

The Impact of Artificial Intelligence on Financial Services**Evidence from the United Kingdom Financial Sector**Author: Stephan Sayegh¹*Affiliation:*

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Abstract:

This study examines how artificial intelligence is changing financial services, using the 2024 Bank of England and Financial Conduct Authority survey as the main empirical source. The survey received responses from 118 regulated firms across banking, insurance, non-bank lending, investment and capital markets, and financial market infrastructure. The analysis compares adoption indicators from 2022 and 2024 and evaluates deployment, automation, governance, expected benefits, and perceived risks. The proportion of firms already using AI increased from 58% in 2022 to 75% in 2024, a rise of 17 percentage points or 29.3%. The share of AI use cases supplied by third parties almost doubled from 17% to 33%. Firms expected the median number of use cases to increase from 9 to 21 within three years, representing projected growth of 133.3%. AI was concentrated in internal process optimisation, cybersecurity, fraud detection, data analysis, and customer support. Although 55% of use cases included some automated decision-making, only 2% were fully autonomous. Governance practices were common: 84% of firms had an accountable person for the AI framework and 81% used explainability methods. At the same time, 46% reported only partial understanding of the AI technologies they used, compared with 34% reporting complete understanding. The evidence indicates that AI is already producing broad operational and analytical effects, but its financial impact remains mostly assistive rather than fully autonomous. Data privacy, model risk, cyber threats, bias, and third-party concentration require continued human oversight. The study concludes that AI can improve efficiency, risk detection, personalisation, and access, but sustainable value depends on governance, transparency, data quality, and accountability.

Keywords:

Artificial intelligence, financial services, banking, machine learning, automation, financial regulation, model risk

Introduction:

1.1 Background and Context

Artificial intelligence has moved from a specialised analytical tool to a widely used part of financial services. Banks, insurers, investment firms, payment providers, and market infrastructures now apply machine learning and generative AI to large volumes of transactional, behavioural, and market data. The technology supports fraud detection, credit assessment, anti-money-laundering controls, customer service, trading research, claims processing, cyber defence, and internal operations. Its importance comes from the combination of speed, scale, and pattern recognition: an AI model can analyse data that would be too large or too fast-changing for manual review.

The transformation is not limited to cost reduction. AI can change how financial institutions make decisions, design products, evaluate customers, monitor risk, and interact with clients. Aldasoro et al. (2024) describe an emerging intelligent financial system in which AI improves information processing across payments, insurance, lending, and asset management. In credit markets, digital information can add predictive value beyond traditional credit records (Berg et al., 2020). In investment management, machine-learning models can extract complex relationships from large sets of firm and market characteristics (Gu et al., 2020). These capabilities can improve decisions, but they can also make those decisions harder to explain.

The 2024 Bank of England and Financial Conduct Authority survey provides a timely view of adoption within regulated firms. Seventy-five percent of the 118 respondents reported that they were already using AI, and another 10% planned to adopt it within three years. Adoption had therefore moved beyond isolated experiments. However, third-party dependence, incomplete understanding, automated decisions, and data-related risks also increased in importance. The financial impact of AI must consequently be assessed as a balance between operational benefits and new forms of model, conduct, consumer, and systemic risk (Bank of England and Financial Conduct Authority, 2024).

1.2 Problem Statement

Financial institutions face pressure to use AI because competitors can process information faster, automate repetitive work, and offer more personalised services. Yet rapid adoption does not automatically create financial value. A model can be accurate in testing but unreliable after market conditions change. A customer-service system can reduce response time but give incorrect or unsuitable guidance. A credit model can improve average prediction while distributing benefits unevenly across demographic groups. Outsourced models may lower implementation costs while concentrating operational dependence on a small number of technology providers.

The central problem is therefore not whether AI is present in finance, but how it is affecting financial-service activities and whether firms can control the risks created by greater automation. Public discussion often describes AI as either a complete transformation or a dangerous replacement for human judgment. The available evidence suggests a more measured reality: adoption is widespread, the number of use cases is rising quickly, but most applications remain low in materiality and retain human involvement. This study evaluates that evidence systematically.

1.3 Research Question and Objectives

The main research question is: How is artificial intelligence affecting the operations, decision-making, benefits, and risks of financial-service firms?

The study has five objectives. First, it measures the change in AI adoption between the 2022 and 2024 surveys. Second, it identifies where financial firms are deploying AI and how quickly the number of use cases is expected to grow. Third, it evaluates the degree of automated decision-making and the continuing role of human oversight. Fourth, it compares governance capacity with the risks created by data, models, cyber threats, and third-party providers. Fifth, it develops practical recommendations for financial institutions and regulators.

1.4 Research Hypotheses

H1 states that AI adoption among responding financial firms increased between 2022 and 2024. H2 states that the current impact of AI is concentrated in decision support, operational optimisation, and risk detection rather than fully autonomous financial decisions. H3 states that firms expect the benefits of AI to grow faster than its risks, although stronger governance remains necessary because of data and third-party vulnerabilities.

1.5 Significance and Scope

This topic is significant because financial services combine sensitive personal data, high transaction volumes, legal duties, and decisions that can materially affect consumers. An error in a recommendation system is inconvenient; an error in credit approval, fraud detection, insurance pricing, or trading can create financial loss and unfair treatment. Understanding the actual pattern of adoption helps separate measurable change from speculation.

The empirical scope is the United Kingdom financial sector, using aggregated responses from the 2024 Bank of England and FCA survey and selected comparison indicators from the 2022 survey. The results describe firms regulated in the United Kingdom and may not represent every jurisdiction. Because respondent-level data are not publicly available, the analysis is descriptive and does not claim that AI adoption caused changes in firm profitability, employment, or consumer welfare.

Literature Review:

2.1 Artificial Intelligence in Financial Intermediation

Artificial intelligence in finance includes machine learning, natural-language processing, computer vision, optimisation systems, and generative or foundation models. Traditional statistical models normally require analysts to specify relationships in advance. Machine-learning systems can identify nonlinear interactions from data and update predictions when new information becomes available. Foundation models extend this capability to unstructured text, images, audio, and code. In financial services, these technologies can support the core functions of transferring value, allocating capital, managing risk, and producing information (Aldasoro et al., 2024). Blockchain technology has been found to improve the performance of firms (Khalife et al., 2024) and enhance SMEs growth (Rizk & Sassine, 2023) using big data analytics (Subrahmanyam et al., 2024). AI and digitalization was also found to be a catalyst for innovation according to a study by Kamel et al. (2026). Overall, The economic value of AI comes partly from reducing information and processing costs. Financial institutions are information businesses: they collect data about borrowers, transactions, claims, markets, and regulations, then convert those data into decisions. Better prediction can reduce fraud losses, improve credit pricing, target customer support, and detect abnormal activity. The Bank of England and FCA (2024) found that operations and information technology represented about 22% of all reported AI use cases, twice the share of retail banking, the next largest business area. This concentration indicates that institutions first capture value through internal processes and analytical support before delegating high-impact decisions.

2.2 Credit Assessment and Financial Inclusion

Credit scoring is one of the clearest applications of machine learning. Khandani et al. (2010) showed that machine-learning techniques applied to borrower and transaction information could improve consumer credit-risk modelling. Berg et al. (2020) found that even simple digital-footprint variables could match the information content of traditional credit-bureau scores and complement them. Such methods may help evaluate applicants with limited formal credit histories and may support financial inclusion when alternative data are relevant and legally usable. AI enables the measurement of investor sentiment (Khalife et al., 2025) and attribute to organizational success (Azoury et al., 2024) especially in data-driven cultures. Furthermore, literature discuss how AI can predict financial distress (Elia et al., 2021) and even forecast economic quadrants (Nasser et al., 2025) thus allowing executives to take smarter decisions (Subrahmanyam & Beainy, 2027).

Greater predictive accuracy does not guarantee equal outcomes. Fuster et al. (2022) found that machine learning can improve mortgage prediction while producing unequal changes across borrower groups; Black and Hispanic borrowers were disproportionately less likely to benefit in their study. This result is important because flexible algorithms can exploit correlations that are statistically useful but socially sensitive. Fairness testing, explainability, representative data, and human review are therefore central to responsible credit decisions. The European Union AI Act classifies AI systems used to evaluate the creditworthiness of natural persons as high-risk, reflecting the potential effect on access to essential financial services (European Parliament and Council, 2024).

2.3 Fraud Detection Cybersecurity and Compliance

Fraud and financial crime generate large numbers of transactions and alerts, making them suitable for AI-assisted pattern recognition. Models can compare current activity with historical behaviour, identify networks of related accounts, and prioritise suspicious cases for investigation. In the 2024 survey, cybersecurity and fraud detection were among the most common current applications, while anti-money-laundering and fraud control ranked among the highest perceived benefits. These tools can increase the speed of detection and reduce the burden of manually reviewing low-risk alerts. AI has been identified as an audit catalyst (Sawaya et al., 2026) allowing for more transparent financial statements (Saber & Sassine, 2022), however, the same technology is available to attackers. Generative AI can produce convincing phishing messages, synthetic identities, voice clones, deepfakes, and automated social engineering. The Financial Stability Board (2024) identifies cyber risk, third-party dependencies, market correlations, model risk, and data quality as vulnerabilities with potential systemic consequences. By 2026, the FSB proposed organisation-wide sound practices covering governance and the AI lifecycle, emphasising that rapid adoption requires guardrails rather than reliance on model performance alone (Financial Stability Board, 2026).

2.4 Customer Service Personalisation and Markets

Natural-language systems can summarise documents, answer routine questions, assist employees, and personalise customer communications. These uses may lower service costs and make financial information easier to access. The FCA (2026) notes that AI could improve personalisation, customer understanding, service quality, and household financial management. However, unsuitable recommendations, hallucinated facts, opaque product ranking, or manipulation of vulnerable customers could weaken trust. The financial institution remains responsible for the outcome even when the interface or model is supplied externally. AI can also create influencers to influence buying decisions (Mawad & Freiha, 2024), while in capital markets, AI supports research, signal construction, trade execution, surveillance, and risk management. Gu et al. (2020) demonstrated the ability of machine-learning methods to capture complex relationships in asset returns. The IMF (2024) argues that AI may improve market analysis, price discovery, and liquidity, but similar strategies and shared data may also increase market correlation and volatility during stress. Market participants surveyed by the IMF continued to view a human in the loop as essential for large capital-allocation decisions.

2.5 Governance Explainability and Third Party Risk

AI governance covers responsibility, data quality, model validation, explainability, monitoring, change management, and escalation when a system performs poorly. Explainability matters because customers, managers, auditors, and regulators may need to understand why a model produced a decision. Yet complex models and third-party services can reduce transparency. In the 2024 survey, 46% of firms reported only partial understanding of their AI technologies, compared with 34% reporting complete understanding. The gap was linked particularly to externally developed models. For AI to be optimized, proper governance is needed (Athari et al., 2023) in addition to technological adaptations (Bejjani et al., 2024). Third-party use creates a second governance problem. A specialised provider may offer superior technology and lower costs, but a failure or vulnerability at a widely used provider can affect many institutions at the same time. The survey found that third-party implementations increased from 17% of use cases in 2022 to 33% in 2024. The three largest providers accounted for 73% of reported cloud providers,

44% of model providers, and 33% of data providers. Crisanto et al. (2024) conclude that existing financial regulation covers many AI risks, but governance, skills, model risk, data governance, new providers, and third-party services require continuing supervisory attention. AI was also found as a significant variable impacting sustainability and ESG practices (Kaspard et al., 2025 ; Kaspard et al., 2026), however this also increases risk of greenwashing without proper governance (Daou et al., 2025).

2.6 Research Gap and Study Contribution

The literature shows that AI can improve prediction and processing, but most academic studies focus on a single application such as credit scoring or asset pricing. Policy reports discuss broader risks, yet they do not always connect adoption measures, automation, governance, and expected impact in one analysis. This study addresses that gap by organising the 2024 survey evidence into four dimensions: diffusion, operational deployment, decision autonomy, and control capacity. The comparison with 2022 provides a measurable indication of the pace of change, while the literature helps interpret what the survey indicators mean for firms and consumers.

Methodology:

3.1 Research Design

The study uses a quantitative descriptive case-study design. It analyses aggregated survey statistics published by the Bank of England and the Financial Conduct Authority and interprets them using peer-reviewed finance research and official regulatory reports. The approach is appropriate because the research question concerns the scale, location, and nature of AI adoption rather than the causal effect of one firm-level treatment.

3.2 Data Sources and Sample

The principal source is Artificial Intelligence in UK Financial Services 2024, published jointly by the Bank of England and the FCA on 21 November 2024. The survey received 118 responses from UK banks, international banks operating in the United Kingdom, insurers, non-bank lenders, investment and capital-market firms, and financial market infrastructure, payment, and other regulated firms. Results were anonymised and reported in aggregated form.

Selected adoption measures are compared with the 2022 Machine Learning in UK Financial Services survey. The two surveys are not treated as a balanced panel of identical firms; the comparison describes reported sector-level change. Supporting sources include the BIS, IMF, FSB, FCA, EU legislation, and peer-reviewed studies of credit and asset-pricing applications.

3.3 Variables and Indicators

Table 1 Variables and Indicators

Indicator	Measurement	Analytical role
Current adoption	Percent of respondent firms already using AI	Measures diffusion
Planned adoption	Percent planning adoption within three years	Measures near-term intention

Indicator	Measurement	Analytical role
Use-case intensity	Median number of AI use cases per firm	Measures depth of use
Third-party exposure	Share of use cases implemented by external providers	Measures outsourcing dependence
Decision automation	Share of use cases with some or full automated decision-making	Measures autonomy
Governance capacity	Accountability, explainability, and understanding indicators	Measures control environment
Benefit and risk outlook	Reported direction of expected benefit and risk	Measures anticipated net impact

Note. All indicators are based on aggregated survey results; respondent-level observations were not available.

3.4 Analytical Procedures

The analysis reports percentages, percentage-point changes, relative changes, ratios, and rankings. The percentage-point change equals the 2024 percentage minus the 2022 percentage. Relative growth equals the percentage-point change divided by the 2022 value. The projected increase in median use cases equals 21 minus 9, while projected relative growth equals 12 divided by 9. These calculations are descriptive and are not statistical estimates of the full population of financial institutions.

The hypotheses are evaluated against observable patterns. H1 is supported if current adoption is higher in 2024 than in 2022. H2 is supported if AI is concentrated in operational and analytical tasks while fully autonomous decisions remain rare. H3 is supported if expected benefits grow faster than expected risks while governance and data-risk indicators remain material.

3.5 Methodological Limitations

The study has four main limitations. First, participation in the survey was not a random sample of every UK financial firm, so the results may overrepresent institutions with stronger AI programmes. Second, survey answers are self-reported and may reflect different interpretations of AI, materiality, and risk. Third, only aggregate statistics are publicly available, preventing firm-level regression, significance testing, and control for firm size or sector. Fourth, the study measures adoption and perceived impact rather than realised changes in profit, productivity, consumer outcomes, or employment. The terms impact and effect are therefore used in an operational and descriptive sense, not as claims of causation.

Results:

4.1 Growth in AI Adoption

Current AI adoption increased from 58% of responding firms in 2022 to 75% in 2024. The 17-percentage-point increase equals relative growth of 29.3%. When firms planning adoption are

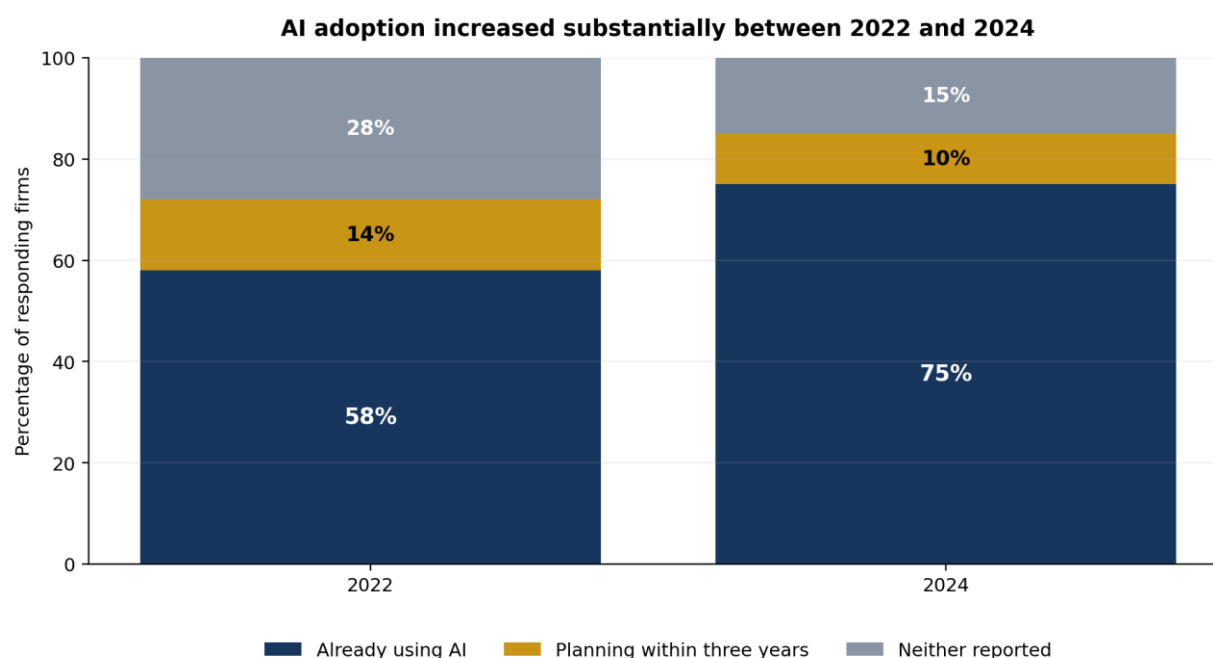
added, the share already using or planning to use AI reached 85% in 2024, compared with 72% in 2022. The residual share reporting neither current nor planned use fell from 28% to 15%.

Table 2 Change in Reported AI Adoption

Status	2022	2024	Change
Already using AI	58%	75%	+17 percentage points
Planning within three years	14%	10%	-4 percentage points
Using or planning	72%	85%	+13 percentage points
Neither reported	28%	15%	-13 percentage points

Note. The 2022 comparison uses the adoption figures reported in the 2024 survey. Percentages may describe different respondent groups across the two survey years.

Figure 1 AI Adoption in 2022 and 2024



Note. Source: Bank of England and Financial Conduct Authority (2024). Neither reported is calculated as the remainder to 100%.

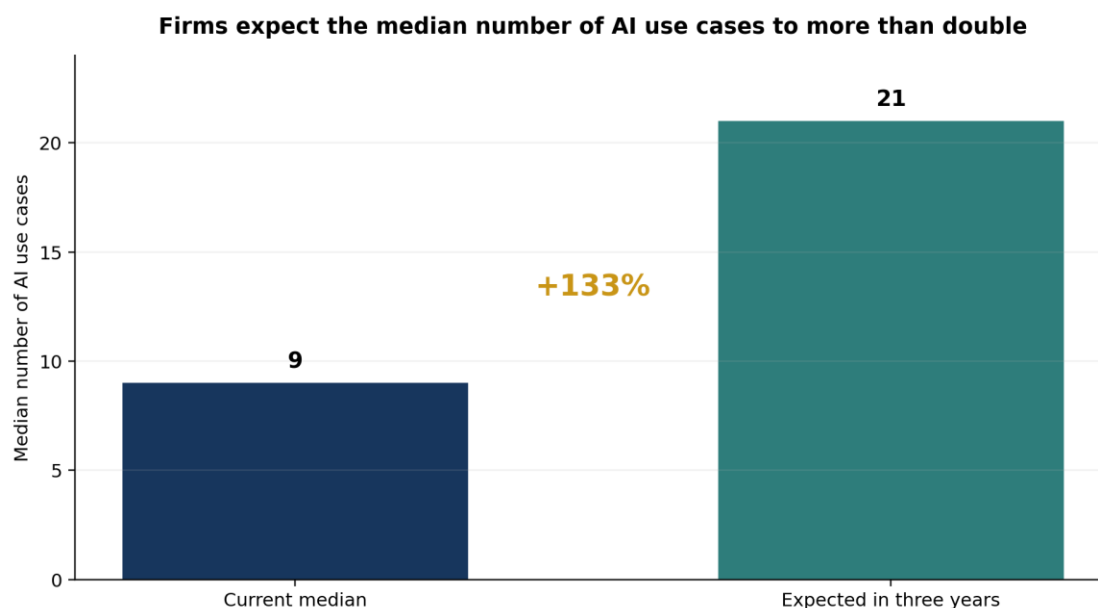
Adoption varied by sector. Insurance reported the highest current use at 95%, followed by international banks at 94%. Financial market infrastructure, payments, and other firms reported the lowest rate at 57%. The 38-percentage-point difference indicates that AI diffusion is broad but uneven. Data-rich sectors with repeated prediction and classification tasks appear to have moved fastest.

4.2 Expansion and Location of Use Cases

The depth of adoption is expected to rise sharply. Respondents projected that the median number of use cases would increase from 9 to 21 over three years. The increase of 12 use cases represents projected growth of 133.3%. At the time of the survey, 56% of firms using AI had 10

or fewer use cases and 10% had more than 50. Looking forward, only 31% expected to remain at 10 or fewer, while nearly one quarter expected more than 50.

Figure 2 Projected Growth in Median AI Use Cases



Note. Source: Bank of England and Financial Conduct Authority (2024). The 133% figure is calculated from the reported medians of 9 and 21.

Operations and IT accounted for approximately 22% of reported use cases, compared with 11% in retail banking and 10% in general insurance. The most common current applications were internal process optimisation, used by 41% of respondents, cybersecurity at 37%, and fraud detection at 33%. Firms expected additional adoption particularly in customer support, regulatory compliance and reporting, fraud detection, and internal process optimisation. These results show that the initial impact is strongest where AI assists staff, analyses large data sets, or monitors repeated activity.

4.3 Automation Model Types and External Dependence

Fifty-five percent of reported use cases involved some degree of automated decision-making. However, only 2% were fully autonomous, and another 2% used dynamic automation. The gap between broad automation and full autonomy shows that AI is usually embedded within controlled processes rather than replacing human responsibility. Gradient boosting was the most common model type at 32% of use cases, while transformer-based models accounted for 10%. Foundation models represented 17% of all use cases.

Table 3 Deployment and Automation Indicators in 2024

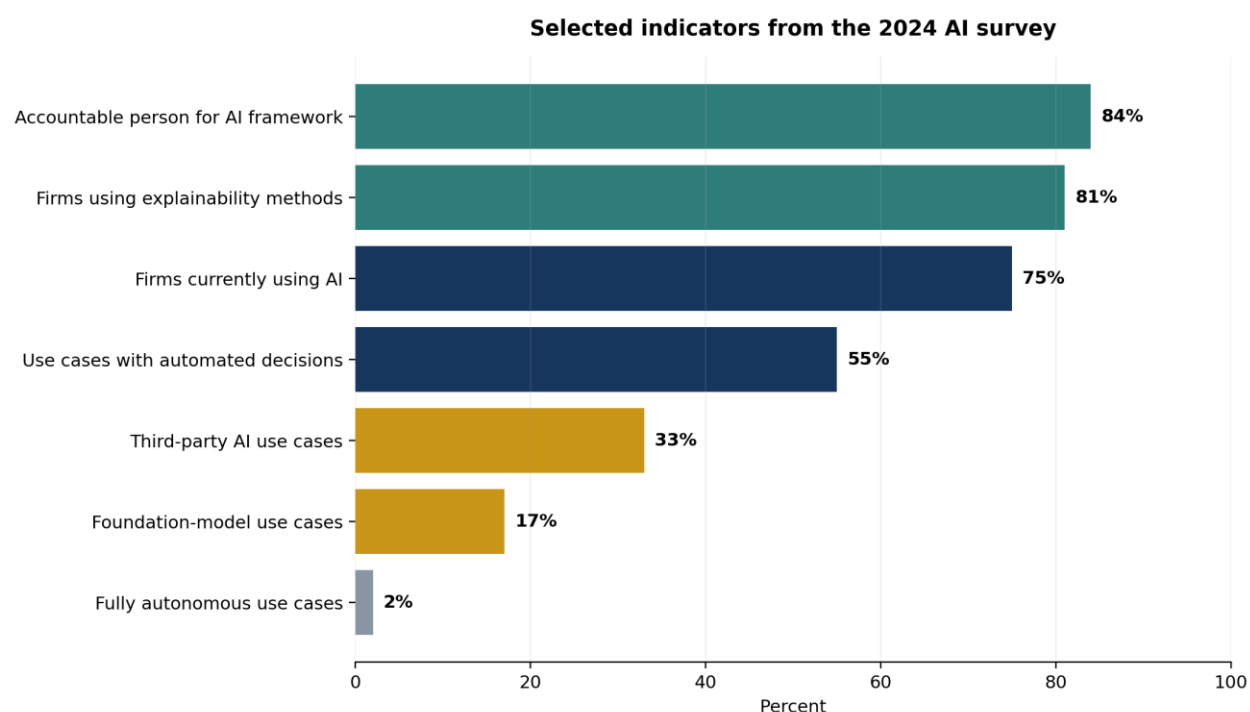
Indicator	Reported value	Interpretation
Use cases with some automated decisions	55%	Automation is widespread
Fully autonomous use cases	2%	Human control remains dominant

Indicator	Reported value	Interpretation
Foundation-model use cases	17%	Generative AI is material but not dominant
Gradient-boosting use cases	32%	Established predictive models remain important
Third-party implementations	33%	External dependence is substantial
Third-party implementations in 2022	17%	Exposure nearly doubled by 2024

Third-party implementations rose by 16 percentage points, from 17% in 2022 to 33% in 2024. This equals relative growth of 94.1%. Outsourcing can accelerate adoption and provide access to specialised models, but it also creates concentration risk. The three largest providers accounted for 73% of reported cloud services, 44% of model providers, and 33% of data providers. A disruption, security weakness, or design problem at a major provider could therefore affect several institutions simultaneously.

4.4 Governance Understanding Benefits and Risks

Governance indicators were relatively strong. Eighty-four percent of firms reported an accountable person for the AI framework, 72% assigned accountability for AI use cases and outputs to executive leadership, and 81% of firms using AI employed at least one explainability method. Feature importance and Shapley-value methods were the most common approaches. These practices indicate that many firms are adapting existing model-risk and management structures to AI.

Figure 3 Selected Adoption and Governance Indicators

Note. Source: Bank of England and Financial Conduct Authority (2024). Indicators have different denominators as defined in the source survey.

Governance did not eliminate the knowledge gap. Forty-six percent of firms reported only partial understanding of the AI technologies they used, while 34% reported complete understanding. The 12-percentage-point gap was associated particularly with third-party models. This finding matters because accountability is difficult to exercise when a firm cannot adequately explain, test, or monitor an externally supplied system.

Table 4 Main Benefits Risks and Constraints

Dimension	Highest-ranked areas	Implication
Current benefits	Data and analytical insights; AML and fraud; cybersecurity	AI creates value through information and detection
Fastest-growing expected benefits	Operational efficiency; productivity; cost base	Financial impact is expected to broaden
Current firm and consumer risks	Data privacy; data quality; data security; bias	Data governance is the central control issue
Fastest-growing expected risks	Third-party dependence; model complexity; hidden models	Complex supply chains reduce visibility
Highest systemic risk	Cybersecurity	AI may amplify system-wide digital vulnerability
Largest regulatory constraint	Data protection and privacy	Compliance shapes feasible deployment

Dimension	Highest-ranked areas	Implication
Largest non-regulatory constraint	Safety, security, and robustness	Technical reliability limits adoption

Across all areas, firms expected the average perceived benefit of AI to increase by 21% over three years, compared with a 9% increase in perceived risk. Expected benefit growth was therefore about 2.33 times expected risk growth. The result does not mean that risk will fall; both were expected to increase. It means respondents anticipated that the opportunity would expand faster than the risk rating, provided controls developed with adoption.

4.5 Evaluation of the Hypotheses

Table 5 Hypothesis Evaluation

Hypothesis	Evidence	Decision
H1 Adoption increased	Current use rose from 58% to 75%	Supported
H2 Impact is mainly assistive rather than fully autonomous	Operations and risk detection lead; only 2% fully autonomous	Supported
H3 Benefits are expected to grow faster while governance remains necessary	Benefit growth 21% versus risk growth 9%; data and third-party risks remain high	Supported descriptively

Note. The decisions are descriptive evaluations of published survey indicators, not inferential hypothesis tests based on respondent-level data.

Discussion and Conclusion:

5.1 Interpretation of the Main Results

The results show that AI has already affected the structure of financial work. Adoption is high, expected use-case growth is rapid, and firms apply AI across internal processes, cyber defence, fraud detection, compliance, and customer support. The most immediate financial effect is therefore not the removal of human decision-makers. It is the ability to process more information, prioritise cases, support employees, and make routine operations faster and more consistent.

The difference between 55% of use cases containing some automated decision-making and only 2% being fully autonomous is especially important. Financial institutions appear willing to automate parts of a process while retaining human approval for critical or ambiguous decisions. This pattern is consistent with legal responsibility, model uncertainty, and the high cost of errors. It also matches IMF evidence that market participants remain uncomfortable with autonomous investment strategies that humans do not understand (International Monetary Fund, 2024).

The projected increase from 9 to 21 median use cases suggests that AI will become an organisational capability rather than a small collection of experiments. As models spread across departments, governance must also shift from project-level approval to enterprise-level inventory,

monitoring, and accountability. A firm may control each individual use case reasonably well while still failing to recognise shared data, provider, or model dependencies across the organisation.

5.2 Comparison With Previous Research

The emphasis on data and analytical insight agrees with studies showing that machine learning creates value from information. Berg et al. (2020) demonstrate that digital footprints can add predictive content to credit scoring, while Gu et al. (2020) show that machine learning can model complex patterns in asset returns. The survey extends these application-specific findings by showing that financial firms are deploying related techniques across many functions.

The results also support the caution in the literature. Fuster et al. (2022) show that better prediction can be distributed unevenly across borrower groups. The survey identifies bias and representativeness among the leading data risks and finds that almost half of firms have only partial understanding of their AI technology. Technical performance must therefore be evaluated together with fairness, explainability, and consumer outcomes.

Third-party concentration links firm-level adoption to financial stability. The near doubling of external implementations is consistent with the FSB (2024) concern that common providers and models can increase correlated exposure. The survey also identifies cybersecurity as the highest perceived systemic risk. These findings suggest that AI can make an individual firm more efficient while simultaneously increasing common dependencies across the sector.

5.3 Practical Implications

For financial institutions, the results favour selective scaling rather than uncontrolled expansion. Firms should prioritise use cases with measurable benefits, reliable data, and clear human ownership. Internal process optimisation, fraud detection, document analysis, and staff support may offer strong value because outputs can be checked before they directly affect a customer. High-impact applications such as credit decisions, insurance pricing, and investment advice require stricter testing, explanation, and appeal mechanisms.

For consumers, AI can create faster service, more relevant products, improved fraud protection, and possible access for people with limited traditional records. These benefits depend on consent, data quality, and the ability to challenge a decision. Personalisation should not become hidden discrimination or exploitation of vulnerability. Customers should be told when AI materially contributes to an outcome and should have access to a qualified human when the decision is important.

For regulators, the central task is to apply existing standards at the speed and scale of AI. The FCA (2026) argues that many established frameworks remain relevant, but supervisors need stronger technical capacity, testing methods, and monitoring. The EU AI Act takes a risk-based approach and treats creditworthiness assessment as high-risk. Together, these approaches support proportional governance: controls should become stronger as autonomy, complexity, consumer impact, and system-wide dependence increase.

5.4 Limitations and Future Research

The study cannot measure profitability, cost savings, default reduction, fraud losses, customer satisfaction, or employment because the survey does not publish firm-level outcome data. The comparison between 2022 and 2024 also may reflect changes in respondents and definitions as well as genuine adoption. Survey expectations about the next three years may not be realised. Finally, the UK regulatory and technology environment may differ from conditions in Lebanon, the European Union, the United States, or emerging markets.

Future research should obtain a panel of firms with comparable measures of AI investment, operational cost, revenue, loss events, and customer outcomes. Difference-in-differences or matched-sample methods could compare early adopters with similar firms that adopt later. Credit and insurance studies should report model accuracy together with approval rates, pricing, complaints, and fairness indicators. Research should also test whether dependence on common cloud and foundation-model providers increases correlated operational incidents.

5.5 Conclusion

This study examined the impact of artificial intelligence on financial services through evidence from 118 firms in the 2024 Bank of England and FCA survey. AI adoption increased materially between 2022 and 2024, and firms expect the median number of use cases to more than double. The technology is affecting internal operations, data analysis, cyber defence, fraud detection, compliance, customer service, credit, insurance, and markets. Its present impact is broad but mainly assistive: more than half of use cases involve some automated decisions, while fully autonomous decisions account for only 2%.

The evidence supports a positive but conditional conclusion. AI can improve speed, scale, prediction, personalisation, and risk detection, and firms expect benefits to grow faster than risks. However, data privacy, data quality, security, bias, incomplete understanding, and third-party concentration can weaken those gains. The impact of AI is therefore determined not only by model capability but by the governance surrounding its use. Human accountability, explainability, monitoring, and resilience remain essential components of financial innovation.

5.6 Recommendations

First, financial institutions should maintain a complete inventory of AI systems, including embedded models and third-party tools. Each system should have a named owner, a defined purpose, an approved data source, a materiality rating, and measurable performance limits.

Second, firms should keep meaningful human oversight for decisions that affect credit access, insurance coverage, investment suitability, fraud restrictions, or customer vulnerability. Human review must be able to change the outcome rather than merely approve it automatically.

Third, validation should cover fairness, explainability, privacy, cyber resilience, and performance after deployment. Models should be monitored for drift, false positives, unusual customer outcomes, and changes in the quality or representativeness of their data.

Fourth, third-party contracts should provide audit rights, incident notification, model and data documentation, service continuity arrangements, and exit plans. Firms should assess concentration across cloud, model, and data providers instead of evaluating each contract separately.

Finally, regulators and universities should build combined financial, legal, and technical skills. Professionals must understand both AI systems and their effects on markets and consumers. Future research should measure realised financial and social outcomes rather than adoption counts alone.

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