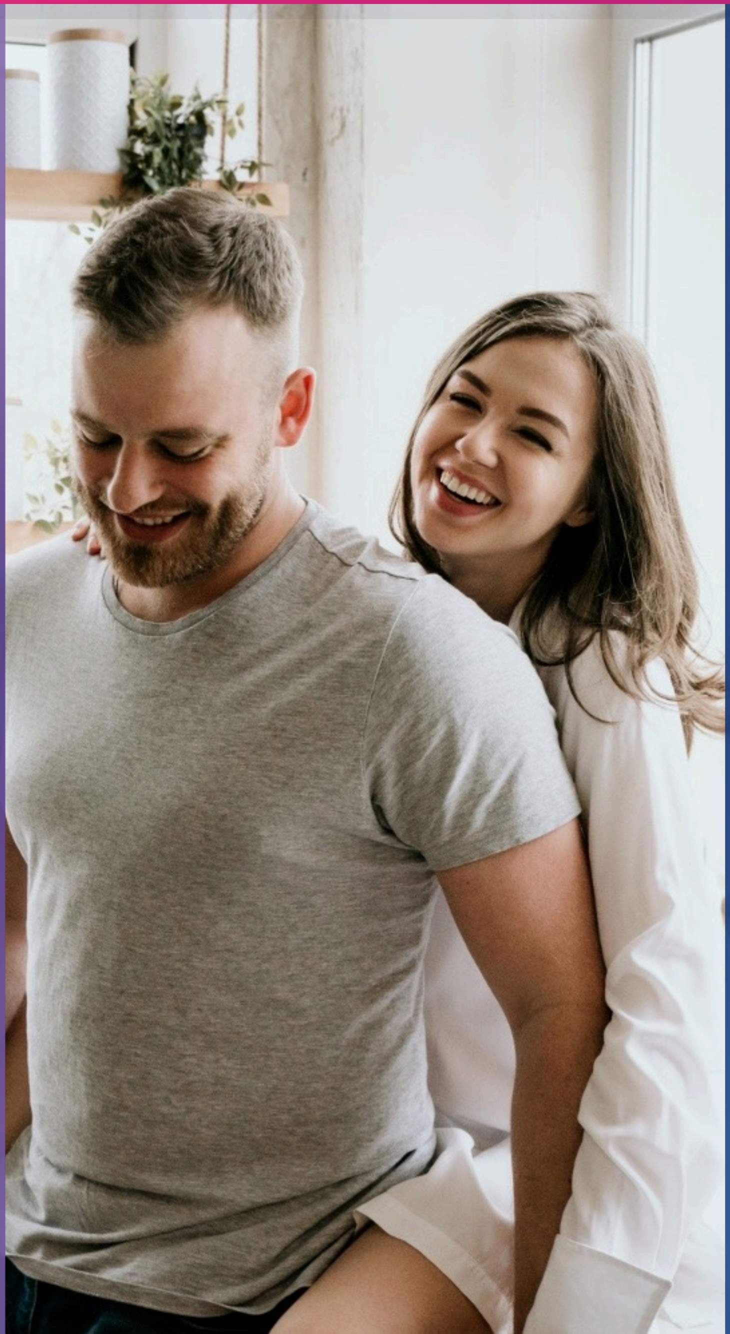
Does ML drive financial inclusion?

Our research findings align with an in-depth study conducted by Experian in Australia, which found that while traditional scorecard models and ML models were equally capable of finding very high-risk consumers, ML models were considerably better at discerning credit behaviour nuances in the middle to low-risk segment. In addition, the report notes that ML was able to find younger, inexperienced borrowers who were highly creditworthy, **thus reducing the degree of subjective discrimination that could otherwise have occurred.**

The report shows that using the same credit-quality strategy, the ML model could increase loan funding by 10% overall and 4% over the traditional model. Additionally, with the same approval rate, the ML model approved 2% more 'good' customers and 2% fewer 'bad' ones.

When the researchers applied a more conservative risk strategy (reducing portfolio credit risk by 50% over that of the lender's existing process), the ML model performed even better, approving 24% more applicants and lending 22% more in funds than the traditional model.

In terms of driving financial inclusion, the ML model significantly benefited inexperienced borrowers, with 19% more applicants with less than 2 years of experience approved and 75% more applicants with 2-5 years of experience approved. **This suggests that ML can provide traditionally underbanked consumers with greater credit opportunities, without increasing risk appetite.**



Benefits of ML adoption for our clients

Experian works with a range of clients to optimise each stage of their ML development and deployment. Some of the results for specific clients can be seen below.

Predictive performance

On average, ML models deliver a 5-20% relative Gini lift over logistic regression bureau models. Here are some examples:

- **Decisioning for instalment loans:** algorithm benchmark resulted in 60% Gini with traditional modelling and 64% Gini with ML.
- **Decisioning for a payment service provider:** algorithm benchmark resulted in 69% Gini with traditional modelling and 72% Gini with ML.
- **Decisioning on dunning measures for customers in distress:** algorithm benchmark resulted in 48% Gini with traditional modelling and 59% Gini with ML.
- **Decisioning for a telco company:** algorithm benchmark revealed +5.5m EUR potential benefit p.a. with traditional modelling and +7m EUR with ML.

Efficiency and time saving

- Rapid model development enables quicker testing of Gini coefficients and predictiveness.
- Accelerates evaluation of alternative data variables, streamlining feature selection.

Resource optimisation

- Reduces dependency on manual analytics, freeing-up resources for strategic tasks.

How GenAI is making it easier to analyse Business Information (BI) data

When ML models are combined with GenAI-assisted Business Information (BI) data analysis, the impact that this technology can provide is even more considerable. GenAI can automate the extraction, analysis and categorisation of large volumes of unstructured BI data, which reduces manual workloads and enhances the accuracy of ML-based credit assessments for SMEs.

GenAI assisted BI data extraction can automate a time-consuming manual process

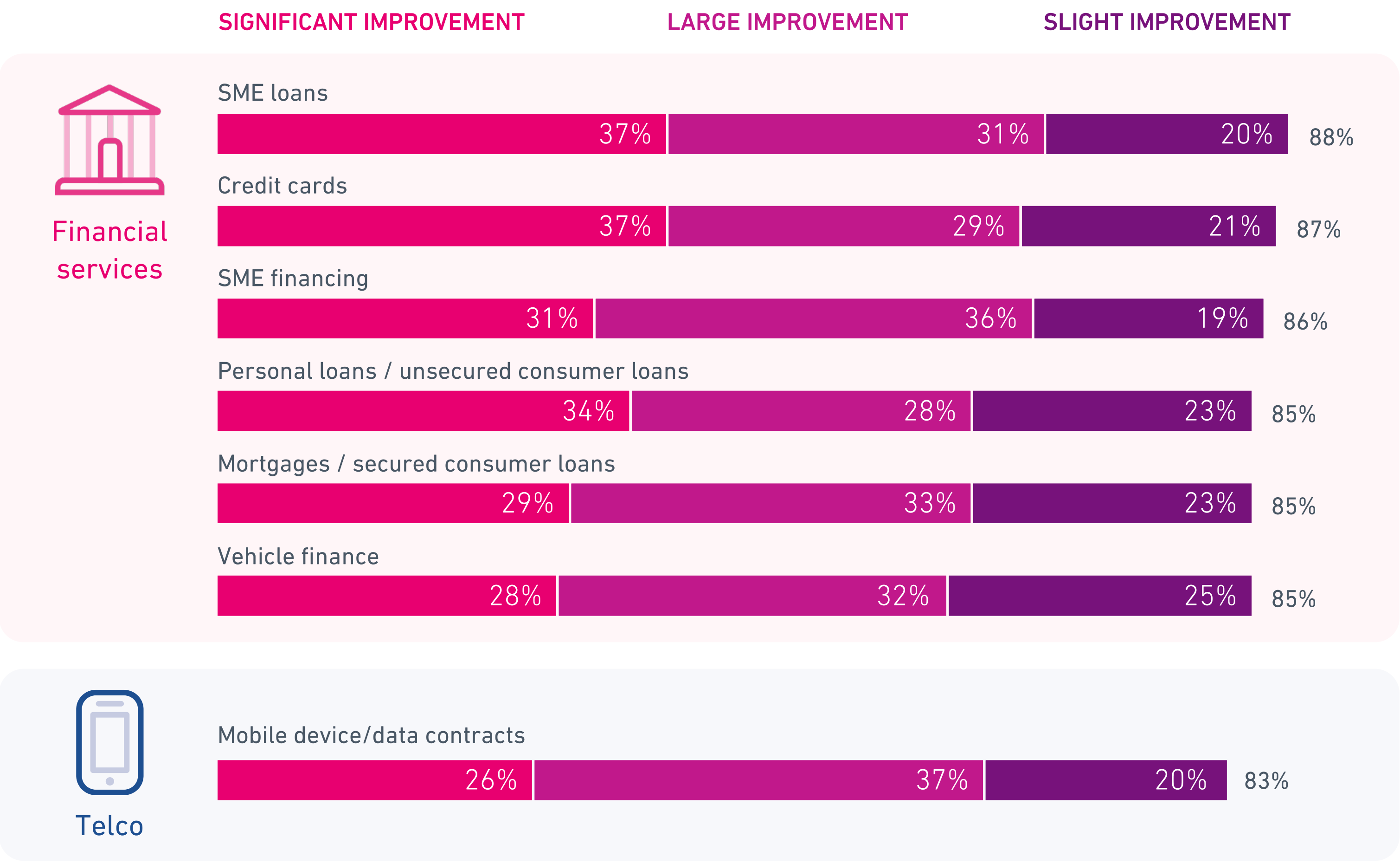
1. Analyse large volumes of unstructured BI data, such as annual reports, P&L and legal documents
2. Summarise and categorise relevant information
3. Then automatically include it in the database for SME credit assessment

Impact of ML on acceptance rates

More than half of organisations that have adopted ML report a significant or large improvement in their acceptance rates for all categories of lending since adoption.

It is interesting to note that the biggest improvement is for SME loans, with 88% seeing an improvement in acceptance rates for this segment.

ML provides a significant improvement in acceptance rates for all credit services



Base: 597 senior decision makers responsible for developing and implementing AI/ML in credit risk
Source: Experian research conducted by Forrester Consulting, July 2025

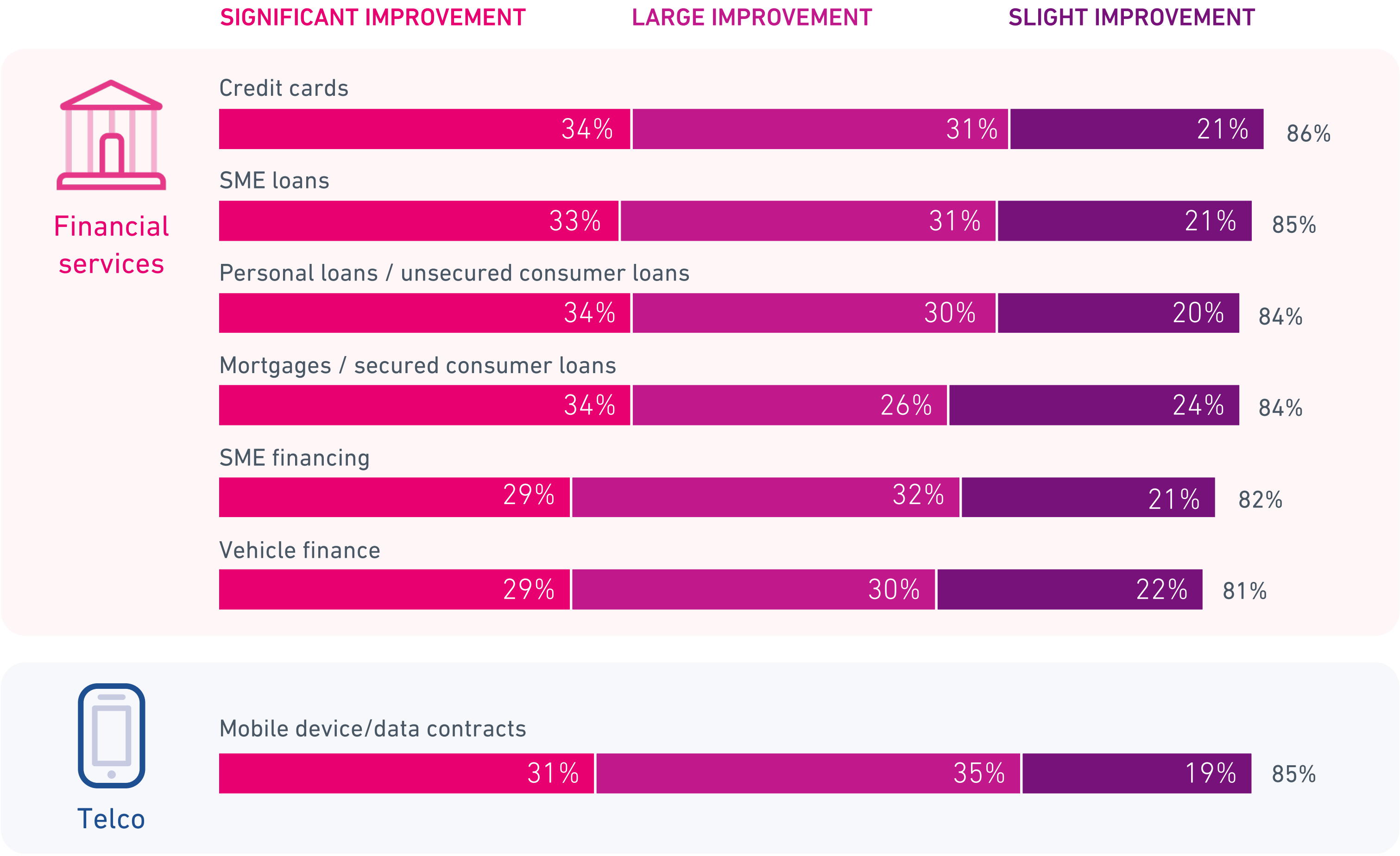
Impact of ML on bad debt rates

Close to two-thirds of all respondents who have implemented ML have seen a significant or large improvement in their bad debt rates since adoption.

Credit cards saw the biggest improvement, with 86% seeing an improvement in bad debt rates since the introduction of ML.

65% of those using ML agree that it has helped them reduce their bad debt rate

ML improves bad debt rates for all credit services



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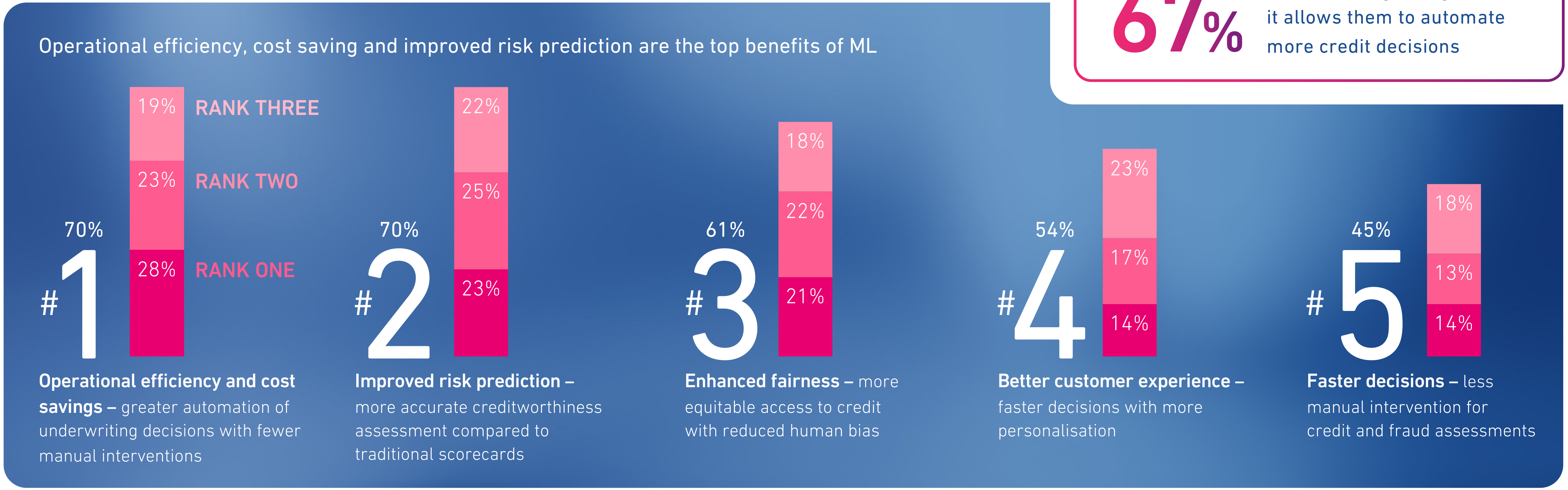
What are the biggest benefits of ML?

Considering the positive impact that ML is having on acceptance rates and bad debt levels, it follows that 70% of respondents using ML ranked **'operational efficiency and cost saving'** as the top benefit of ML. Of equal importance (70%) is the **improved risk prediction accuracy that it provides.**

Both of these are connected to more automation of underwriting decisions, with **more than two-thirds (67%) of those using ML agreeing that it allows them to automate more credit decisions.** As we look into the future of underwriting, 79% of respondents agree that in five years' time, the vast majority of credit decisions will be fully automated.

In light of these benefits, it is unsurprising that **70% of those using ML plan to significantly increase investment in their ML capabilities over the next 1-3 years** – a clear indication that ML is delivering the goods in regard to credit risk.

67% of those using ML agree that it allows them to automate more credit decisions



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What are the biggest challenges with implementing ML?

Our research suggests that the number one challenge associated with implementing ML is the time and resources required. This is closely linked to the second biggest challenge of turning raw data into credit attributes that make up the individual features of each model.

By using verified third-party attributes, lenders can reduce the time and effort required to develop high-quality ML models.

A lack of in-house expertise was also highlighted by half (50%) of respondents. This ties into our finding that access to specialised skilled labour is expected to be a significant or large challenge for two-thirds (66%) over the next few years.

This is where local third-party collaboration can play a crucial role in elevating those organisations that need additional data science expertise.

Biggest challenges of using ML models

#1	Time/resources to implement new ML models	55%
#2	Turning raw credit data into usable credit attributes	53%
#3	Lack of expertise in-house to manage and govern	50%
#4	Lack of sufficient data for model development and testing	50%
#5	Avoiding bias	48%

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What are attributes, and what role do they play in ML model development?

Credit attributes represent the relationship between data points that are used to describe the financial characteristics of a borrower. They provide greater insight into credit behaviour than a standard credit score by aggregating and combining individual data points, like credit utilisation and balances, into time-based ratios, such as a debt-to-income ratio over 24 months.

Credit attributes enhance the accuracy of lending decisions by providing a more comprehensive understanding of a borrower's financial situation. This goes beyond a basic credit score as it includes factors like financial stability over time and debt management history to paint a more detailed overall picture.

These attributes can be used in the development of ML-powered credit risk models and scores to improve the precision of lending decisions. They can also be used without the need for new models as an overlay to improve customer and prospect segmentation accuracy.

For more information about Experian's attributes, download our PDF guide:

Precision Decisions: Unlocking the value of attributes

Download →

The impact of regulations on ML adoption

Global AI/ML regulations are similar to privacy regulations in that there is a patchwork of different laws, with different requirements across different countries. Further complicating this fragmented legal environment is the fact that regulatory activity lags behind technical innovation.

This is having a direct impact on ML adoption and creating inertia that is negatively affecting innovation within credit risk. **Three-quarters (75%) of respondents agree that regulatory compliance is limiting their organisation's ability to innovate within credit decisioning.**

Our research findings emphasise this challenge, with 70% of respondents who have adopted ML holding back on implementing more automated ML credit decisions due to concerns about regulatory backlash. A similar percentage (66%) agree that their national regulators lack a clear, consistent understanding of how ML models function in practice.

Research from Experian, shows that 95% of the financial institutions surveyed say the number of regulations for the credit risk models that they need to comply with has increased in the last few years, with 85% reporting that regulators are becoming more stringent.

One of the most exciting developments in the regulatory compliance space is GenAI Assistants that can automate the production of regulatory documentation while a model is being developed. This means that instead of this process being sequential, with many iterations, it can now happen in parallel – so regulatory validation and documentation happen as the model is developed.

Top ML use cases

When we look at where organisations have adopted ML, we make the distinction between implementation into live decisioning with and without human oversight for every decision. This is an important distinction to make, as it shows where automation is being applied.

The findings show the ML use case with the highest adoption (74%) is probability of default models, which also has the greatest percentage of automation. At the other end of the spectrum, credit affordability assessments show the highest percentage of implementation with human oversight of every decision.

It is clear that many early adopters of ML have moved past experimental use, with roughly **two-thirds using it in live decisioning** and only around one-quarter using it experimentally.

Considering that 80% of respondents **agree that time-to-decision has become a key differentiator between digital credit offers,** those that are using ML to automate or speed up credit assessment processes may be able to outcompete those that are still relying on slower manual assessments.

ML adoption across different use cases

	Full implementation into live decisioning without human oversight of every decision	Full implementation into live decisioning but with human oversight of every decision	Experimental use only	Full implementation
Probability of default models	38%	36%	16%	74%
Customer risk segmentation	34%	34%	20%	68%
Customer behaviour segmentation	29%	37%	21%	66%
Automated loan decision making	29%	32%	31%	61%
Risk-based interest rate pricing	26%	35%	24%	61%
Credit affordability assessment	20%	39%	25%	59%

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No: Why is ML not being adopted?

The AI genie is out of the bottle and not going back, so is ML adoption in credit risk an inevitability? And why have some not taken steps to use ML in risk?

For those organisations that have not adopted ML, the two responses with the highest percentage of strongly agree were that **the cost involved with implementing ML outweighs the perceived benefits** (66% total agree), **and that they do not fully understand the value of implementing ML models** (59% total agree).

Investing in new technology for technology's sake is pointless – why change to new systems if the old systems are still working? The answer is when the technology is likely to be a critical component of the next big step for lending institutions in hyper-personalisation – then failing to adopt it can be seen as a strategic error.

Risk-averse organisations often follow a 'wait and see' approach to assess the learnings achieved by first movers. As with any technology transition, the move from traditional models to advanced ML in credit risk requires a clear business case. Although ROI is the ultimate goal, developing a better understanding of the processes involved with ML adoption is a success in its own right that usually leads to value in the long run.

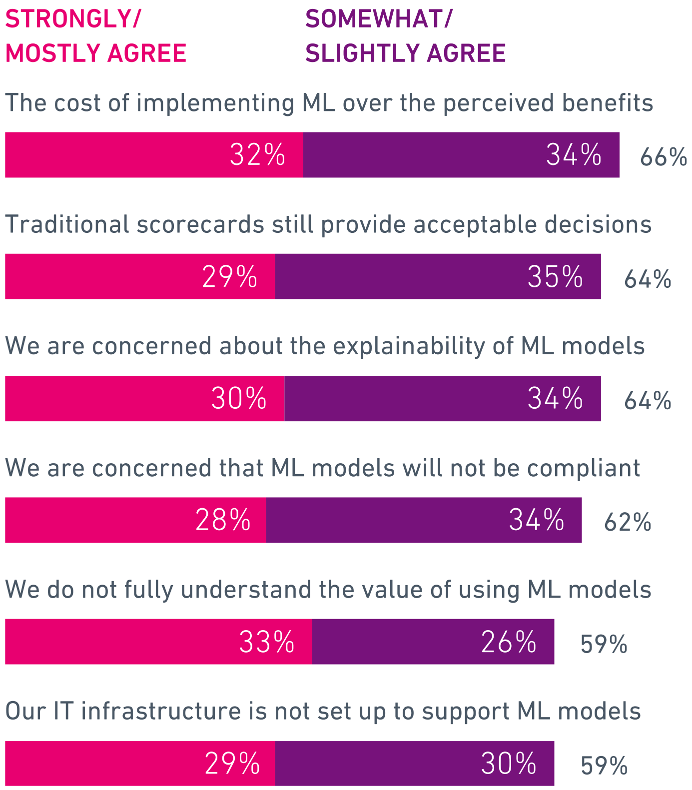
Those organisations that are unsure of the advantages of advanced ML can apply a champion/challenger approach, which allows them to test their traditional models in parallel with ML to measure the benefits before live implementation.

Looking at the other reasons for non-adoption, nearly two-thirds (64%) agree that traditional scorecards are still delivering acceptable lending decisions. However, the best time to make large operational changes is when you're strong and have the budget. Avoiding change until you're in trouble and have no other option to stay competitive is a recipe for disaster.

62% of those not using ML agree they tend to take a conservative approach to adopting new technology

> "As digital offerings have become table stakes in the credit world, lenders that can use the power of ML to rapidly deliver personalised interest rates with tailored products and services will be at a significant advantage."

Why have businesses not adopted ML?



Explainability and trust

Apart from questioning the perceived value of ML, concerns about explainability and regulations are also impacting adoption. 64% of non-ML users are **concerned about the explainability of ML models.** While the outputs from some types of AI are not transparent, the ML used in credit decisioning must follow a well-established explainability protocol to ensure that the features and their individual contribution to the decision are clearly available.

With the latest tools, even previously difficult to explain models such as neural networks can be transparent. Explainability techniques can also be retroactively applied to existing models. Although ML models can be fully explainable, with clear reasons for every decision, it appears this process is still causing headaches for many organisations.

Closely linked to these perceived concerns is the issue of trust. More than half (58%) of non-ML adopters state that **their risk team does not sufficiently trust the outputs of ML models.** With the performance uplift of ML clear to those who have embraced the technology, the question non-adopters must ask themselves is – what would help to build trust so they can start to take advantage of the opportunity?

Capacity and infrastructure

The final set of concerns for why ML has not been adopted centres around internal skills and data architecture. 59% stated that their **IT infrastructure is not set up to support ML** models. While this appears as a significant hurdle, third-party cloud-based services can help these organisations leapfrog technological debt.

Trusted, locally-based, third-party consultants can also directly address skills shortages and data availability concerns. 56% of non-ML adopters agreed that they **lack internal expertise to confidently implement ML models,** and the same percentage said that they **do not have enough quality data to effectively train ML models.**

60% of those not using ML agree that their leadership team sees ML as more of a reputational risk than a strategic asset

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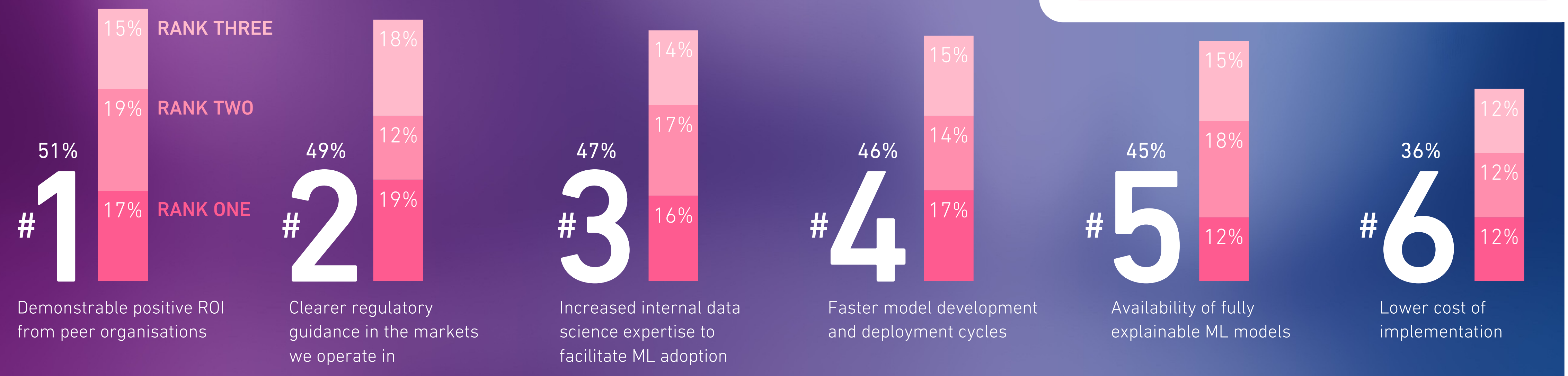
What would encourage ML adoption?

The big factors that would encourage ML adoption align with the reasons for non-adoption: positive ROI, clearer regulatory guidance and the skills gap. Our research indicates that regulatory confusion is holding back greater ML implementation.

Looking across all the countries we surveyed, a trend emerges that suggests that countries with clearer guidelines, such as India, have more ML adoption. It is interesting to note that even among the non-adopters of ML, 59% are actively exploring pilot projects involving ML in credit risk. And a similar number (58%) view the adoption of ML as a long-term possibility but not an immediate priority.

54% of non-ML users believe their risk models perform adequately, and see no immediate need for ML

What factors would encourage ML adoption for those yet to implement it?



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Analytical sandbox environments

To maximise the potential of ML requires a sandbox environment. Why? Because one of the biggest benefits of ML over traditional scorecards is the ability to analyse alternative and unstructured data – this allows ML models to deliver more accurate decisions.

However, this requires a central access point for data to develop models. A sandbox environment can help resolve this by harmonising data across multiple databases, allowing for easier cross-category analysis. **72% of those using sandboxes agree that it has greatly improved collaboration between data science, risk and compliance teams.**

Another important benefit of a sandbox is that it can fast-track the process of pushing models into production. More than three-quarters **(76%) of respondents agree that organisations able to develop and deploy models in faster cycles will increasingly have a competitive advantage.**

During periods of uncertainty and rapid economic changes, the ability to develop and deploy models in faster cycles is crucial to adapt and grow. If the model takes too long to go live, the underlying conditions may have changed – making the model less accurate and negatively impacting ROI.

Sandbox environments can speed up data preparation and the development of model attributes, which our research has shown is a common pain point in model production. The ability to clean and pin data required for specific use cases is key to improving model development time.

Ultimately, it is the combination of data and data-science expertise that makes a sandbox successful. Without the right data (cleaned and aggregated), there is no algorithm that will improve decisioning accuracy. But having access to a sandbox allows organisations to test and experiment with combinations of different features that can be used to power ML models.

76% agree that organisations able to develop and deploy models in faster cycles will increasingly gain a competitive advantage

Sandbox use cases

Top use case

Attributes	Analysis	Segmentation	Regulatory	Reject	Models
Attribute development to be used in models and strategies	Vintage analysis to track and evaluate the performance of groups of loans over time	Segmentation analysis to better tailor credit strategies and support targeting for products	Regulatory analytics to support key requirements (e.g., BASEL, IFRS9, CECEL or equivalent)	Reject inferencing to identify lost opportunities from applicants previously denied credit	Custom model development

HIGH PRIORITY

Attributes	Analysis	Segmentation	Regulatory	Reject	Models
38%	35%	32%	32%	35%	37%

MEDIUM PRIORITY

Attributes	Analysis	Segmentation	Regulatory	Reject	Models
34%	36%	37%	37%	33%	30%
72%	71%	69%	69%	68%	67%

Base: 922 senior decision makers responsible for developing and implementing AI/ML in credit risk
Source: Experian research conducted by Forrester Consulting, July 2025

Top 3 reasons why some organisations are not using sandbox environments

Less than a quarter (23%) of all respondents do not have a sandbox environment, with data infrastructure, cost and IT resources cited as the top reasons why some organisations are yet to implement them.

#1 65%

"Our current data infrastructure makes it difficult to safely work with regulated data and innovate with model development."

#2 65%

"The cost associated with setting-up a sandbox."

#3 64%

"Internal IT resources are the biggest reason my organisation has not implemented a sandbox environment."

Despite these challenges, **more than half (52%) of non-adopters agree there is a growing internal interest** in setting up a sandbox, with a similar number **(56%) saying they plan to implement a sandbox environment** in the next 12 months.

GenAI applications in credit risk

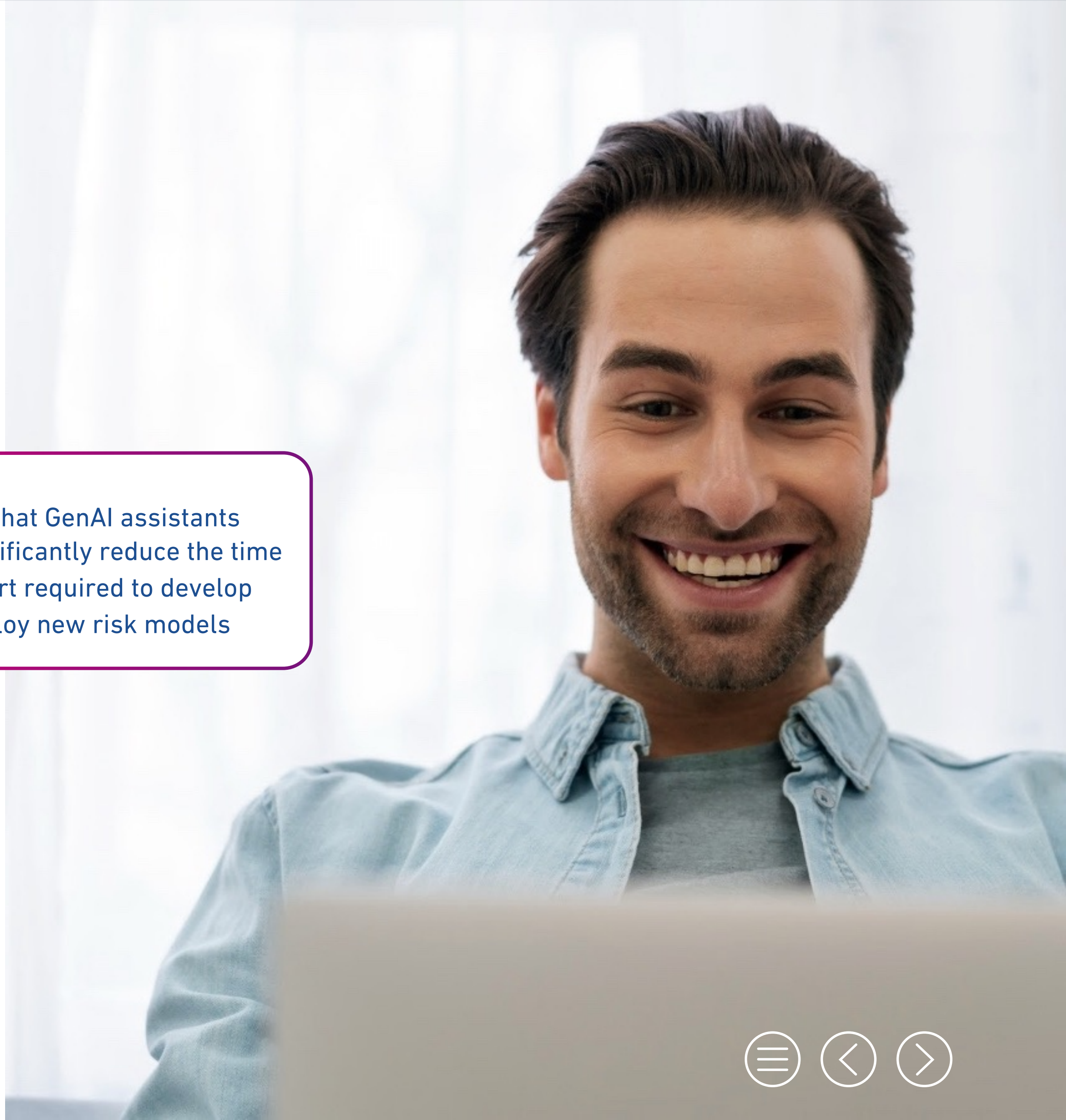
In this final section, we look at the future of credit risk. Without a doubt, the most exciting technology in this space is GenAI, and in particular, GenAI assistants that can augment the productivity of data scientists and engineers.

These assistants can support the processes involved with the development and deployment of ML models – and have the potential to significantly reduce model ops timeframes.

At the time of publication, GenAI models are still unexplainable, black box models. This means that they are unsuitable for credit risk assessment. However, GenAI can be used as a supportive tool in the model development process – helping with data recall, coding, regulatory documentation and model monitoring.

Close to three-quarters (73%) of respondents agree that a GenAI assistant that is highly trained on credit risk data could help their data scientists be more productive. A similar percentage (70%) agree that using a GenAI assistant to generate code would improve the productivity of their data science and analytics teams.

73% believe that GenAI assistants can significantly reduce the time and effort required to develop and deploy new risk models



Top GenAI use cases in credit risk

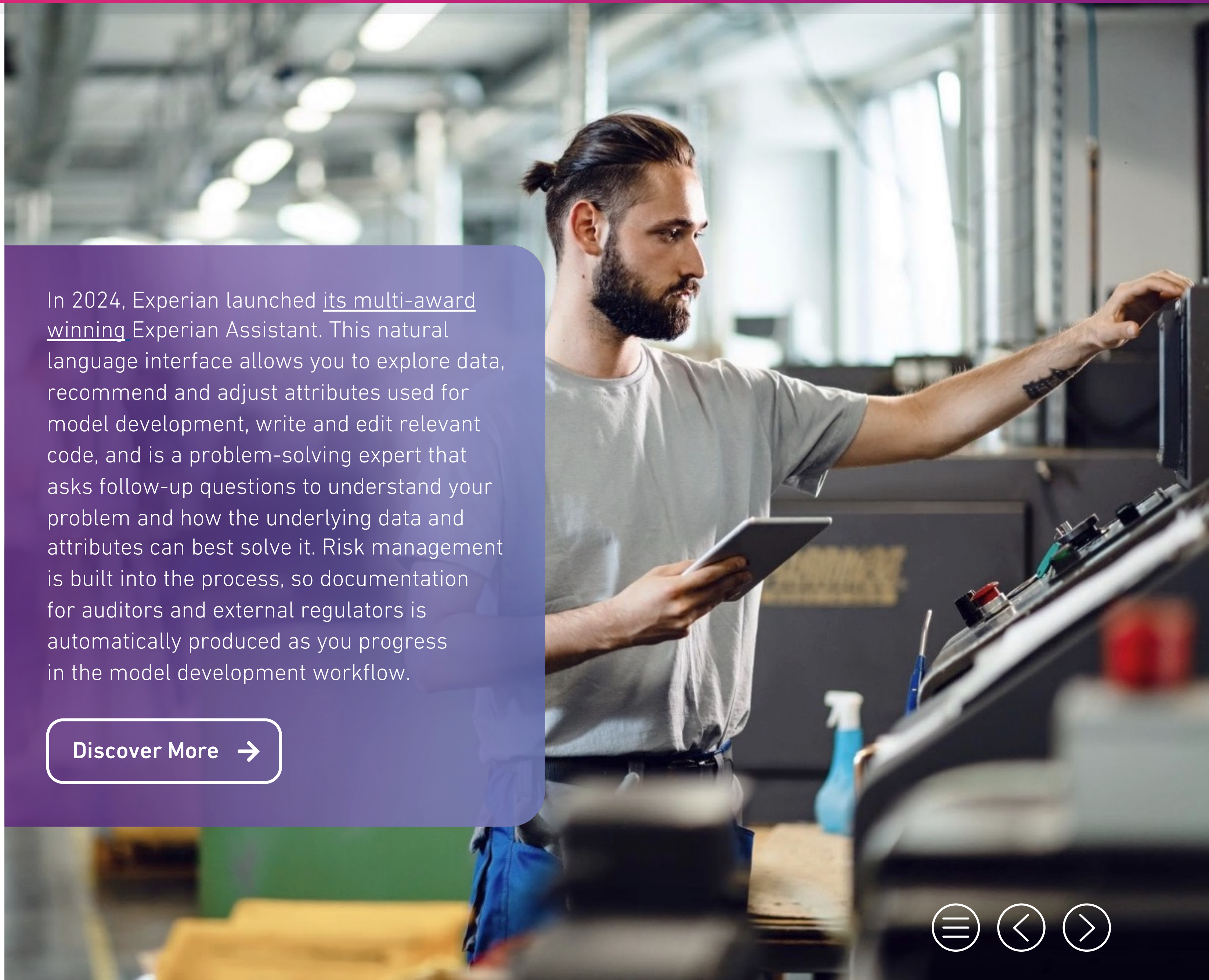
Automate model documentation

Model validation has historically been a back-and-forth process with many iterations. Creating a regulatory-compliant GenAI-assisted workflow to improve this pain point is groundbreaking.

Documentation is developed in tandem with the model, so instead of a sequential process – where validation and regulatory documentation is compiled after the model is developed – this can now happen in parallel, so that the model validator can look at the model while it is being developed, make any changes and document the whole process so concerns can be addressed immediately. **More than two-thirds (67%) agree that the biggest advantage of a GenAI assistant is to reduce the time required to produce regulatory documentation.**

SME BI data extraction

These datasets are usually made up of large volumes of unstructured data, such as PDF reports, profit and loss (P&L) statements and legal documents. Up until now, the extraction of this data has required the manual review and labelling of data before it could be included in an ML risk assessment model. With the right GenAI assistant, this process can be automated, and the accuracy of the final model can be improved.



In 2024, Experian launched its multi-award winning Experian Assistant. This natural language interface allows you to explore data, recommend and adjust attributes used for model development, write and edit relevant code, and is a problem-solving expert that asks follow-up questions to understand your problem and how the underlying data and attributes can best solve it. Risk management is built into the process, so documentation for auditors and external regulators is automatically produced as you progress in the model development workflow.

Discover More →

Key takeaways

For those who have adopted ML

ML is improving acceptance rates and reducing bad debt. It has an essential part to play in the future of lending, helping to create more equitable access to financial services worldwide. However, adopting ML is not a simple process, the journey from data to decision is complex and achieving the desired results is only possible with sufficient quality data and the right architecture.

For those who have not adopted ML

Concerns about cost, regulations, explainability, IT skills and legacy data infrastructure are holding back ML adoption. Demonstratable ROI and clearer regulatory guidelines would encourage greater adoption. Testing advanced ML with a champion/challenger approach allows the benefits to be measured before live implementation.

GenAI is a rapidly emerging productivity tool

The use of GenAI represents a seismic change in lending – a considerable step up in a process that has remained largely unchanged for decades. These tools provide a significant competitive advantage to early adopters and are likely to be fundamental to credit risk in the near future.

Experian's data-to-decision platform works like a complex highway interchange, with multiple on-ramps and off-ramps, where different microservice components can be consumed individually or collectively.

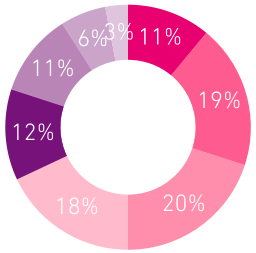
All of these potential routes are seamlessly connected and integrated so that, regardless of the number of services used, there is an overall cohesive flow, with outputs feeding into inputs to continually refine the process.

Our global team of expert data scientists can help your organisation optimise your credit and fraud prevention systems. And our highly experienced local consultants can analyse your existing processes and identify how and where you can improve the accuracy of your decisions – no matter how big or small your operation is.

Contact us today to speak to a local consultant so that together we can drive financial inclusion for all and help create long-term sustainable growth.

Firmographics and respondent demographics

COMPANY REVENUE



- $5bn+
- $1bn to $5bn
- $500m to $999m
- $400m to $499m
- $300m to $399m
- $200m to $299m
- $100m to $199m
- $50m to $99m

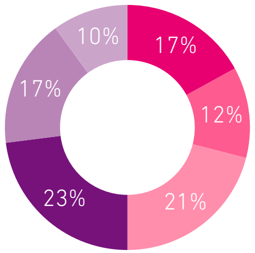
GEOGRAPHY

N=~109 each country

Denmark, Spain, Italy, Germany, South Africa, Norway

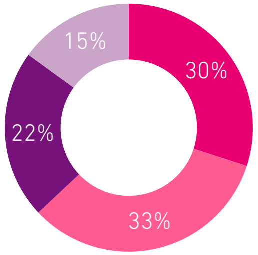
Singapore, New Zealand, Australia, Malaysia, India

RESPONDENT LEVEL



- C-level executive (e.g., CEO, CMO, CIO)
- Executive Vice President (EVP)
- Senior Vice President (SVP)
- Vice President (VP)
- Director
- Manager

COMPANY SIZE



- 500-999 employees
- 1,000-4,999 employees
- 5,000-19,999 employees
- 20,000 or more employees

INDUSTRY

Financial services

50/50 Traditional institutions/Fintechs (N=755) 63%

We surveyed 755 decision-makers from the financial services sector, with 50% representing traditional institutions and 50% representing fintech. These decision-makers represent organisations operating across various financial services sectors, including digital payments, banking, automotive financing, commercial finance/leasing, consumer lending, and robo-advisors.

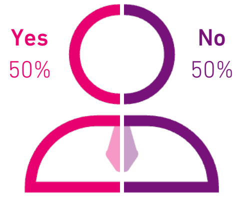
Telcos

37%

DIRECT RESPONSIBILITY FOR DECISION-MAKING

I lead credit risk function or have decision authority	I oversee or champion the use of AI/ML in credit risk	I develop or validate AI/ML models used in credit risk
37%	34%	30%

"Does your organisation currently use advanced **ML algorithms (such as Gradient-Boosted trees or others, but not linear or logistic regression)** in the following credit underwriting applications: credit scoring, default predictions, risk-based interest rate pricing, automated loan decision making or customer segmentation?"



About Experian

Experian is a global data and technology company, powering opportunities for people and businesses around the world.

We help to redefine lending practices, uncover and prevent fraud, simplify healthcare, deliver digital marketing solutions, and gain deeper insights into the automotive market, all using our unique combination of data, analytics and software. We also assist millions of people in realising their financial goals and help them to save time and money.

We operate across a range of markets, from financial services to healthcare, automotive, agrifinance, insurance, and many more industry segments.

We invest in talented people and new advanced technologies to unlock the power of data and innovate. As a FTSE 100 Index company listed on the London Stock Exchange (EXPN), we have a team of 25,200 people across 32 countries. Our corporate headquarters are in Dublin, Ireland.

Learn more at experianplc.com

Discover More →

Contact your **local Experian consultant** or visit **experianacademy.com**

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