

EFAMA

European Fund and Asset Management Association

AI IN ASSET MANAGEMENT

Industry Report • November 2026

A snapshot of AI deployment in the European Asset Management Sector

Introduction

The **AI in Asset Management Industry Report** provides an overview of the maturity, current practices and growth potential of AI across the European asset management sector.

The report is based primarily on the results of the **AI in Asset Management Survey**, conducted jointly by EFAMA and the Association of the Luxembourg Fund Industry (ALFI).

The survey collected 125 complete responses from asset management firms headquartered in more than 20 jurisdictions. Participating firms varied considerably in size, investment strategies and portfolios. The survey covered a broad range of topics, including AI maturity and adoption, governance and organisation, investment priorities, technology and infrastructure, regulatory challenges, and future deployment strategies.

The report has two main objectives. First, it seeks to assess the level of AI maturity and adoption across European asset management firms and to identify the main operational, technological and regulatory challenges they face. Second, it aims to identify policy areas which could benefit from further public debate given the concerns and needs of the European fund and asset management industry. The data collected in this survey can help inform the future evolution of the regulatory framework in Europe.

EFAMA and ALFI thank the organisations and individuals who participated in the survey and contributed their responses.

Percentages refer to respondents to the relevant question or subgroup, unless otherwise stated. Respondent bases vary; multiple-response questions need not total 100%, and rounding may cause small differences in totals.

Executive Summary

The EFAMA AI Industry Report draws on a survey conducted jointly by EFAMA and the Association of the Luxembourg Fund Industry (ALFI), covering 125 asset management firms headquartered in more than 20 jurisdictions. It offers a snapshot of adoption, practices and expectations among participating firms.

AI adoption and the next stage of investment

AI adoption is already widespread: 64.0% of respondents report AI use cases live in business processes, while 36.0% remain in experimentation. Most production deployment remains limited in scale: 47.2% of all respondents are at limited production, compared with 16.8% at scaled production or advanced/strategic adoption. Among firms still experimenting, two-thirds are already developing or testing applications. The immediate opportunity is therefore both to bring these applications into operational use and to extend existing deployments across firms.

At the same time, AI maturity varies by organisation size. While 62% of small firms remain in the experimentation phase, this falls to 26% of medium-sized firms and 10% of large firms. At the more advanced end of the maturity spectrum, 41% of large firms report scaled production or advanced/strategic adoption, compared with 10% of medium-sized firms and 9% of small firms.

Against this backdrop, 91.0% of respondents expect AI investment to increase over the next three years, suggesting considerable scope to scale deployment and capabilities. External AI solutions and providers are the leading investment priority (70.4%), followed by staff training and upskilling (52.0%), internal development and customisation (46.4%), and IT infrastructure and compute (40.8%). The breakdown by firm size shows that large firms place greater emphasis on infrastructure, internal development, data acquisition and management, while staff training and upskilling is comparatively more important for small and medium-sized firms.

Although investment expectations suggest a strong ambition to build on this early development, measurement frameworks remain relatively underdeveloped: 21.5% have a formal return-on-investment (ROI) model and 38.0% have implemented key performance indicators (KPIs). As investment grows, firms are likely to face increasing pressure to assess whether expenditure delivers the expected benefits.

AI use is concentrated in information-heavy functions: document analysis leads at 74.4%, followed by investment research at 62.4% and IT/development at 58.4%. Moreover, newer AI technologies coexist with established techniques: 96.8% of respondents reported using Generative AI, while 47.2% use machine learning. Reported use of agentic AI, which can perform sequences of actions with a degree of autonomy, reaches 55.2%, showing growing interest in this technology type, particularly as approaches to defining and applying the technology continue to evolve.

Data quality and availability is the top barrier identified by a majority of firms (57.6%). This should be considered alongside the finding that 64.5% of firms rely on multiple data sources, underlining the importance of access to diverse, high-quality datasets. This points to a potential area for policy action, including consideration of where data costs, gaps or access needs could be addressed through third-party licensed or open data. Other barriers firms identified include: lack of internal expertise (42.4%), regulatory or compliance restrictions (40.8%), and difficulty assessing business value or return on investment (37.6%). The size breakdown identifies data, expertise and compliance as more prominent barriers among larger firms, while smaller firms place greater emphasis on approval processes, internal governance and vendor-related risks.

Third-party dependencies and hosting

Third-party vendors play a central role in AI adoption: among respondents to this question, 48.8% report that external vendors primarily provide their AI capabilities, while 39.0% combine vendor solutions with internal development. Taken together, 93.9% of respondents currently using AI rely on third-party vendors

to some degree for their AI capabilities, while only a small minority rely primarily on internally developed systems.

Separately, 64.8% report developing or customising systems or tools internally. Internal work therefore often complements external provision, allowing firms to adapt applications to their needs while still depending on vendors for parts of their AI capabilities.

Among respondents reporting an applicable hosting arrangement, 94.5% expect externally provided AI systems to use public/private or hybrid cloud environments. For internally developed systems, 75.9% report such arrangements, with on-site hosting accounting for the remaining 24.1%. Internal development therefore does not necessarily mean independence from cloud infrastructure, but it is associated with lower reliance on exclusively cloud-based hosting.

Governance and human oversight

Alongside the 64.0% reporting live deployment, 78.2% report an AI governance framework in place or under development. This suggests that firms widely recognise governance as an important component of AI adoption. Risk-management practices remain uneven: 63.2% have an enterprise-wide AI inventory, while 48.0% have integrated AI into corporate risk management.

These risk-management practices are also more common among firms with AI in production than among those in the experimentation phase: 71% versus 49% have conducted an enterprise-wide AI inventory, 53% versus 39% have integrated AI into their corporate risk-management framework, and 56% versus 34% have assessed business continuity risks arising from AI-system failure. This suggests an association between greater AI maturity and more formalised governance and risk management, although these practices remain uneven even among firms with AI already in production.

Human oversight is nearly universal for material decisions: 95.9% subject AI outputs to human review and 96.6% allow users to override them. Its implementation is less standardised, including differences in risk-based approaches and documentation. Investor-facing disclosure, fairness and bias assessments, and model-drift monitoring are also uneven and remain minority practices.

The EU AI Act is already influencing firms' governance and strategy: 67.7% report limited or significant influence, rising to 82.0% when firms without a formal governance or strategy framework are excluded. For most firms, the influence is present but not dominant.

Workforce transformation and skills

Over the next three years, 74.2% of respondents expect some change in workforce size or role allocation. The most common expectation is role reallocation without a significant change in headcount (46.0%). More firms expect workforce growth (18.5%) than reductions (9.7%), while 19.4% consider it too early to assess. These findings suggest workforce transformation rather than contraction in the near term.

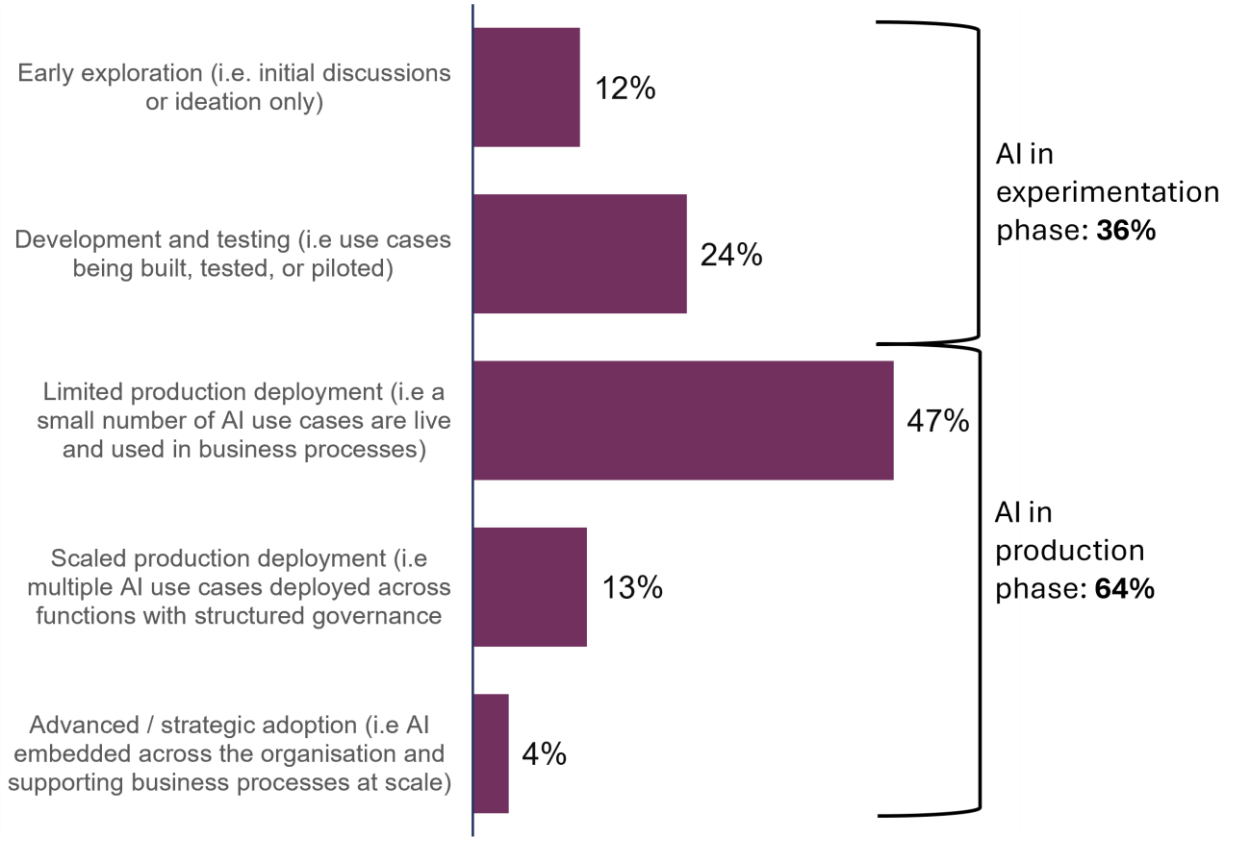
AI's impact is already visible across core investment and client-facing activities. Investment research/portfolio management is the function most frequently identified as affected (71.2%), followed by operations/middle office (49.6%). Compliance/surveillance and client servicing/distribution are also affected.

Firms are actively responding to skills needs: 76.4% have implemented AI upskilling programmes, yet 76.7% still identify significant additional training needs. Only 9.5% have formal staff reconversion programmes to prepare employees for new or substantially adapted roles. Compared with the scale of expected role reallocation, this points to a gap between anticipated workforce change and structured programmes supporting that transition. Such approaches remain less developed than general training and upskilling.

Sections

State of AI Adoption

Figure 1: How would you best describe the current stage of AI adoption within your organisation?



The data show that 64.0% of respondents are at a stage where AI can be considered to be “in production” (i.e. with AI use cases already live in business processes), including firms with limited production deployment, scaled production deployment, or advanced/strategic adoption.

The remaining 36.0% are still in the experimentation phase, either in early exploration or development and testing. This shows that most respondents already have AI deployed in live use cases, while a substantial share of firms still need to transition from experimentation to production.

The most common response was Limited production deployment, selected by 47.2% of the total sample. This means that almost half of firms in the sample have a small number of AI use cases already live and used in business processes.

Development and testing was the second most common response, representing 24.0% of all respondents. This category includes firms that have moved beyond initial exploration and are actively building, piloting, or testing AI use cases, but have not yet deployed them into production.

A relatively small share of firms reported being at the Scaled production deployment stage (12.8%), meaning that multiple AI use cases are deployed across functions with structured governance. A similar share remain in Early exploration (12.0%), the lowest AI maturity category, where adoption is limited to initial discussions or ideation. Finally, only 4.0% of firms reported being in the highest maturity category, Advanced/strategic adoption, where AI is embedded across the organisation and supports business processes at scale.

Looking more closely at firms with AI in production, adoption remains concentrated in the earlier stages of deployment. Limited production accounts for 73.8% of this group, while 20.0% are at the scaled production deployment stage and only 6.3% are at the most advanced maturity stage, advanced/strategic

adoption. This suggests that, while AI deployment is already widespread, relatively few firms have yet reached the most advanced stages of adoption.

Similarly, within the experimentation group, firms in the Development and testing stage represent 66.7%, indicating that most firms still in the early phases of adoption have already moved beyond initial exploration and are actively preparing AI applications for operational use.

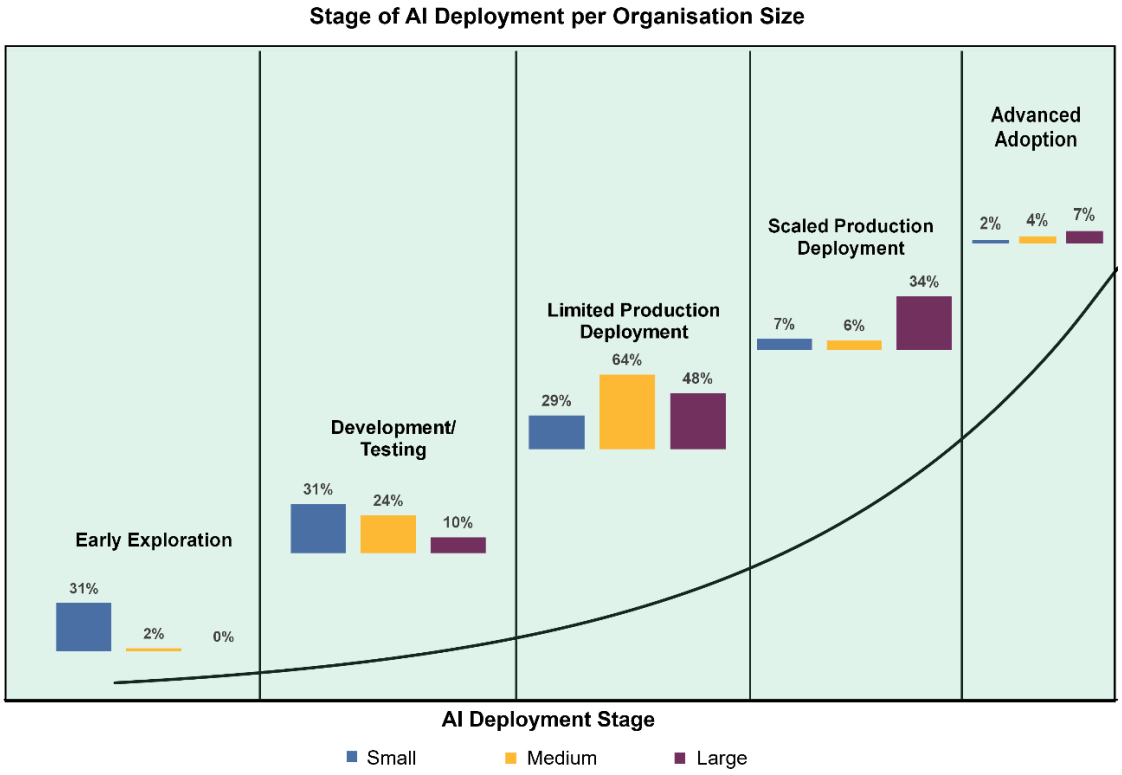
Taken together, Development and testing and Limited production deployment account for 71.2% of the total sample. This shows that most respondents are concentrated around the transition from experimentation into production or the early stages of production deployment, leaving considerable scope for AI adoption to deepen and become more widely embedded across firms over time.

AI maturity by firm size

Respondents were separated into three categories based on their reported number of employees: small firms with 0–50 employees, medium-sized firms with 51–500 employees, and large firms with 501 or more employees. This allows the analysis to assess whether reported levels of AI maturity differ according to organisation size. These size categories are used consistently throughout the report. Figure 2 shows the results.

From left to right, the stages shown are early exploration, development and testing, limited production deployment, scaled production deployment, and advanced/strategic adoption.

Figure 2



Note: Organisation size categories are based on employee count.
Small = 0-50 employees; Medium = 51-500 employees; Large = more than 500 employees

The results show a clear association in the sample between organisation size and reported AI maturity, with larger firms tending to report more advanced stages of AI deployment. In particular, no large firms report being in early exploration, while only a small minority (10%) report being in the development/testing phase. By contrast, 31% of small firms report being in early exploration and a further 31% in development/testing. Overall, 62% of small firms responding to the survey can therefore be placed in the AI experimentation phase outlined above, i.e. firms with no reported AI use cases in production.

Medium-sized firms generally report more advanced levels of AI maturity than small firms. Only a small minority of medium-sized firms are in early exploration (2%), while approximately one quarter are in development/testing (24%). This means that 26% remain in the experimentation phase, compared with 62% of small firms.

The pattern becomes more pronounced at higher maturity levels. Large firms are considerably more represented in scaled production deployment (34%) and advanced/strategic adoption (7%), while almost half (48%) report limited production deployment. Medium-sized firms are particularly concentrated in limited production deployment (64%), with a further 10% reporting either scaled production deployment (6%) or advanced/strategic adoption (4%). By comparison, only 9% of small firms report these two more advanced stages of deployment.

The CSSF's June–August 2024 survey, conducted approximately two years before the present survey, provides a useful indicative comparison of AI adoption. Among its 261 responding authorised investment fund managers (IFM/AIFM), 24% reported concrete AI use cases in production or development, 27% were experimenting or undertaking a proof of concept, either ongoing or planned within the following 12 months, and 49% did not plan to use AI within that period.[1] In the EFAMA survey, 64% of respondents reported AI use cases in production, with a further 24% in development and testing.

While the surveys posed the AI maturity question differently and covered different samples (EFAMA's survey has a broader European scope, whereas the CSSF category concerns Luxembourg-authorised fund managers), the findings still merit comparison. In the CSSF's 2024 survey, 24% reported concrete AI use cases in production or development, while the EFAMA survey two years later recorded 64% of firms reporting AI use cases in production. This contrast is consistent with a substantial rise in AI adoption in the fund sector over the intervening two years, although differences in the samples and maturity definitions prevent a like-for-like assessment of change.

[1] CSSF, Thematic review on the use of Artificial Intelligence in the Luxembourg financial sector, May 2025, pp. 9–10 (survey period and respondent category) and pp. 19–20, Figure 22 (adoption by entity type).

State of AI Adoption – Key Takeaways

- **AI adoption is already widespread:** 64.0% of respondents report having AI use cases live in business processes, while 36.0% remain in the experimentation phase.
- **Most production deployment remains limited in scale:** 47.2% of all respondents are at the limited production stage, representing 73.8% of firms with AI in production.
- **Most experimenting firms have moved beyond initial exploration:** Development and testing represents 66.7% of the experimentation group, indicating that most firms still outside production are already actively building, piloting, or testing AI use cases.
- **More advanced adoption is still relatively uncommon:** only 16.8% of all respondents have reached scaled production or advanced/strategic adoption, representing 26.3% of firms with AI already in production. This indicates significant room for further organisational scaling and integration.
- **Most respondents are concentrated around the transition into production or the early stages of production deployment:** Development and testing and limited production deployment together account for 71.2% of the total sample. This indicates that a large share of firms are either preparing AI use cases for production or have only recently begun deploying them in live business processes.
- **AI maturity increases with organisation size:** larger firms tend to report more advanced stages of AI deployment. While 62% of small firms remain in the experimentation phase, this falls to 26% of medium-sized firms and 10% of large firms. More advanced deployment is concentrated among larger firms: 41% of large firms report scaled production or advanced/strategic adoption, compared with 10% of medium-sized firms and 9% of small firms.

Governance & Risk Management

AI governance architecture

AI governance frameworks are widespread among respondents.

78.2% of firms indicated that they have an AI governance framework in place and/or under development, while 21.8% indicated that they do not.

The results show that a substantial majority of responding firms either have an AI governance framework in place or are currently developing one. This suggests that firms widely recognise governance as an important component of AI adoption.

Among firms with an AI governance framework, group-level arrangements predominate.

- Most firms (66.7%) reported that their AI governance framework is managed primarily at the group/global level. This suggests that group-level structures and capabilities play an important role in establishing and managing the policies, standards and processes governing AI deployment.
- A further 19.6% reported adopting a hybrid approach, combining group/global and local governance. This could, for example, involve a common group-level framework establishing baseline principles, policies or standards, complemented by entity-level arrangements tailored to local operational or regulatory requirements.
- By comparison, only 13.7% indicated that governance is managed primarily at the local entity level, with responsibility sitting predominantly with the individual entity rather than at group level.

Taken together, 86.3% of firms with an AI governance framework manage it either primarily at group/global level or through a hybrid model. This indicates that the vast majority rely, at least to some extent, on group-level structures and capabilities.

Overall, these findings highlight the importance of group-level structures in developing and managing AI governance frameworks. In a global, cross-border industry, such structures can act as internal standard-setters, with policies and governance arrangements developed centrally and then applied across different entities and jurisdictions.

AI strategy and roadmap

59.7% of firms indicated that they have a formally approved AI strategy or roadmap, while 40.3% reported having no defined strategy.

A majority of respondents therefore have a formally approved AI strategy or roadmap, although this proportion is lower than the share of firms reporting an AI governance framework in place or under development.

Formal AI strategies are most commonly managed at group/global level.

- **Group/global level:** 63.9%
- **Local entity level:** 22.7%
- **Hybrid approach:** 13.4%

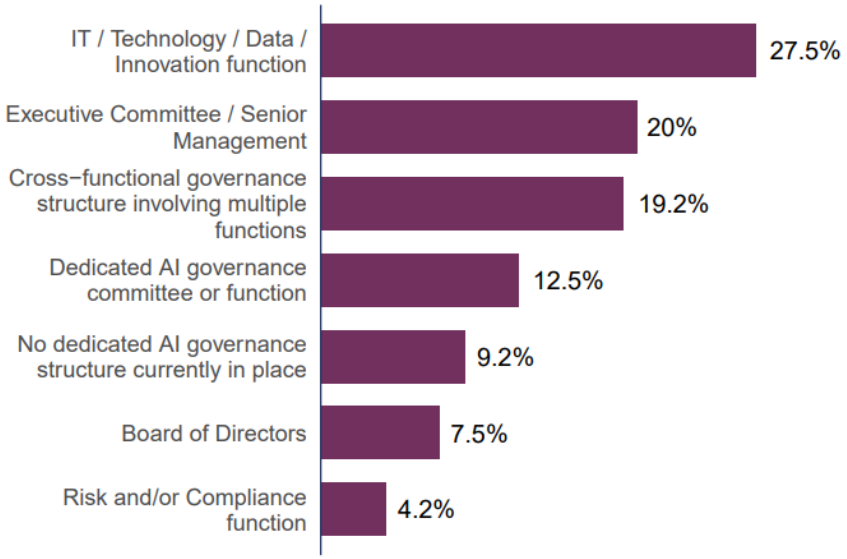
The results broadly mirror those concerning the organisational level at which AI governance frameworks are managed.

A similar proportion of firms reported that their AI strategy is defined at the group/global level (63.9%) as reported that their AI governance framework is managed primarily at that level (66.7%). This suggests that both strategic direction and governance are often established centrally within the organisation.

Some differences nevertheless emerge. AI strategies or roadmaps are more commonly defined at the local entity level (22.7%) than AI governance frameworks are managed at that level (13.7%). Conversely, hybrid approaches are less common for AI strategies or roadmaps (13.4%) than for AI governance frameworks (19.6%). This may indicate that firms are somewhat more likely to centralise governance standards while allowing greater flexibility for local entities in defining strategic priorities and implementation plans.

Governance ownership and senior-level oversight

Figure 3: Which function or body is primarily responsible for the oversight and governance of AI within your organisation?



The results show there is considerable divergence across the industry in how firms assign ownership of AI governance, with no single function or body emerging as the dominant model.

Technology-related functions were the most commonly identified primary owners of AI governance, selected by 27.5% of respondents. This suggests that many firms still view AI governance as closely connected to technological expertise, system implementation, and innovation.

Senior management (20.0%) and cross-functional governance structures (19.2%) were also prominent, indicating that firms recognise the strategic and multidisciplinary nature of AI governance.

A further 12.5% of firms reported having a dedicated AI governance committee or function. This may indicate a more specialised and formalised approach, in which responsibility is assigned to a body specifically established to coordinate AI oversight and governance across the organisation.

Relatively smaller shares of firms assigned primary responsibility to the Board of Directors (7.5%) or the Risk/Compliance function (4.2%).

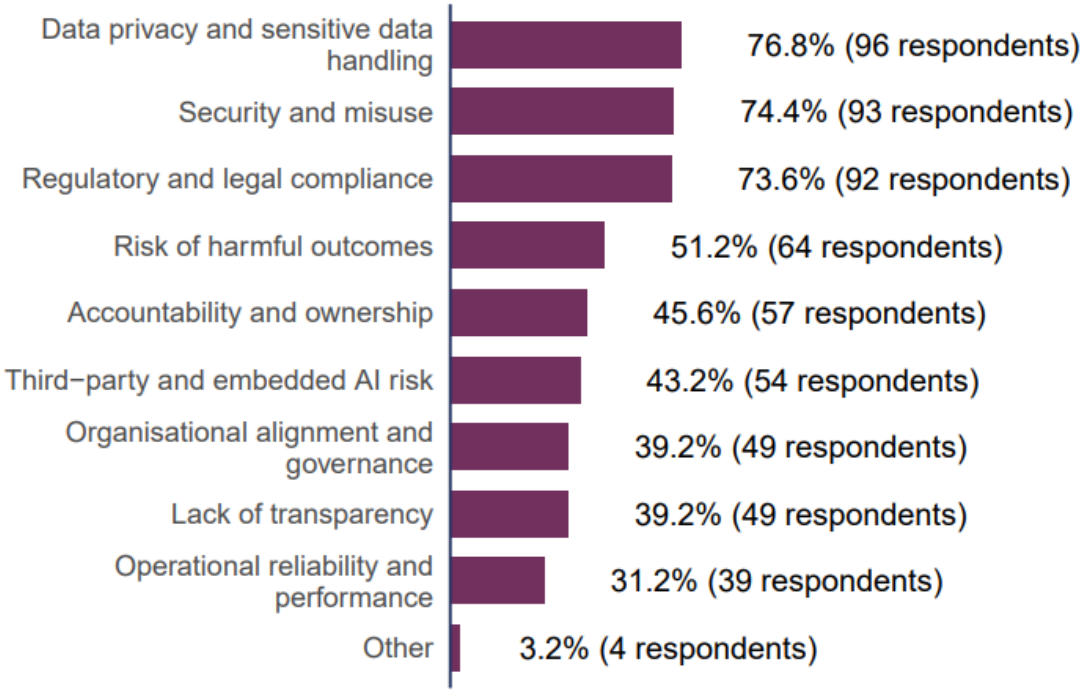
Regular reporting on AI strategy or risks provides another channel for senior-level oversight.

62.3% of firms indicated “Yes”, while 37.7% indicated “No” when asked whether senior management or the Board receive regular dedicated reporting on AI strategy or risks.

The results show that regular dedicated reporting is relatively common. This suggests that AI is often treated as a matter requiring senior-level oversight, with senior management or the Board kept informed of developments relating to AI strategy and associated risks.

Key risks and priorities for AI governance

Figure 4: What are your top concerns related to AI that a governance framework should address?



The three most frequently identified concerns that respondents considered AI governance frameworks should address were **data privacy and sensitive data handling (76.8%)**, **security and misuse (74.4%)**, and **regulatory and legal compliance (73.6%)**. The narrow differences indicate that respondents view all three areas as central priorities for AI governance.

The three leading responses suggest that firms do not view AI governance as being centred on a single dominant risk. Rather, governance frameworks are expected to address an interconnected set of data protection, security, and legal requirements that underpin the responsible use of AI.

Although selected less frequently than the three leading concerns, a substantial proportion of respondents also identified **risk of harmful outcomes (51.2%), accountability and ownership (45.6%), third-party and embedded AI risk (43.2%), organisational alignment and governance (39.2%), and lack of transparency (39.2%).**

These results demonstrate the importance firms place on clear responsibilities, appropriate human oversight, and governance arrangements that allow them to understand, review and challenge AI-generated outputs. This is particularly relevant given that accountability and ownership and lack of transparency were identified as key concerns that AI governance frameworks should address.

Third-party and embedded AI risk also emerged as an important concern. The results suggest that firms are attentive to risks arising from reliance on vendor-provided AI capabilities and AI functionality embedded within broader third-party products, particularly where this may reduce firms' visibility or control over how those capabilities operate.

Finally, operational reliability and performance (31.2%) was the least frequently selected concern. "Other" was selected by 3.2% of respondents.

Overall, the results appear to distinguish between two broad tiers of concern. The first consists of foundational controls relating to privacy, security, and compliance, each selected by almost three-quarters of respondents. The second includes organisational and implementation-related issues such as accountability, third-party dependencies, transparency, and internal alignment. This may suggest that firms are prioritising the core controls required to support the safe use of AI, while also beginning to address the more complex questions that arise as AI becomes more deeply embedded across their organisations.

Integration of AI into risk management

Integration of AI into corporate risk management remains uneven. In this regard, 48.0% of respondents answered "Yes", while 52.0% answered "No" when asked whether AI systems are integrated into their corporate risk management framework.

Therefore, the results suggest that, although a significant proportion of firms have already incorporated AI into their broader risk-management architecture, most firms have not yet done so.

Similarly, responses were almost evenly divided among firms when asked whether they had assessed business continuity risks arising from AI system failure, with a slight majority answering negatively. Among respondents, 51.6% reported that they had not assessed business continuity risks arising from AI-system failure, while 48.4% indicated that they had.

> Business continuity risk refers to assessing the potential impact on business functions and operations if an AI system were suddenly unavailable or unable to perform its intended function.

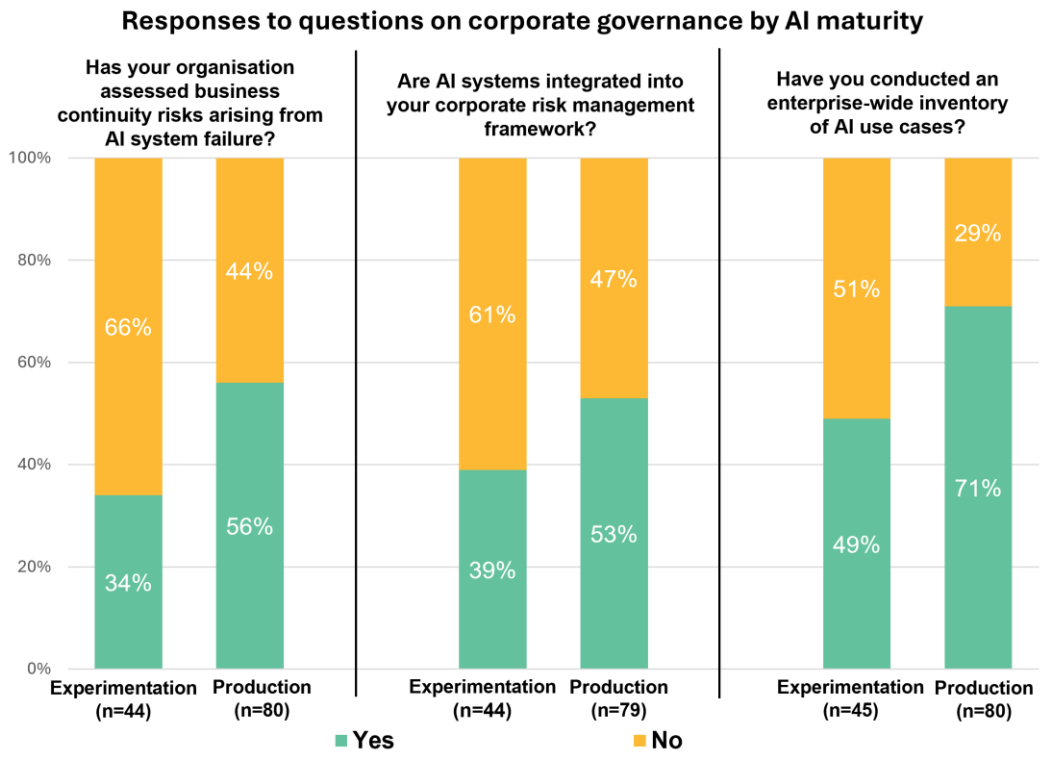
Finally, firms were asked whether they had conducted an enterprise-wide inventory of AI use cases. 63.2% of firms indicated they had an inventory, while 36.8% indicated they did not.

Governance and risk management by AI maturity

This analysis examines whether AI maturity is associated with differences in three governance and risk management practices: assessing business continuity risks arising from AI-system failure; integrating AI systems into corporate risk management frameworks; and conducting enterprise-wide inventories of AI use cases.

Respondents were separated into two broad categories based on their reported stage of AI adoption, following those outlined in the "State of AI Adoption" section. Firms reporting early exploration or development/testing were classified as being in the "experimentation phase", with no AI use cases yet live in business processes. Firms reporting limited production deployment, scaled production deployment, or advanced/strategic adoption were classified as being in the "production phase", with AI use cases already live in business processes. These AI maturity categories are used consistently throughout the report. Figure 5 shows the results.

Figure 5



The breakdowns point to a consistent association between AI maturity and more formalised governance and risk management arrangements. Firms with AI in production are more likely than those in the experimentation phase to have assessed business continuity risks (56% compared with 34%), integrated AI systems into their corporate risk management framework (53% compared with 39%), and conducted an enterprise-wide inventory of AI use cases (71% compared with 49%). The difference between the two groups is equally pronounced for continuity risk assessment and AI inventories, at 22 percentage points, compared with 14 percentage points for risk management integration.

Nevertheless, none of these practices is universal, even among firms already operating AI systems in live business processes. Enterprise-wide inventories are the most widely adopted of the three, although 29% of firms with AI in production have not conducted one. Gaps are more widespread for continuity risk assessment and corporate risk management integration, which 44% and 47% of firms in production, respectively, have not undertaken. Taken together, the findings suggest that more mature firms generally have more developed governance and risk management arrangements, while practices remain uneven even within the production group.

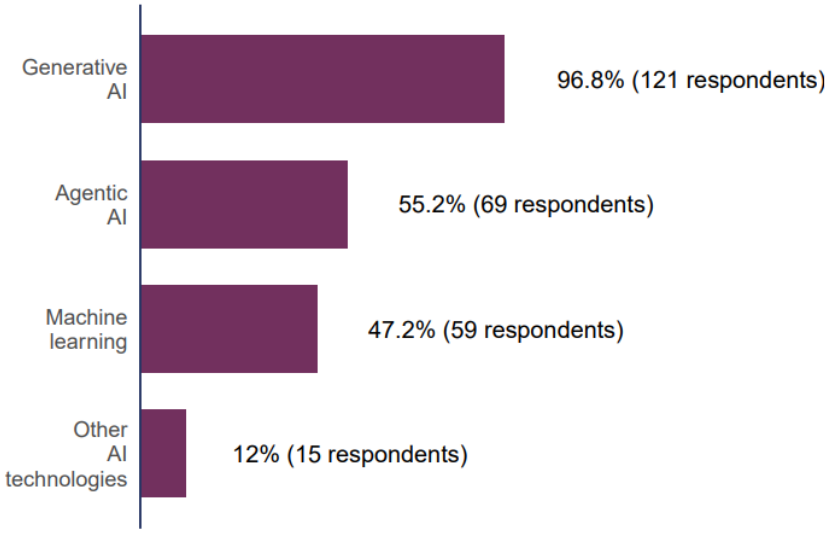
Governance and Risk Management – Key Takeaways

- **Formal AI governance and strategic planning are widespread:** 78.2% of firms report having an AI governance framework in place or under development, while a smaller but still substantial majority, 59.7%, have a formally approved AI strategy or roadmap.
- **Group-level structures play a prominent role in AI governance:** 66.7% of firms with an AI governance framework manage it primarily at group/global level, while 86.3% rely on group-level capabilities either primarily or through a hybrid model.
- **Ownership of AI governance remains diverse:** technology-related functions are the most common primary owners at 27.5%, followed by senior management at 20.0% and cross-functional governance structures at 19.2%. No single organisational model dominates across the industry.
- **Senior-level oversight is relatively common:** 62.3% of firms report that senior management or the Board receives regular dedicated reporting on AI strategy or risks.
- **Privacy, security and regulatory compliance dominate firms' governance concerns:** data privacy and sensitive data handling was selected by 76.8% of respondents, security and misuse by 74.4%, and regulatory and legal compliance by 73.6%. Accountability and ownership, third-party risk, organisational alignment and transparency are also identified as significant concerns.
- **AI risk-management practices remain uneven across firms:** 63.2% have conducted an enterprise-wide inventory of AI use cases, while only 48.0% have integrated AI into their corporate risk-management framework and 48.4% have assessed business continuity risks arising from AI-system failure. Across all three measures, firms with AI in production report higher adoption rates than those in the experimentation phase: 71% vs. 49% for AI inventories, 53% vs. 39% for integration into risk-management frameworks, and 56% vs. 34% for business continuity risk assessment.

AI Type / Technology Leveraged

Figure 6: What type(s) of AI are you using?

Multiple responses permitted



The results show that **Generative AI is by far the most prevalent category of AI technology type firms report using, selected by 96.8% of respondents**. Its near-universal presence among respondents illustrates the widespread use of Generative AI across the asset management industry. This is particularly noteworthy given that its widespread adoption is relatively recent, especially compared with machine learning, which has been used in financial services for considerably longer.

Agentic AI was selected by 55.2% of respondents.

> Agentic AI refers broadly to AI systems designed not only to generate outputs but also to pursue objectives and perform sequences of actions with a degree of autonomy, potentially using tools, accessing information and making intermediate decisions to complete a task.

The relatively high proportion of firms reporting its use is particularly noteworthy given the comparatively recent emergence of Agentic AI. However, these results should be interpreted with caution, as the concept remains relatively new and respondents may differ on what constitutes an Agentic AI system. Nevertheless, the results indicate substantial reported use of increasingly autonomous AI capabilities across participating firms.

Machine learning was selected by 47.2% of respondents, indicating that it remains an important component of the industry's AI landscape, with almost half of participating firms reporting its use.

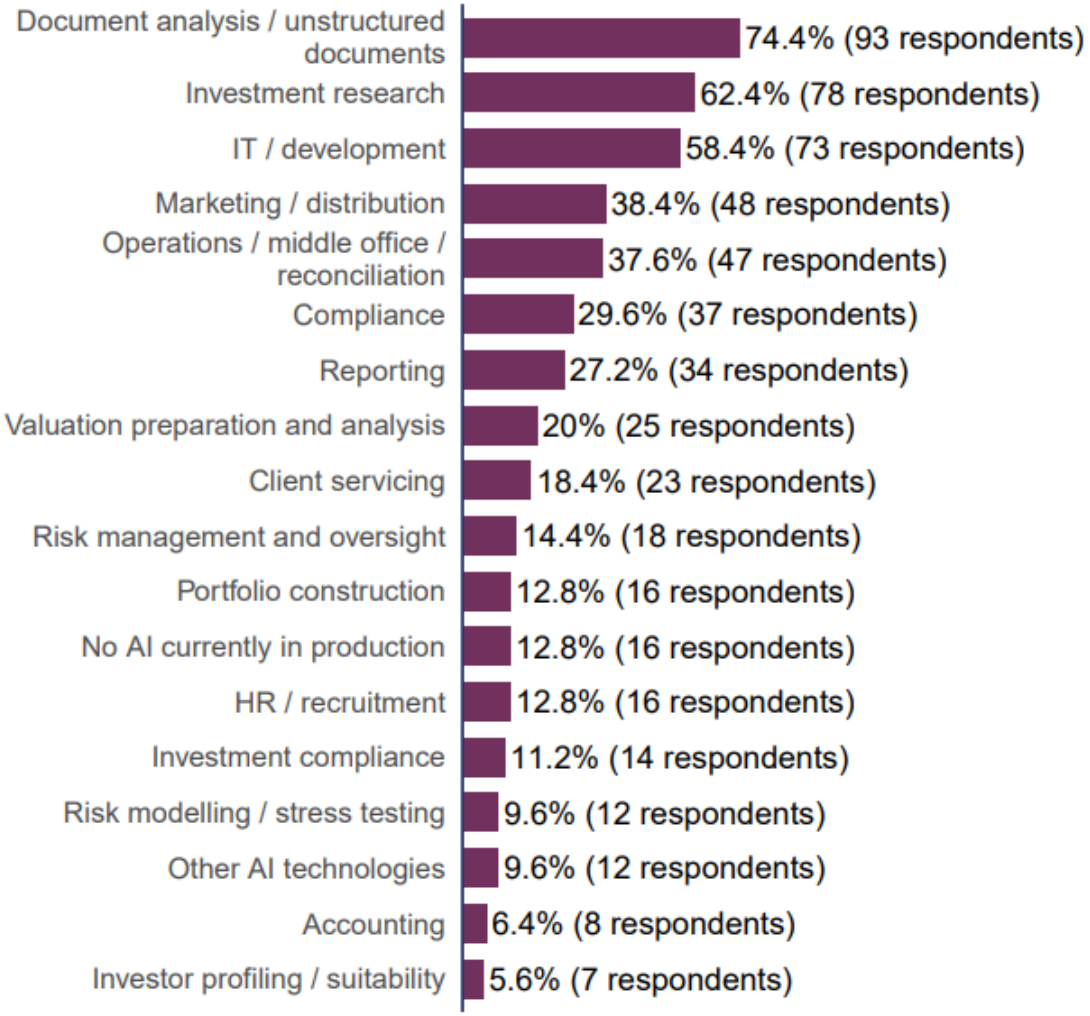
Finally, **12.0% of respondents** reported using other AI technologies. While this indicates that the technological landscape extends beyond the three main categories identified in the survey, Generative AI, Agentic AI and machine learning represent the principal types of AI reported by participating firms.

AI Type / Technology Leveraged – Key Takeaways

- **Generative AI is now near-universal among respondents:** 96.8% report using Generative AI, making it by far the most prevalent technology category across the sample.
- **Agentic AI has already gained significant traction:** 55.2% of respondents report using Agentic AI, although the result should be interpreted cautiously given the relative novelty of the concept and potential differences in how firms define it.
- **Machine learning remains an important part of the technology mix:** 47.2% of respondents report using machine learning, indicating that established AI techniques continue to coexist with newer technologies such as Generative and Agentic AI.
- **AI technology use is highly overlapping:** the categories are not mutually exclusive, suggesting that firms often rely on a combination of technologies rather than a single AI approach.

AI Use Cases

Figure 7: In which areas/functions is AI currently used in production?



The clearest concentration regarding reported AI use cases across areas and functions is in **document-intensive and analytical activities**. **Document analysis and unstructured documents** was the most frequently selected use case, at **74.4%**, followed by **investment research (62.4%)** and **IT/development (58.4%)**. These results suggest that current deployment is strongest in areas where AI can support the processing of large volumes of information, analytical work and software-related activities.

A second group of functions shows a more moderate level of adoption. **Marketing/distribution (38.4%)** and **operations/middle office/reconciliation (37.6%)** were selected by close to four in ten respondents, followed by **compliance (29.6%)** and **reporting (27.2%)**. AI therefore appears to be used across both client-facing and operational functions, although less extensively than in document analysis, research and technology.

Adoption is more limited in several specialised functions. **Valuation preparation and analysis (20.0%)** and **client servicing (18.4%)** sit at or below the 20% mark, while **risk management and oversight (14.4%)**, **portfolio construction (12.8%)**, **HR/recruitment (12.8%)**, **investment compliance (11.2%)** and **risk modelling/stress testing (9.6%)** were selected by relatively smaller shares of respondents. **Accounting (6.4%)** and **investor profiling/suitability (5.6%)** were the least frequently reported areas.

Overall, the results show that AI use in production is already spread across a broad range of business functions, but adoption is uneven. It is currently most prevalent in information-processing, research and technology-related activities, while use in more specialised investment, risk and control functions

remains comparatively limited. Notably, **12.8%** of respondents reported having **no AI currently in production**.

AI Use Cases – Key Takeaways

- **AI use is concentrated in information-heavy functions:** document analysis leads at 74.4%, followed by investment research at 62.4% and IT/development at 58.4%.
- **Adoption is broader but more moderate across operational and client-facing areas:** marketing/distribution (38.4%), operations/middle office (37.6%), compliance (29.6%) and reporting (27.2%) form a second tier of use cases.
- **Use remains comparatively limited in specialised investment, risk and control functions:** most of these categories were selected by fewer than 20% of respondents.

EU AI Act Impact

Figure 8: Has the EU AI Act influenced your organisation's global AI governance or strategy framework?

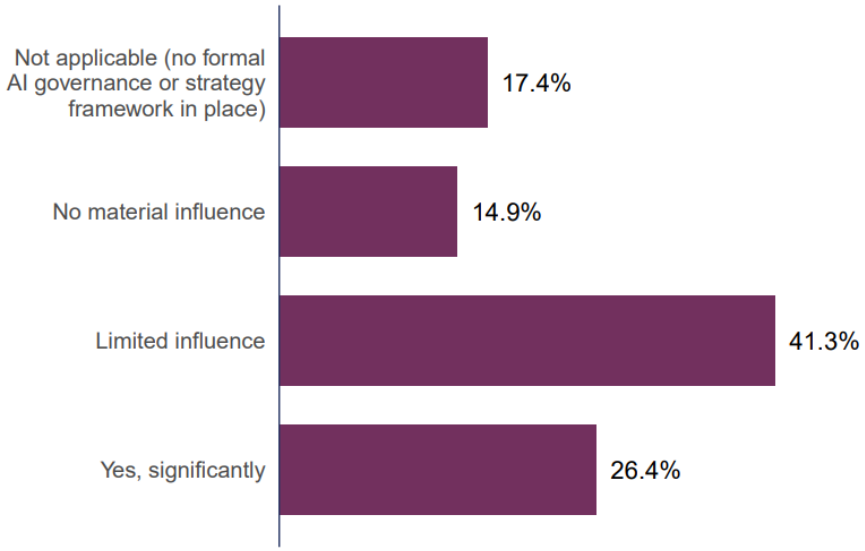


Figure 8 shows that 67.7% of respondents reported the EU AI Act had either limited or significant influence on their organisation's global AI governance or strategy framework, while 17.4% selected "Not applicable".

Excluding firms without a formal AI governance or strategy framework, the responses were distributed as follows (percentages rounded):

- **Limited influence:** 50.0%
- **Significant influence:** 32.0%
- **No material influence:** 18.0%

The results show that among firms with a formal AI governance or strategy framework in place, 82.0% reported the EU AI Act had either a limited or significant influence on their framework, while 18.0% reported no material influence.

The most common response was "Limited influence", selected by 50.0% of firms with a relevant framework in place. This suggests that, for many firms, the EU AI Act has influenced certain aspects of their governance or strategic approach without necessarily being the principal factor shaping those

frameworks. Rather, firms may be incorporating considerations arising from the EU AI Act into broader governance and strategic arrangements shaped by other regulatory, operational and business considerations.

At the same time, 32.0% of firms indicated that the EU AI Act had significantly influenced their governance or strategy. This represents almost one third of respondents and suggests that, for a considerable segment of the industry, the EU AI Act has played an important role in shaping their overall approach to AI governance and strategy.

EU AI Act Impact – Key Takeaways

- **The EU AI Act is already influencing firms' governance and strategy:** 82% of firms with a formal AI governance or strategy framework report being influenced by the AI Act.
- **For most firms, the influence is present but not dominant:** 50.0% report limited influence and 32.0% significant influence.

Third-party Dependencies, Hosting and Concentration Risk

Third-party dependency and concentration risk

Views on the risk of dependency on a limited number of large AI providers are divided.

This question seeks to provide an indication of asset managers' perception of concentration risk. In this context, the risk arises where firms depend on a relatively small number of providers for access to AI tools, models, infrastructure or capabilities.

The results show a relatively even division of views. A slight majority of respondents (55.4%) considered the risk of dependency on a limited number of large AI providers low, while a substantial minority (44.6%) considered it high.

These results indicate no clear industry consensus on the severity of concentration risk in the provision of AI services. Although a slight majority assess the risk as low, the proportion of firms considering it high is sufficiently large to suggest that concentration risk is a material concern for a significant part of the industry.

Overall, the findings point to a divided industry perception: concentration risk is not regarded as high by a majority of respondents, but it is not a marginal concern either. A substantial proportion of firms view dependency on a limited number of large AI providers as a significant risk.

Reliance on third-party capabilities

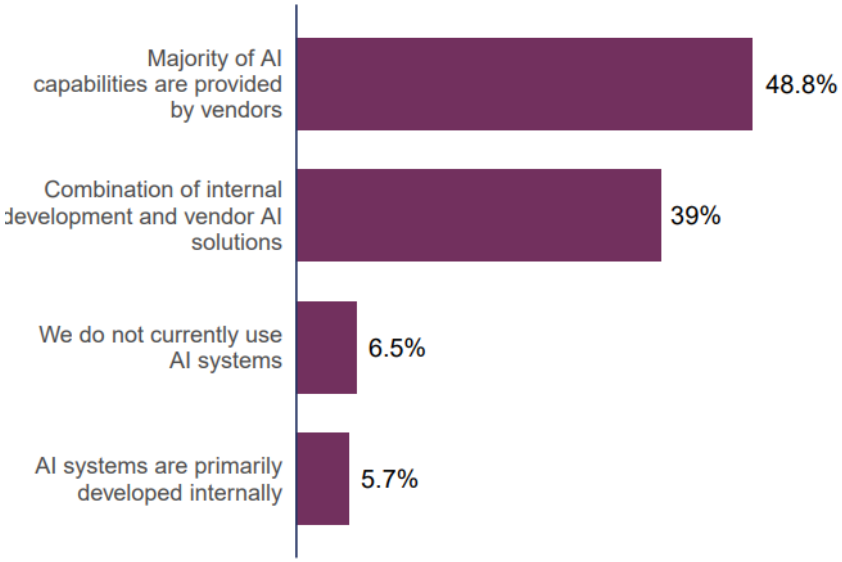


Figure 9: To what extent does your organisation rely on third-party vendors for AI capabilities?

The results show that the most common approach is for firms to have the majority of their AI capabilities provided by external vendors, selected by 48.8% of respondents.

A considerable proportion of firms also report using a combination of internal development and vendor AI solutions (39.0%).

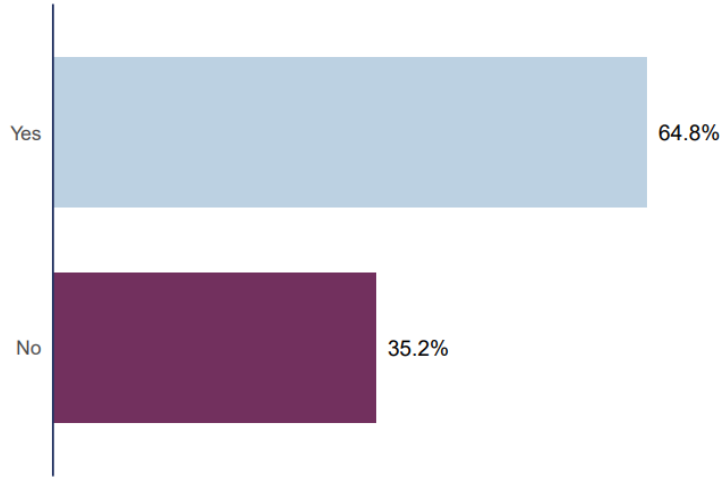
By contrast, firms reporting that their AI systems are primarily developed internally represent a relatively small minority, accounting for 5.7% of all respondents.

Taken together, the results illustrate the significant role third-party vendors play in supporting AI adoption across the asset management industry.

If firms relying primarily on vendors are combined with those using a mix of vendor solutions and internal development, 93.9% of respondents currently using AI rely on third-party vendors to some degree for their AI capabilities.

This suggests that external providers form an important part of the technological ecosystem supporting AI deployment across the industry.

Figure 10: Does your organisation internally develop or customise AI systems or AI-enabled tools?



The results show that 64.8% of respondents reported that their organisation internally develops or customises AI systems or AI-enabled tools, while 35.2% answered "No".

The results indicate that internal development also plays a meaningful role. The fact that almost two-thirds of respondents report some degree of internal development or customisation suggests that this is a common practice among many firms. This also indicates that AI adoption across the industry frequently involves more than simply acquiring ready-made technological solutions from external providers.

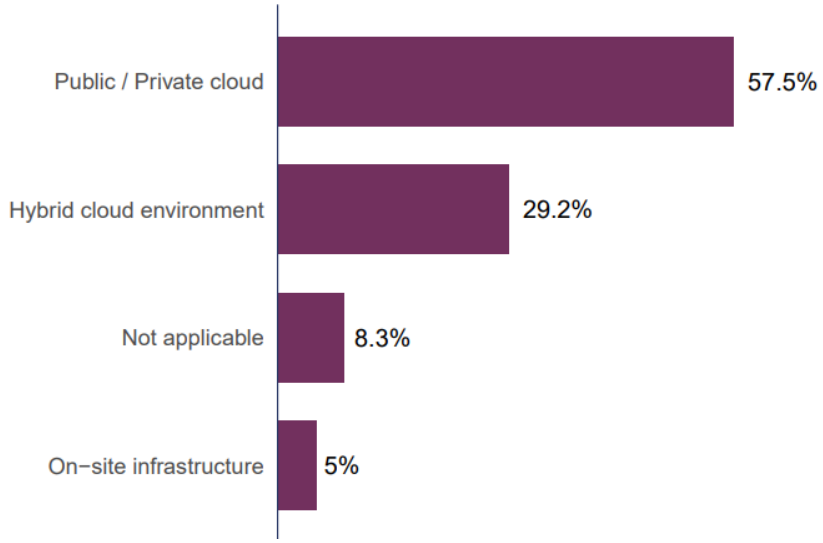
At the same time, the 35.2% answering "No" represents a considerable share of respondents, indicating that internal development or customisation of AI systems is far from universal across the industry.

Read together, the two questions show that internal development and third-party reliance frequently co-exist. Firms may develop or customise certain AI systems or tools internally while continuing to rely substantially on external providers for their broader AI capabilities.

Overall, the findings point to an industry in which third-party provision is highly prevalent, but the degree and form of reliance vary significantly across firms. External vendors appear to play a central role in supporting AI adoption across the asset management industry, while internal development or customisation remains an important complementary component for a substantial proportion of respondents.

Hosting arrangements for AI systems

Figure 11: If you use external vendors' AI systems: where do you expect those AI systems to be hosted?



The question illustrated in Figure 11 focuses on the hosting environment through which external vendors make AI systems available to asset management firms. In practical terms, it indicates the infrastructure arrangements typically used to run externally provided AI systems, distinguishing between cloud-based environments, on-site infrastructure, and hybrid models combining both on-site and cloud-based environments.

The most common response was public/private cloud, selected by 57.5% of respondents. This indicates that, for most firms, externally provided AI systems are expected to operate primarily in a cloud environment rather than exclusively on the asset manager's own physical infrastructure. The result illustrates the importance of cloud infrastructure in supporting the provision and deployment of third-party AI systems across the industry.

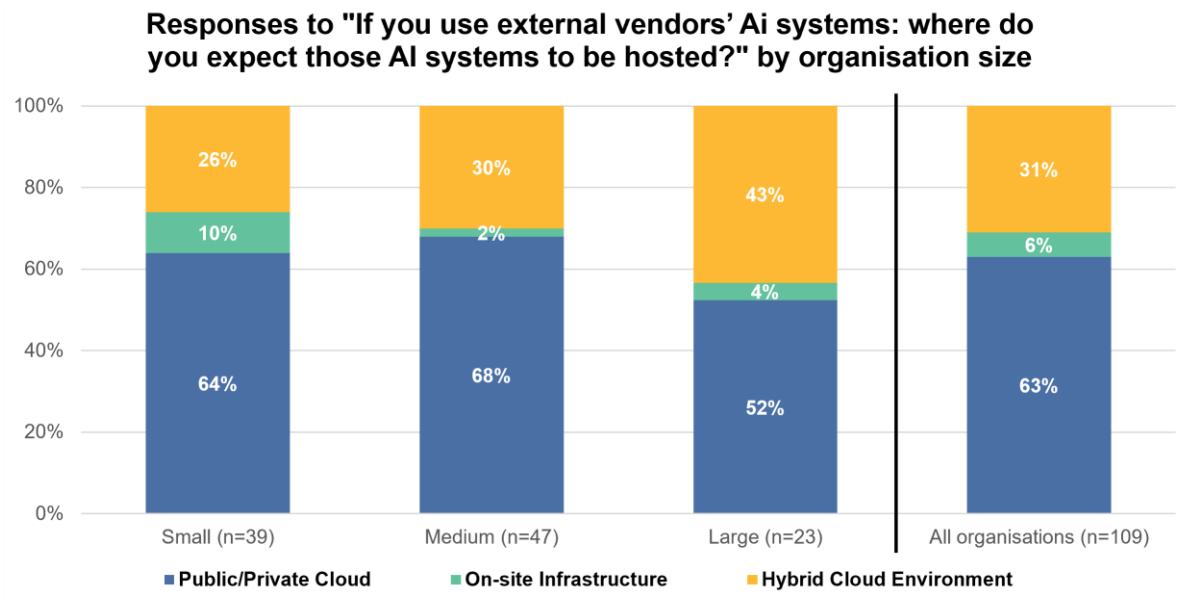
A further 29.2% of respondents indicated that they expect external vendors' AI systems to operate within a hybrid cloud environment. A hybrid model generally combines cloud-based infrastructure with other environments, such as private or on-premises infrastructure, allowing different elements of a system or workload to be operated across different settings. The relatively high prevalence of this model (close to three in ten respondents) suggests that a substantial segment of the industry does not rely exclusively on a single type of hosting environment.

By contrast, only 5.0% of respondents indicated that externally provided AI systems are expected to be hosted on-site. In such arrangements, the vendor may provide the AI technology or software while the system itself is deployed on infrastructure operated or controlled more directly by the asset manager.

Taken together, the results point to the clear predominance of cloud-based infrastructure in the provision of externally supplied AI systems. Among respondents reporting an applicable hosting arrangement, **94.5%** expect external vendors' AI systems to operate through either public/private cloud or a hybrid cloud environment, while only **5.5%** report on-site infrastructure. Cloud-based infrastructure therefore appears to constitute the predominant technical environment through which externally provided AI capabilities are deployed across the asset management industry.

Figure 12 shows expected hosting arrangements for external vendors' AI systems by organisation size, excluding respondents who selected "Not applicable".

Figure 12



Note: Organisation size categories are based on employee count.
Small = 0-50 employees; Medium = 51-500 employees; Large = more than 500 employees

The most noticeable result is that large firms are more likely to report hybrid cloud environments than their small and medium-sized counterparts. Hybrid cloud is reported by 26% of small firms and 30% of

medium-sized firms, compared with 43% of large firms. This represents a 17 percentage-point difference between small and large firms.

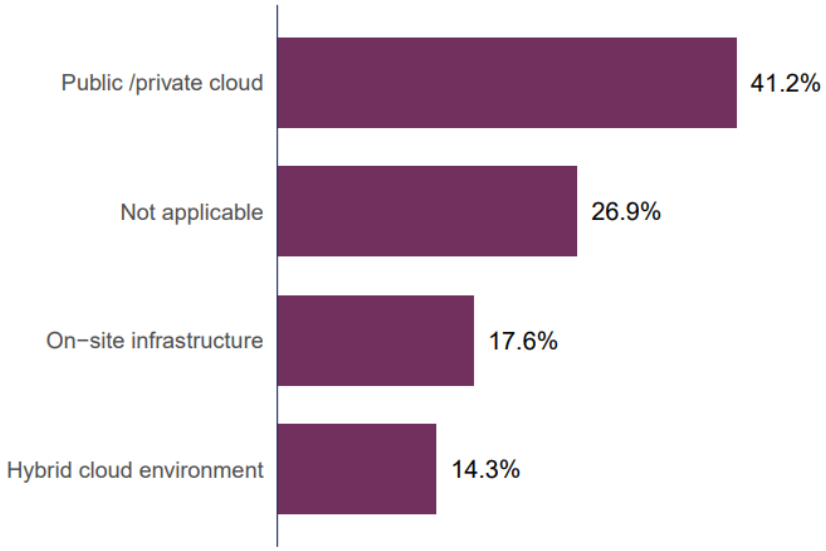
Public/private cloud nevertheless remains the most commonly reported hosting arrangement across all three size categories, accounting for 64% of small firms, 68% of medium-sized firms and 52% of large firms. The difference therefore appears primarily in the balance between public/private cloud and hybrid arrangements: while a majority of large firms continue to rely primarily on public/private cloud, they are considerably more likely than small- and medium-sized firms to report a hybrid environment.

One plausible explanation is that larger firms may have more complex requirements for handling confidential or sensitive data, making hybrid arrangements attractive where they wish to retain certain AI workloads under their direct control. They may also have greater capacity to absorb the costs of establishing and maintaining on-premises infrastructure, while smaller firms may find cloud-based services more affordable than operating their own systems. These are possible explanations; the survey does not establish the reasons for these differences.

By contrast, exclusive reliance on on-site infrastructure remains relatively uncommon across all size categories, reported by 10% of small firms, 2% of medium-sized firms and 4% of large firms. Consequently, the overwhelming majority of firms in each category rely on cloud infrastructure to at least some extent, either through public/private cloud or a hybrid environment: 90% of small firms, 98% of medium-sized firms and 96% of large firms.

Overall, the results suggest an association between organisation size and infrastructure choices, with large firms more likely to rely on hybrid cloud environments than their small and medium-sized counterparts. At the same time, cloud-based infrastructure remains predominant across firms of all sizes.

Figure 13: If you use internal AI systems: where are your AI systems primarily hosted?



Although public/private cloud represents the most common hosting environment for internal AI systems, selected by 41.2% of respondents, this proportion is considerably lower than the 57.5% observed in the previous question concerning third-party-provided AI systems. This indicates that cloud hosting, while still the most common arrangement for internally developed AI systems, is less predominant than it is for externally provided systems.

The most significant difference compared with the previous question concerns the use of on-site infrastructure. While only 5.0% of respondents reported on-site hosting for externally provided AI systems, 17.6% selected this option for internally developed AI systems.

The difference becomes even clearer when respondents selecting “Not applicable” are excluded from both questions. Among firms reporting an applicable hosting arrangement for internally developed AI systems, 24.1% rely primarily on on-site infrastructure, compared with approximately 5.5% for third-party-provided AI systems. On-site hosting is therefore more than four times as prevalent, proportionally, for

internally developed AI systems and represents almost one in four respondents for which the internal-system hosting question was applicable.

Hybrid cloud environments account for 14.3% of responses, compared with 29.2% for third-party-provided AI systems. Unlike on-site infrastructure, hybrid hosting is therefore less prevalent both in absolute terms and relative to public/private cloud hosting for internally developed systems. Hybrid hosting represents approximately 34.7% of the prevalence of public/private cloud hosting for internal AI systems, compared with approximately 50.8% for third-party-provided systems. The data therefore do not indicate that firms are more likely to adopt hybrid arrangements when AI systems are internally developed. Rather, the clearest difference between the two questions is the greater role played by on-site infrastructure.

Nevertheless, cloud-based infrastructure remains clearly predominant even for internally developed AI systems. Among respondents reporting an applicable hosting arrangement, 75.9% use either public/private cloud or hybrid cloud environments, while 24.1% primarily rely on on-site infrastructure. This compares with 94.5% using public/private or hybrid cloud and only 5.5% using on-site infrastructure for externally provided AI systems.

Taken together, the results suggest that internally developed AI systems are less exclusively oriented towards cloud-based infrastructure than externally provided systems, with firms making considerably greater use of on-site hosting. At the same time, the fact that approximately three-quarters of applicable respondents still use public/private or hybrid cloud environments demonstrates that internal development does not imply technological independence from cloud infrastructure. Cloud-based hosting remains the predominant model even where the AI system itself is developed or customised internally.

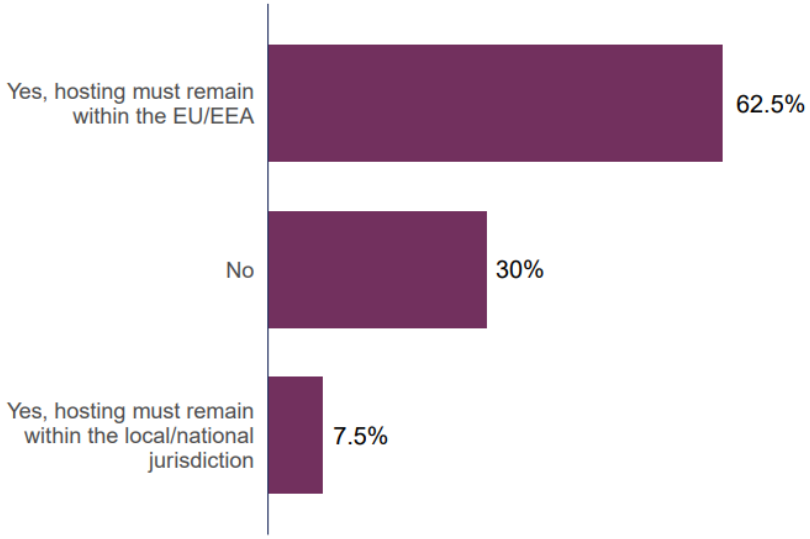


Figure 14: Do you consider sovereign hosting as a mandatory requirement?

Sovereign hosting refers to keeping the physical or cloud infrastructure needed to operate AI systems, such as servers, computing resources, and data-processing environments, within a specific geographical and/or legal jurisdiction. The objective is to ensure that the AI system and its associated computing resources and data processing remain within a defined territory, providing greater assurance on matters such as the applicable legal framework, data protection and data residency, and the availability and control of the underlying infrastructure.

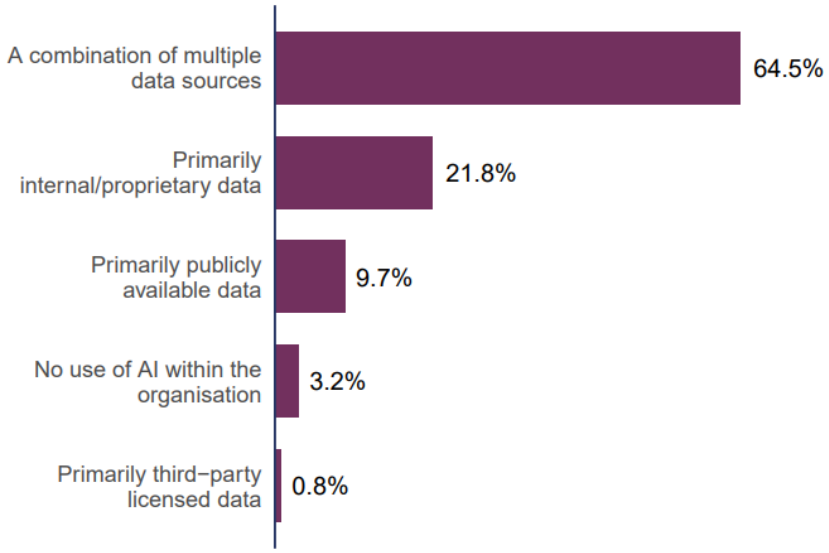
The results show that a majority of firms require the infrastructure supporting the AI systems they use to remain within the EU/EEA (62.5%). This represents a significant proportion of respondents. Combined with the smaller group of firms requiring hosting to remain within their local or national jurisdiction (7.5%), which is a more restrictive and geographically granular requirement, the results show that 70.0% of respondents impose some form of sovereign-hosting requirement, either at the EU/EEA or national level.

Although a significant proportion of respondents (30.0%) do not impose such a requirement, they remain a minority compared with the firms that require some form of geographic restriction on where their AI systems are hosted.

The results therefore indicate a clear preference among a majority of asset management firms for maintaining the infrastructure supporting their AI systems within the EU/EEA or their local jurisdiction.

Data sources supporting AI applications

Figure 15: What is the primary source of data used in your organisation's AI applications?



The most common arrangement by a considerable margin is for firms to draw on a combination of multiple data sources for their AI applications, selected by 64.5% of respondents. The sources involved may include any combination of internal/proprietary data, publicly available data and third-party licensed data.

A significant proportion of respondents, 21.8%, reported relying primarily on internal/proprietary data. This indicates that, for around one in five firms, internally held information constitutes the predominant data source supporting their AI applications.

Finally, a smaller proportion of firms reported relying primarily on publicly available data (9.7%), while only 0.8%, corresponding to a single respondent, identified third-party licensed data as their predominant source.

Third-party Dependencies, Hosting and Concentration Risk – Key Takeaways

- **Third-party vendors play a central role in AI adoption:** 93.9% of respondents currently using AI rely on external vendors to some degree, while 64.8% report internally developing or customising AI systems or tools. The findings show that internal development and third-party reliance often coexist rather than being mutually exclusive.
- **Views on concentration risk are divided:** 44.6% of firms consider dependency on a limited number of large AI providers to represent a high risk, while 55.4% assess it as low. The results therefore show no clear industry consensus on the severity of provider concentration risk.
- **Cloud infrastructure is the predominant hosting model:** among respondents with an applicable hosting arrangement, 94.5% use public/private or hybrid cloud for externally provided AI systems, compared with 75.9% for internally developed systems. On-site hosting is more common for internally developed systems (24.1% vs. 5.5% for externally provided systems), although cloud-based hosting remains predominant in both cases. For externally provided AI systems, cloud-based hosting also remains dominant across firms of all sizes, although large firms are more likely to report hybrid cloud environments (43%) than medium-sized (30%) or small firms (26%).
- **Sovereign-hosting requirements are widespread:** 70.0% consider sovereign hosting as a mandatory requirement, including 62.5% requiring infrastructure to remain within the EU/EEA and 7.5% requiring local or national hosting.
- **Most firms rely on multiple data sources for AI applications:** 64.5% use a combination of data sources, while 21.8% rely primarily on internal/proprietary data, 9.7% on publicly available data and 0.8% on third-party licensed data.

“Human in the loop” (Human Oversight and Intervention)

Firms were asked whether AI outputs were subject to human review before making material decisions: 95.9% of firms answered “Yes”, while 4.1% answered “No”.

This indicates that, at the current stage of AI deployment in asset management, AI systems are generally integrated into firms’ activities in a way that preserves an important role for human oversight.

In practice, this suggests that AI systems largely support or inform human decision-making rather than independently determining material outcomes. The findings therefore indicate that, at least for material decisions, AI deployment remains predominantly human-supervised rather than fully automated.

Similarly, 96.6% of firms answered “Yes”, while 3.4% answered “No” when asked whether users also generally retain the ability to override AI-generated outputs.

This similarly high proportion of positive responses reinforces the previous finding. In almost all responding firms, human users retain the ability not only to review AI-generated outputs but also to override them where necessary. Taken together, the two data points indicate that human experts generally retain ultimate control over whether they rely on AI-generated outputs in material decisions.

This suggests that AI is currently used primarily to support or automate particular elements of business processes, while human intervention remains available before material decisions or actions are taken.

Override actions are recorded less consistently: 59.3% of firms answered “No”, while 40.7% answered “Yes” to the relevant question.

The data show that, while almost all firms retain human review and override capabilities, those interventions are recorded far less consistently. Although 96.6% of firms allow users to override AI-generated outputs, only 40.7% report logging those override actions. In this sense, a distinction can be drawn between the widespread adoption of human oversight as a general principle and greater variation in how firms implement and document it.

Finally, 54.1% of firms answered "No", while 45.9% answered "Yes" when asked whether their "human-in-the-loop" approach differed depending on the risk assessed for the use case. The results show that the industry is relatively evenly divided in this area. A slight majority apply the same approach regardless of risk, while a substantial minority tailor their approach to the level of risk involved.

The fact that 45.9% of firms differentiate their approach by risk indicates that a substantial portion of the industry has adopted a more tailored approach to human intervention, compared with 54.1% applying the same approach across use cases regardless of risk.

Read together with the previous findings, this reinforces the distinction between the near-universal presence of human oversight and the greater diversity in how that oversight is implemented in practice. While the principle of maintaining human oversight appears to be almost universally applied, there is considerably less consistency in how that oversight is structured.

Human Oversight and Intervention – Key Takeaways

- **Human oversight is nearly universal for material decisions:** 95.9% of firms report that AI-generated outputs are subject to human review before material decisions are taken.
- **Human users generally retain ultimate control over AI outputs:** 96.6% of firms allow users to override AI-generated outputs, reinforcing the finding that AI is currently used primarily to support rather than fully replace human decision-making.
- **Approaches to human oversight vary considerably across firms:** 45.9% tailor their human-in-the-loop approach according to the risk of the use case, while 54.1% apply the same approach irrespective of risk. Moreover, only 40.7% of firms log override actions, compared with 59.3% that do not.
- **Human oversight is well established, but its implementation is less standardised:** while review and override capabilities are almost universal, firms differ substantially in the degree to which oversight is risk-based, formalised and documented.

Transparency, Explainability and Fairness

Disclosure of AI use in asset management processes to investors remains limited.

Given the available response options, 67.8% of firms indicated that they had no disclosure in place at this stage, while 32.2% reported disclosing such information to investors.

The results show that a considerable majority of firms, approximately two out of three, do not currently disclose to investors their use of AI in asset management activities. This indicates that, although such disclosure is not uncommon, it is not yet a widespread industry practice. This result could reflect the types of AI systems firms deploy and the fact that few are external/client-facing. The survey questions did not delve into that level of detail.

Fairness and bias assessments are also relatively uncommon.

A fairness or bias assessment can broadly be understood as an evaluation of whether an AI system produces outputs that may systematically disadvantage certain individuals or groups based on

characteristics that should not materially influence the outcome. This is particularly relevant where AI-generated outputs may affect individuals, as biased outcomes could be reproduced or applied at scale.

68.2% of firms responded “No”, while 31.8% responded “Yes” when asked whether they perform fairness or bias assessments on AI systems where relevant.

The results indicate that most firms do not currently perform fairness or bias assessments on AI systems. With only 31.8% reporting that they conduct such assessments, this appears to remain a relatively limited practice across the industry.

Active monitoring of model drift remains a minority practice. Model drift refers broadly to changes over time that may reduce the reliability or effectiveness of an AI system as the data, environment or conditions in which it operates evolve.

61.5% of firms answered “No”, while 38.5% answered “Yes” when asked whether model drift is actively monitored where relevant.

A considerable majority of firms therefore do not appear to actively monitor model drift. Read together with the previous question on fairness and bias assessments, the results suggest that certain controls aimed at monitoring the ongoing performance and behaviour of AI systems are not yet widely implemented across the industry. While these practices are not uncommon, they remain a minority approach among responding firms.

Transparency, Explainability and Fairness – Key Takeaways

- **Transparency and certain AI oversight practices remain uneven across firms:** the results show that investor-facing disclosure, fairness and bias assessments, and model drift monitoring are all present across the industry, but none are yet predominant.
- **Investor-facing disclosure of AI use remains limited:** 67.8% of firms report no disclosure to investors at this stage, while 32.2% disclose such information.
- **Fairness and bias assessments are not yet widely implemented:** 68.2% of firms do not currently perform such assessments where relevant, compared with 31.8% that do.
- **Model drift monitoring is also a minority practice:** 61.5% of firms do not actively monitor model drift where relevant, while 38.5% do.

Investment and Future Development

Main areas of AI investment

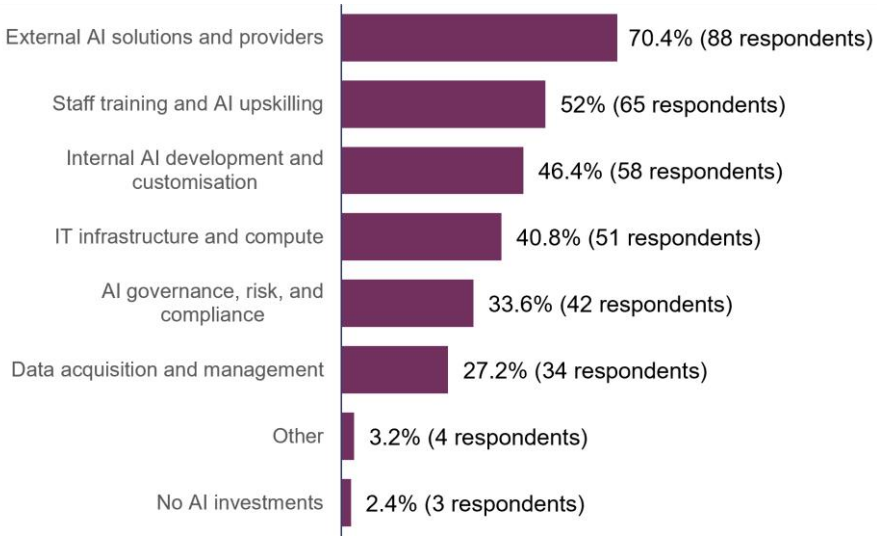


Figure 16: Which areas represent the main focus of your AI investment?

Multiple responses permitted

The results show that external AI solutions and providers are the main area of investment, selected by 70.4% of respondents. This is consistent with the findings in the earlier section on third-party dependencies, where 93.9% of respondents currently using AI reported relying on third-party vendors to at least some extent for their AI capabilities. Taken together, the results show that external providers are not only widely used, but also represent a major destination for firms' AI-related spending.

Investment in staff training and AI upskilling is the second most common focus area, selected by 52.0% of respondents, followed by internal AI development and customisation at 46.4%. These results suggest that firms are also allocating substantial resources to building internal capabilities alongside their use of externally provided technology. In practice, this includes both preparing staff to use AI effectively and allocating resources to adapting and customising AI tools to better serve the firm's specific needs.

A similar point can be made for IT infrastructure and compute, selected by 40.8% of respondents. Around four in ten firms therefore identify the underlying technical infrastructure required to deploy and operate AI as a main investment priority. Taken together, the results on training, internal development and infrastructure indicate that firms are investing not only in accessing AI technology, but also in developing the organisational and technical capabilities needed to use it effectively.

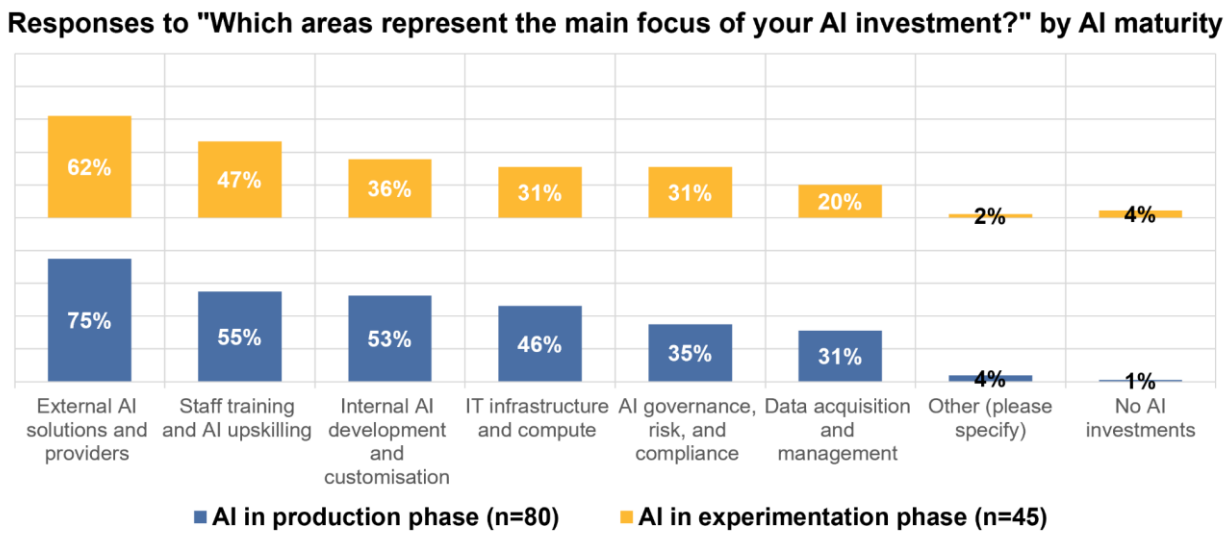
AI governance, risk and compliance was identified as a main investment area by 33.6% of respondents. This is a meaningful share, with around one in three firms allocating significant attention and resources to governance and compliance alongside technological deployment. The result highlights that investment in AI is not limited to innovation-related expenditure, but also includes the internal frameworks, controls and processes required to govern its use.

Finally, data acquisition and management was selected by 27.2% of respondents. While this is the least frequently selected substantive investment category, it remains an important area for more than one in four firms.

Overall, the results show that AI investment is currently concentrated first and foremost on accessing external technology, but that firms are also devoting substantial resources to building the internal capabilities required to make effective use of it. Staff skills, internal development and technical infrastructure all feature prominently, while governance, compliance and data management represent additional areas of investment for a sizeable share of respondents.

AI investment priorities by AI maturity

Figure 17



Note: Respondents could select multiple investment areas. Percentages are based on the number of respondents in AI maturity group.

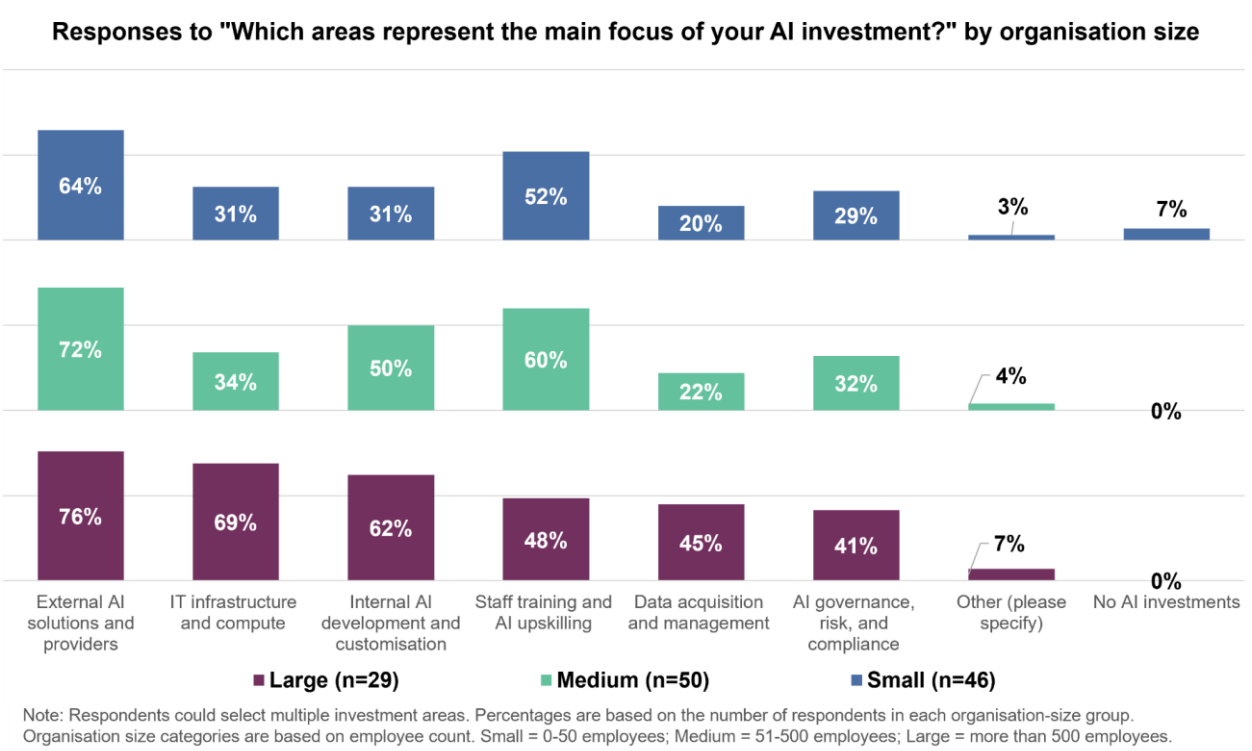
The results show a broadly consistent pattern of AI investment priorities across firms at different stages of AI maturity, in line with the overall investment priorities identified in the preceding subsection. External AI solutions and providers remain the leading investment focus among both firms with AI in production (75%) and those in experimentation (62%), followed by staff training and upskilling (55% and 47%, respectively) and internal AI development and customisation (53% and 36%). IT infrastructure and compute, AI governance, risk and compliance, and data acquisition and management follow in broadly the same order, with IT infrastructure and governance equally prioritised among firms in experimentation (31%).

Despite these similarities, firms with AI in production are more likely to identify each of the six main areas as an investment priority. The largest difference concerns internal AI development and customisation (17 percentage points), followed by IT infrastructure and compute (15 percentage points), external AI solutions and providers (13 percentage points), and data acquisition and management (11 percentage points). Differences are less pronounced for staff training and upskilling (8 percentage points) and AI governance, risk and compliance (4 percentage points). These findings suggest that, as firms move toward operational deployment, their investment priorities do not fundamentally change, but their focus broadens to include a wider range of complementary capabilities, particularly internal development and the technical infrastructure needed to support AI deployment.

The greater emphasis on internal development and customisation among firms with AI in production is also consistent with the broader survey finding that 64.8% of respondents develop or customise AI systems or tools internally, despite the widespread reliance on external providers. This suggests that advancing AI maturity may increasingly involve adapting externally sourced solutions to firms' specific operational needs, rather than relying exclusively on off-the-shelf products.

AI investment priorities by firm size

Figure 18



Note: Respondents could select multiple investment areas. Percentages are based on the number of respondents in each organisation-size group. Organisation size categories are based on employee count. Small = 0-50 employees; Medium = 51-500 employees; Large = more than 500 employees.

The results reveal notable differences in AI investment priorities depending on organisation size. While external AI solutions and providers remain the leading investment focus across all three groups (76% of large firms, 72% of medium-sized firms and 64% of small firms), the relative importance of other investment areas varies considerably. This suggests that, although reliance on external AI solutions is a common feature across the industry, the complementary capabilities firms prioritise differ according to their size.

The most pronounced difference concerns IT infrastructure and compute, identified as an investment priority by 69% of large firms, compared with 34% of medium-sized firms and 31% of small firms, representing differences of 35 and 38 percentage points, respectively. This is the second most frequently selected investment area among large firms, but ranks fourth among medium-sized firms and joint third among small firms. These findings suggest that larger organisations place considerably greater emphasis on developing the technical infrastructure needed to support AI deployment, potentially reflecting the greater scale and complexity of their operations.

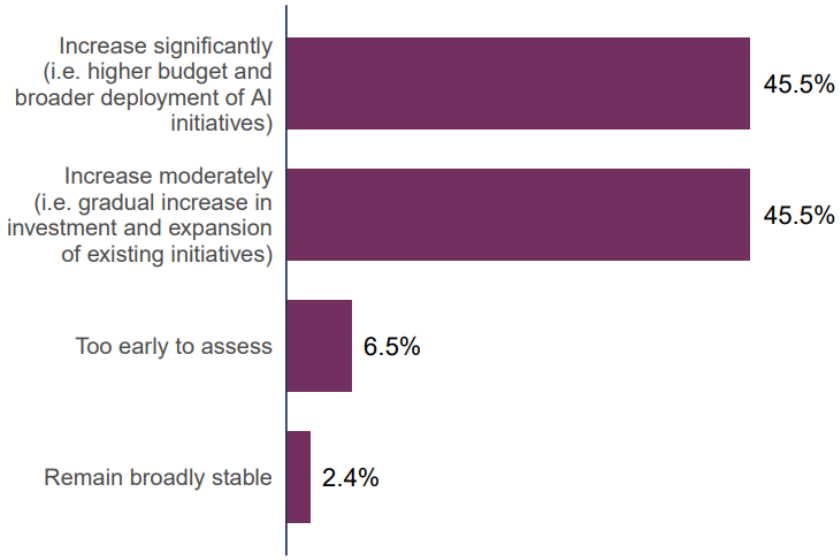
Other substantial differences emerge in internal AI development and customisation and data acquisition and management. Internal development and customisation is prioritised by 62% of large firms, compared with 50% of medium-sized firms and 31% of small firms, representing differences of 12 and 31 percentage points, respectively. This suggests that larger firms are better positioned to invest in adapting AI solutions to their specific operational needs, while smaller firms may rely more heavily on standardised, off-the-shelf solutions. Similarly, data acquisition and management is identified by 45% of large firms, compared with 22% of medium-sized firms and 20% of small firms, representing differences of 23 and 25 percentage points, respectively. Differences are less pronounced for AI governance, risk and compliance, although large firms also select this area more frequently (41%) than medium-sized (32%) and small firms (29%).

Staff training and AI upskilling is the notable exception to this pattern. It is an investment priority for 60% of medium-sized firms and 52% of small firms, compared with 48% of large firms, differences of 12 and 4 percentage points, respectively. In fact, training and upskilling is the second most frequently selected investment priority among both small and medium-sized firms, but ranks fourth among large firms. This may suggest that smaller and medium-sized organisations place relatively greater emphasis on developing their workforce's AI capabilities, potentially reflecting their earlier stages of adoption and the need to build internal expertise before expanding deployment.

Overall, the findings suggest that larger firms tend to identify a broader range of AI investment priorities, with a particularly strong focus on technical infrastructure, internal development and data management. Smaller and medium-sized firms, by contrast, place relatively greater emphasis on staff training and upskilling, while external AI solutions remain a central investment focus across all organisation sizes.

Expected growth in AI investment

Figure 19: How do you expect your organisation's approach to AI investment to evolve over the next three years?



The results strongly indicate that AI investment is expected to grow over the next three years. An equal share of respondents expect their investment to increase moderately or significantly (45.5% each).

91.0% of firms expect their AI investment to increase, while only 2.4% expect it to remain broadly stable and 6.5% consider it too early to assess.

This finding is particularly relevant when considered alongside the results on AI maturity. As shown earlier, 64.0% of respondents have reached a stage where AI use cases are live in business functions, but almost three-quarters of those firms, corresponding to 47.2% of the total sample, remain at the limited production stage. At the same time, a further 36.0% of respondents are still in the early exploration, development, or testing phases, with substantial scope to progress towards live deployment and expand their AI capabilities. Taken together, the results suggest considerable room for firms across the maturity spectrum to scale AI deployment over the coming years.

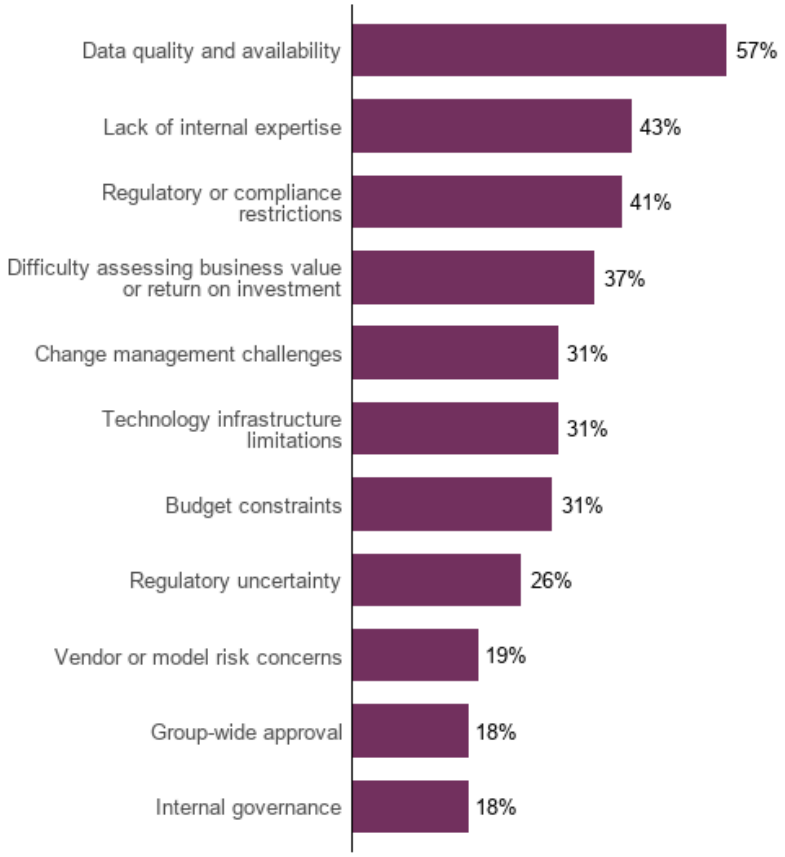
In this sense, increased investment may support scaling existing initiatives, deploying AI across additional functions, or further developing the internal capabilities and infrastructure required to use the technology.

Overall, the results indicate that firms expect AI investment to continue growing strongly in the near term. Combined with the current maturity profile of respondents, this suggests that the next three years are

likely to be characterised by further expansion and scaling of AI deployment across the asset management sector.

Main barriers to broader AI adoption

Figure 20: What are the main barriers to broader AI adoption in your organisation?



The most frequently identified barrier to broader AI adoption was data quality and availability, selected by 57.6% of respondents.

The results indicate that access to suitable and reliable data remains a central challenge for broader AI adoption. This should be considered alongside earlier findings that most firms draw on multiple data sources to support their AI applications (64.5% of respondents), suggesting that broader AI deployment increasingly depends on access to diverse, high-quality datasets.

This creates a clear policy concern for the sector, including consideration of where data costs, gaps or access needs could be addressed through third-party licensed and open data. One such area is investment research, a core asset management activity and the second most frequently identified AI use case in production, cited by 62.4% of respondents.

Lack of internal expertise was the second most frequently selected barrier, at 42.4%, followed closely by regulatory or compliance restrictions at 40.8%. Together with technology infrastructure limitations, selected by 32.0%, these results point to a broader challenge around the capabilities, resources and conditions required to deploy AI more widely. In particular, the prominence of internal expertise suggests that firms do not only need access to AI technology, but also sufficient in-house skills to implement and use it effectively.

The relatively high share of respondents identifying regulatory or compliance restrictions is also noteworthy. More than four in ten firms consider existing regulatory or compliance requirements to be a barrier to broader AI adoption. By comparison, 26.4% selected regulatory uncertainty. This suggests that firms are more concerned with constraints arising from existing rules and compliance requirements than with uncertainty over how the regulatory framework may evolve.

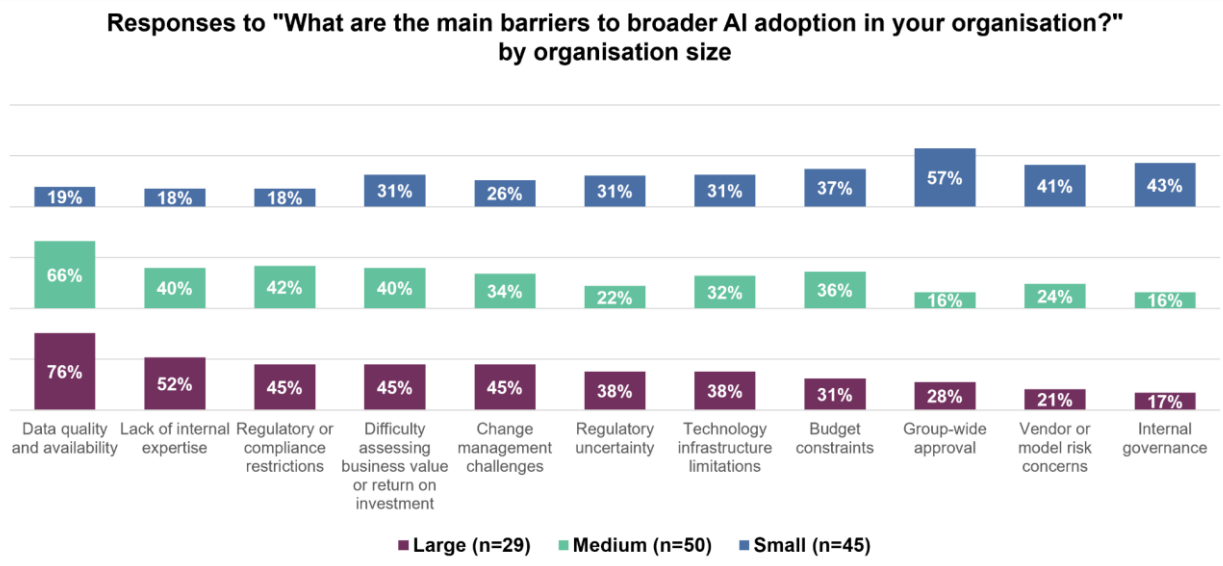
Difficulty assessing business value or return on investment was identified by 37.6% of respondents. This indicates that demonstrating the business case for AI remains an important challenge for a substantial share of firms. This finding is particularly relevant alongside change management challenges and budget constraints, both selected by 31.2%, as broader deployment may depend not only on technological readiness but also on firms' ability to demonstrate value, secure internal support, and allocate sufficient resources.

Other barriers were identified less frequently. Vendor or model risk concerns were selected by 20.0% of respondents, while internal governance and group-wide approval were each selected by 17.6%. This suggests that internal governance and approval processes, while relevant for some firms, are generally less prominent barriers than data, expertise, regulatory constraints or the challenge of demonstrating business value.

Overall, the results point to a heterogeneous set of barriers rather than a single dominant obstacle. Data quality and availability stands out as the leading concern, while internal expertise, regulatory restrictions and the ability to demonstrate business value also feature prominently. Taken together, the findings suggest that broader AI adoption depends on a combination of adequate data and technical capabilities, sufficient internal expertise, a workable regulatory environment and a clear business case for further investment.

Barriers to AI adoption by firm size

Figure 21



Note: Respondents could select multiple investment barriers. Percentages are based on the number of respondents in each organisation-size group. Organisation size categories are based on employee count. Small = 0-50 employees; Medium = 51-500 employees; Large = more than 500 employees.

The results reveal considerable differences in the barriers to broader AI adoption identified by firms of different sizes. The most pronounced difference concerns data quality and availability, the leading barrier for both large (76%) and medium-sized firms (66%), compared with only 19% of small firms, a difference of 57 and 47 percentage points, respectively. In fact, data quality and availability ranks only ninth among the barriers identified by small firms. This substantial divergence may reflect the greater scale and complexity of larger organisations' operations, their more extensive data requirements and their greater emphasis on internally developed or customised AI solutions. This interpretation is consistent with findings elsewhere in the report showing that larger firms tend to be more advanced in their AI adoption and place greater emphasis on internal AI development, IT infrastructure and data management. As firms move towards more sophisticated and widespread deployment, access to high-quality, integrated data may become an increasingly prominent challenge.

An equally striking, but opposite, pattern emerges for group-wide approval processes. This is the most frequently identified barrier among small firms (57%), compared with 28% of large firms and 16% of medium-sized firms, representing differences of 29 and 41 percentage points, respectively. This suggests that organisational approval requirements may represent a particularly important obstacle for smaller firms, potentially reflecting their more limited autonomy in implementing AI initiatives where decisions are subject to approval at group level. A similar pattern emerges for internal governance, identified by 43% of small firms, compared with only 17% of large firms and 16% of medium-sized firms, differences of 26 and 27 percentage points, respectively. Taken together, these findings suggest that smaller organisations may face particular challenges in establishing or navigating the governance and decision-making arrangements necessary to support AI adoption.

Vendor or model risk concerns are also considerably more prevalent among small firms (41%) than among medium-sized (24%) and large firms (21%), representing differences of 17 and 20 percentage points, respectively. This may reflect smaller firms' more limited internal resources and technical capabilities to assess and manage third-party AI risks, as well as potentially greater dependence on external providers. Notably, group-wide approval, internal governance and vendor or model risk concerns are the three most frequently identified barriers among small firms, suggesting that their principal obstacles may relate more to the organisational and risk-management requirements of adopting AI than to the underlying technology itself.

Conversely, larger firms are substantially more likely to identify lack of internal expertise as a barrier (52%), compared with 40% of medium-sized firms and only 18% of small firms, representing a particularly pronounced 34-percentage-point difference between large and small firms. A similar pattern emerges for regulatory or compliance restrictions, identified by 45% of large firms and 42% of medium-sized firms, compared with 18% of small firms. These differences may reflect the more advanced and complex AI applications pursued by larger organisations, which can create greater demand for specialised expertise and expose firms to more extensive regulatory and compliance considerations. This does not necessarily imply that smaller firms have fewer skills gaps or face fewer regulatory requirements, but rather that these challenges may become more apparent as AI deployment expands.

Other differences emerge in change management challenges, identified by 45% of large firms, 34% of medium-sized firms and 26% of small firms, and difficulty assessing business value or return on investment, cited by 45%, 40% and 31%, respectively. Both findings may reflect the additional organisational complexity associated with integrating AI into established business processes and assessing its benefits at scale. Regulatory uncertainty is also more frequently identified by large firms (38%) than by small (31%) and medium-sized firms (22%), although the pattern is less consistent across organisation sizes.

In contrast, budget constraints and technology infrastructure limitations show relatively limited variation across the three groups. Budget constraints are identified by 37% of small firms, 36% of medium-sized firms and 31% of large firms, a maximum difference of only 6 percentage points. Technology infrastructure limitations are similarly consistent, although somewhat more prevalent among large firms (38%) than medium-sized (32%) and small firms (31%). This suggests that financial and infrastructure-related constraints remain relevant across the industry, irrespective of organisation size, even if their underlying nature and scale may differ.

Overall, the findings suggest that the main obstacles to AI adoption differ considerably according to organisation size. Larger firms tend to identify more challenges related to data availability, internal expertise, regulatory compliance and organisational integration, while smaller firms place substantially greater emphasis on approval processes, internal governance and vendor-related risks. These differences may also reflect the close relationship between organisation size and AI maturity identified elsewhere in the report, suggesting that the barriers firms encounter may evolve as they progress from initial experimentation towards broader operational deployment.

Investment and Future Development – Key Takeaways

- **Most firms remain at a limited stage of AI investment, although approaches vary considerably across the industry:** 68.3% of respondents focus their investment on limited initiatives or selected use cases, compared with 26.0% at organisation-wide or strategic stages. The results therefore point to a heterogeneous investment landscape, with most firms still building towards broader and more advanced levels of AI investment.
- **External technology is the leading investment priority:** 70.4% identify external AI solutions and providers as a main investment area. At the same time, firms are investing substantially in internal capabilities, including staff training and upskilling (52.0%), internal AI development and customisation (46.4%), and IT infrastructure and compute (40.8%).
- **Investment priorities vary by firm size:** external solutions lead across all size groups. Large firms place greater emphasis on IT infrastructure, internal development, and data acquisition and management, while staff training and upskilling is comparatively more important for small and medium-sized firms.
- **AI investment is expected to grow strongly:** 91.0% of respondents expect their AI investment to increase over the next three years, evenly divided between those expecting a moderate increase (45.5%) and a significant increase (45.5%).
- **Expected investment growth should be read alongside firms' current AI maturity:** as established earlier in the report, 36.0% of respondents remain in early exploration or development and testing, while 47.2% are at limited production. Against this backdrop, the strong expectation of increased AI investment suggests considerable scope for firms to scale deployment and capabilities over the coming years.
- **Barriers to adoption are varied:** data quality and availability is a barrier identified by a majority of firms, at 57.6%, followed by lack of internal expertise (42.4%), regulatory or compliance restrictions (40.8%), and difficulty assessing business value or ROI (37.6%). The results point to a combination of data, skills, regulatory and business-case challenges rather than a single dominant obstacle. The data challenge points to a clear area for policy action, including consideration of where data gaps or access needs could be addressed through third-party licensed and open data.
- **The reported barriers differ by firm size:** larger firms identify more challenges relating to data availability, internal expertise and regulatory compliance. Smaller firms place greater emphasis on group-wide approval, internal governance and vendor-related risks. Budget and infrastructure constraints show more limited variation across groups.

Return on Investment and KPIs

Measuring the return on AI investment

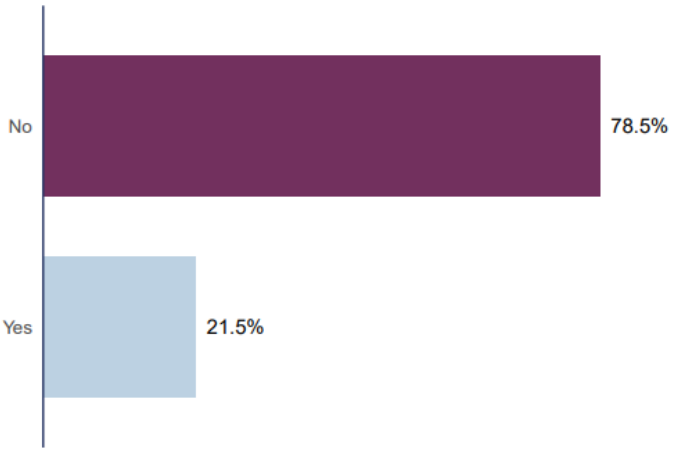


Figure 22: Have your firm implemented a model to measure the ROI of the implementation of AI?

The results show that 21.5% of respondents have a model in place to measure ROI of their AI projects, while 78.5% do not.

This indicates that the large majority of firms have not yet formalised how they measure the financial or business return generated by their AI projects.

Read together with the previous finding that 37.6% of respondents identified difficulty assessing business value or ROI as a main barrier to broader AI adoption, the results suggest that demonstrating and measuring the value generated by AI remains an important issue for a substantial part of the industry. This is particularly relevant given that 91.0% of firms expect their AI investment to increase over the next three years. As investment grows, firms are likely to face increasing pressure to assess whether that expenditure is delivering the expected benefits.

Monitoring AI performance through KPIs

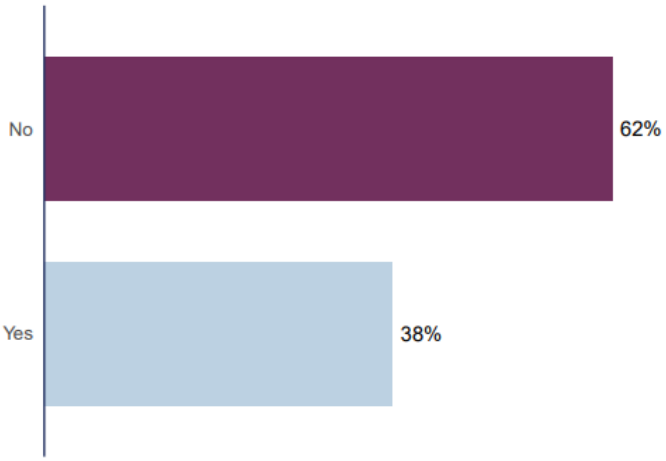


Figure 23: Do you already have KPIs?

In this case, 38.0% of firms responded “Yes”, while 62.0% responded “No”.

The results show that more firms have implemented KPIs to measure AI performance than have a formal model in place to measure the ROI of their AI projects, although both remain a minority. This suggests, firstly, that the absence of a formal ROI model does not necessarily mean that firms lack other metrics to assess whether their AI initiatives are delivering value or benefits. Secondly, KPIs may serve purposes beyond measuring financial returns, for example assessing whether an AI system is performing as expected or whether its use is delivering benefits within specific use cases.

Overall, however, the results reinforce the conclusion that a gap remains in how firms monitor and measure the performance and value of their AI initiatives. A majority of firms (62.0%) have not yet implemented KPIs, while an even larger share (78.5%) do not have a formal ROI measurement model. This is particularly relevant given the strong increase in AI investment expected over the next three years and the broader organisational implications associated with greater AI deployment, including workforce transformation and changes to firms' business models.

ROI and KPI practices by AI maturity

The report also examined whether firms' approaches to measuring ROI and monitoring KPIs vary according to their level of AI maturity. The results are shown in Figures 24 and 25. In both figures, "No" is shown on the left and "Yes" on the right.

Figure 24: Have your firm implemented a model to measure the ROI of the implementation of AI?

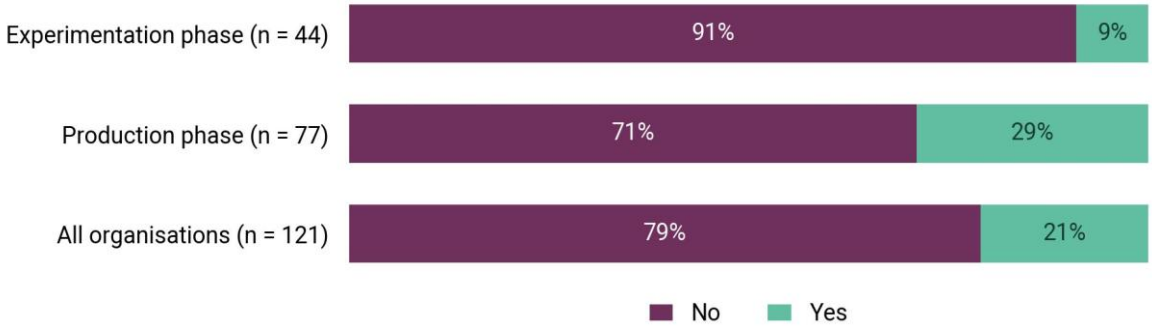


Figure 25: Do you already have KPIs?

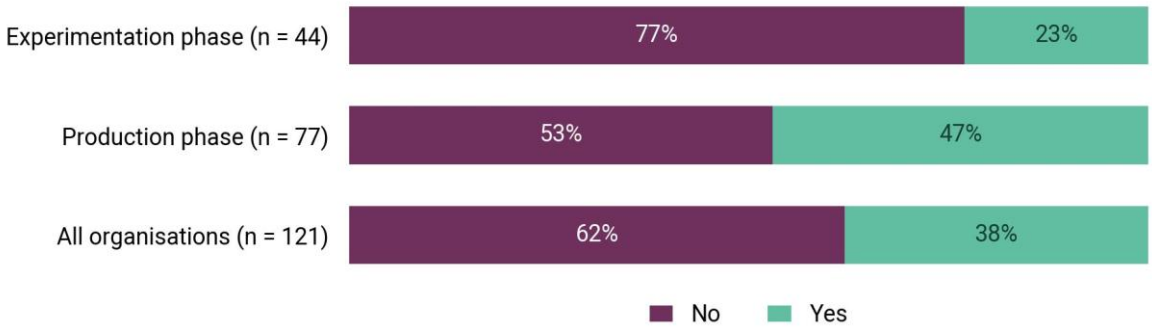


Figure 24 shows that firms with AI in production are more likely to have implemented a model to measure the ROI of their AI deployment. 29% of firms with AI in production report having an ROI model in place, compared with 9% of firms in the experimentation phase, representing a 20 percentage-point difference between the two groups. Despite the difference by maturity, a substantial majority of firms with AI already in production therefore still do not have a formal model for measuring ROI.

Figure 25 shows similar results when looking at whether firms have implemented KPIs to measure AI performance. Almost half (47%) of firms with AI in production report having KPIs in place, compared with 23% of firms in the experimentation phase, a difference of 24 percentage points. Conversely, 53% of firms with AI in production and 77% of firms in the experimentation phase report not having KPIs in place. The difference between the two maturity groups is therefore slightly more pronounced for KPIs than for formal ROI models.

Overall, both data points show a consistent association between greater AI maturity and the adoption of mechanisms to measure AI performance and value. Firms with AI in production are relatively more likely to have both ROI models and KPIs in place than firms in the experimentation phase. However, these practices remain a minority even among firms with AI already in production: only 29% report a formal ROI model and 47% report having KPIs in place. The findings therefore suggest that measurement practices

become more common as AI deployment matures, but do not necessarily develop at the same pace as firms move AI use cases into production.

Return on Investment and KPIs – Key Takeaways

- **Measurement frameworks remain relatively underdeveloped:** only 38.0% of all firms surveyed have implemented KPIs to measure AI performance, while just 21.5% have a formal model in place to measure ROI. This indicates that most firms have yet to formalise how they assess the performance and value generated by their AI investments. Given the strong expectations for future AI investment and growth identified in the previous section, this may be an area that firms will wish to develop further over the coming years.
- **More mature AI adoption is associated with stronger measurement practices:** firms with AI in production are more likely than those in the experimentation phase to have KPIs in place (47% vs. 23%) and to have implemented a formal ROI model (29% vs. 9%). However, both practices remain a minority even among firms with AI already in production, suggesting that measurement frameworks do not necessarily develop at the same pace as AI deployment.

Training and Workforce Impact

Workforce AI skills and upskilling efforts

Most respondents identify a need for further workforce training to adopt AI effectively.

76.7% of respondents indicated that significant additional training or upskilling is required, while 23.3% considered their employees "skilled and sufficiently trained".

The results show that a substantial majority of firms, approximately three out of four, consider that their employees still require further training, skills or expertise to adopt AI effectively or, at the very least, that there remains a gap between their current capabilities and those required for effective AI adoption.

Conversely, only a minority of respondents consider their employees sufficiently prepared at present to deploy AI effectively and do not regard workforce skills as a current issue.

This finding is reinforced by the results presented in the earlier section, "Investment and Future Development", where lack of internal expertise was the second most frequently identified barrier to broader AI adoption, selected by 42.4% of respondents. In this sense, the data indicate that firms not only consider their employees insufficiently equipped to deploy AI effectively, but also view this skills gap as a major barrier to broader AI adoption.

When asked whether they had implemented programmes to upskill employees on AI-related tools and capabilities, 76.4% of respondents answered "Yes", while 23.6% answered "No". Therefore, the data show that a similarly large majority of firms are already taking action to strengthen their workforce's AI-related skills. This indicates that staff training and upskilling are already widespread and represent a priority for many firms. This conclusion is also consistent with the findings from the "Investment and Future Development" section, where staff training and AI upskilling were the second most common focus area of AI investment, selected by 52.0% of respondents.

The two findings are particularly informative when read together. On the one hand, 76.7% of firms consider that their workforce still requires significant additional training or upskilling. On the other, an almost identical share, 76.4%, report that they have already implemented programmes to address these needs.

This suggests that firms are largely aware of the existing skills gap and are actively taking steps to address it.

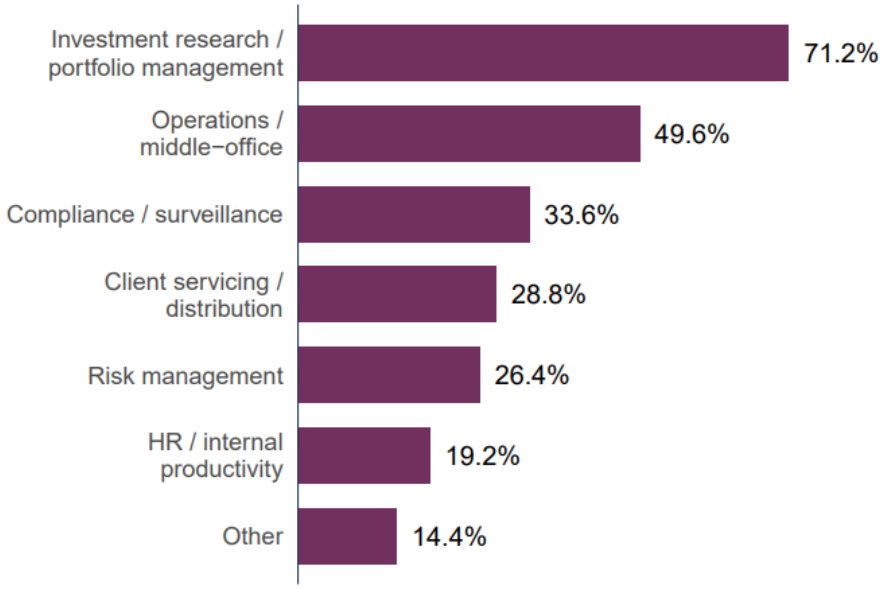
At the same time, the fact that such a high proportion of firms still identify significant additional training needs despite the widespread implementation of upskilling programmes suggests that this remains an ongoing process. Existing initiatives may not yet have fully closed the gap between current workforce capabilities and the skills required for effective AI adoption. This suggests that workforce development will remain important as firms expand their use of AI across a broader range of business activities and deepen its integration within existing functions.

Overall, the results point to a significant workforce skills gap, but also to an industry that is actively investing in addressing it. Firms appear to face a need not only to strengthen employees' current ability to implement and use AI effectively, but also to prepare their workforce for the broader changes that AI may bring to business functions and organisational processes. Given the scale of current training efforts and the continued perception of significant skills needs, workforce upskilling is likely to remain a priority for asset management firms in the near future.

Business functions most impacted by AI adoption

Figure 26: Which functions within your organisation are currently most impacted by AI adoption?

Multiple responses permitted



The data show that the most impacted function at present is investment research/portfolio management, selected by 71.2% of respondents. This indicates that a substantial majority of firms are already seeing an impact from AI in a core asset management activity directly linked to investment decision-making.

Operations/middle office was the second most frequently selected function, at 49.6%. This indicates that approximately half of responding firms have already observed an impact from AI in this area, which includes activities supporting the execution, processing and administration of investment activity.

A further group of functions shows a more moderate level of impact. Compliance/surveillance was selected by 33.6% of respondents, while client servicing/distribution was selected by 28.8%. In broad terms, this means that around one in three firms have observed an impact in these areas. Compliance and surveillance cover activities related to ensuring that firms meet applicable legal and regulatory requirements, while client servicing and distribution encompass activities directed at current or prospective clients, including providing information, offering services and marketing.

Relatively lower levels of impact were identified in risk management at 26.4% and HR/internal productivity at 19.2%, indicating that a smaller share of firms have so far observed an impact from AI in these functions.

Overall, the results indicate that AI is not affecting all business functions in asset management to the same extent. While its impact is observable across a broad range of activities, the degree of impact

varies considerably between functions. The clearest effect is currently seen in investment research and portfolio management, suggesting that AI is already significantly impacting one of the core business activities of asset managers. Operations/middle office and compliance/surveillance also stand out as areas where a meaningful share of firms are seeing an impact.

Client servicing/distribution is also noteworthy. Although the reported impact is lower than for investment research or operations, almost one in three respondents have already observed an impact in this front-office area. This suggests that AI adoption is not confined to internal or operational functions, but is also beginning to affect activities directly linked to client interaction and distribution.

Expected workforce transformation and reconversion

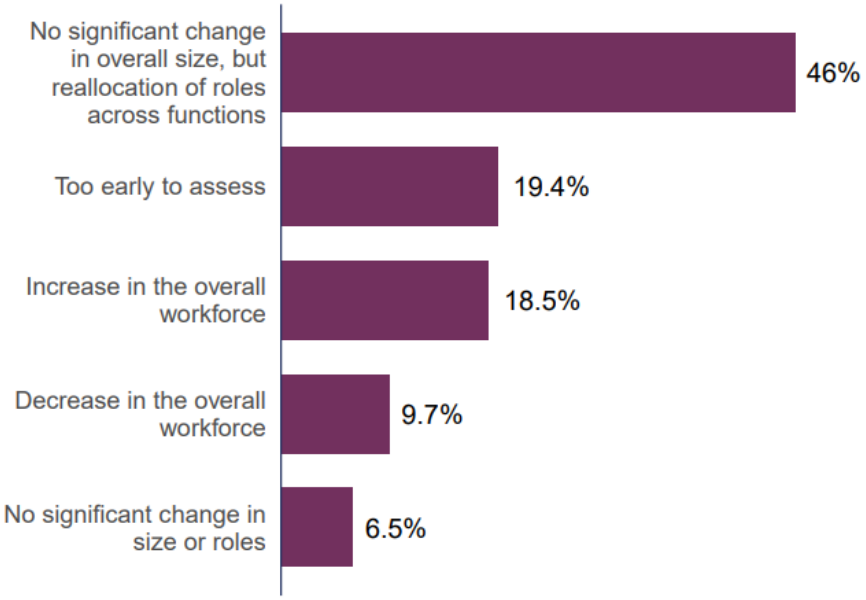


Figure 27: How do you expect AI adoption to impact your workforce over the next 3 years?

The data indicate that 46.0% of firms expect no significant change in overall workforce size, but instead a reallocation of roles across functions.

This means that approximately half of respondents expect AI to lead to changes in how roles are distributed across their organisation in the near future. This is a considerable share of the sample and suggests that, for many firms, the workforce impact of AI is expected to relate more to the types of roles performed and their allocation across functions than to changes in overall employee numbers.

An increase in the overall workforce was selected by 18.5% of respondents. This represents a substantial minority of firms that expect AI adoption to be associated with workforce growth. This could reflect demand for additional employees with the expertise required to deploy AI across existing business functions or to take on new AI-related roles, while staffing needs in other areas remain relatively stable.

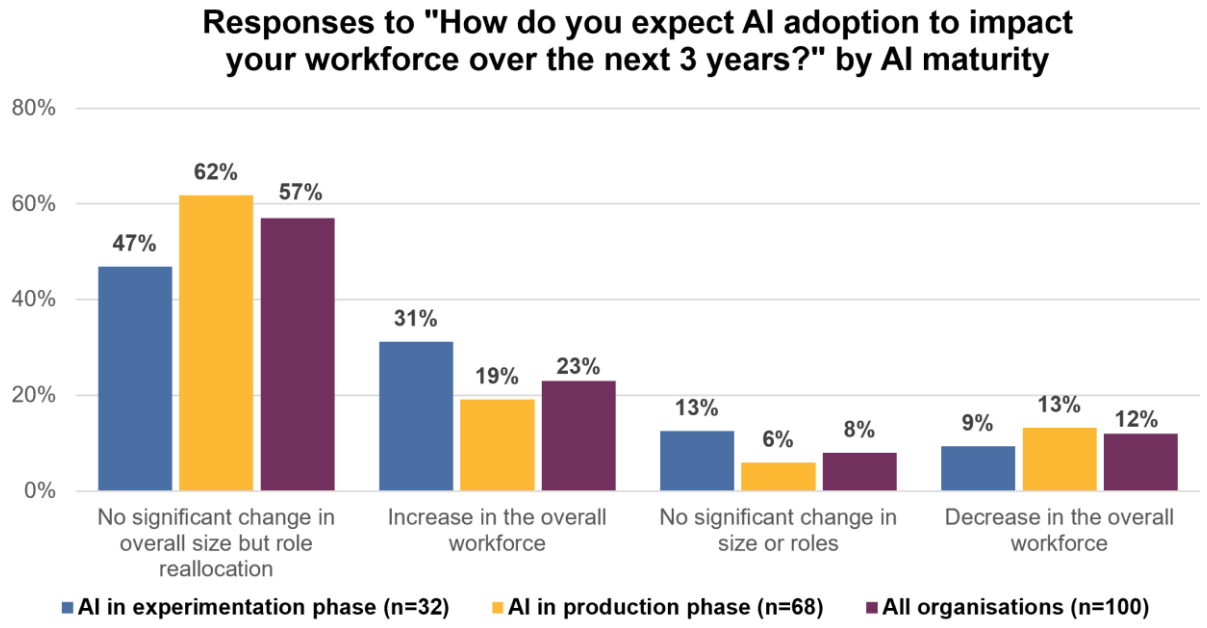
Interestingly, only 9.7% of respondents expect a reduction in their workforce over the next three years. This contrasts with a common perception that increased automation through AI will necessarily translate into lower overall employment. The survey results instead suggest that, at least over the next three years, workforce reduction is not the main outcome most firms anticipate. However, the timeframe of the question is important, as these results do not preclude more structural, longer-term changes to employment in the asset management industry as AI deployment develops further.

It is also noteworthy that 19.4% of respondents consider it too early to assess the impact of AI on their workforce, indicating that a sizeable minority of firms remain uncertain about how these changes will develop. A further 6.5% expect neither a significant change in workforce size nor a reallocation of roles, representing a relatively small share of the sample.

Looking across the responses, 74.2% of firms expect some form of workforce change as a result of AI, whether through an increase or reduction in workforce size or through a reallocation of roles across functions. At the same time, 71.0% do not currently expect AI to lead to a reduction in overall workforce numbers, comprising those expecting an increase, a reallocation of roles without a significant change in size, or no significant change in either size or roles. While almost one in five firms still consider it too early to assess, the results show that a substantial majority already have expectations regarding how AI may affect their workforce over the next three years.

The report also examines whether expectations regarding the impact of AI on the workforce over the next three years vary according to AI maturity. Figure 28 compares firms in the experimentation and production phases. Respondents who selected “too early to assess” were excluded from this analysis, so the comparison focuses only on firms able to express a view on AI’s expected workforce impact. The categories show role reallocation, workforce growth, no significant change in size or roles, and workforce reduction.

Figure 28



The results show that firms with AI in production are more likely to expect a reallocation of roles across functions without a significant change in overall workforce size (62% vs. 47%). This is the most commonly selected outcome for both maturity groups, but is particularly pronounced among firms with AI already in production.

Moreover, firms in the experimentation phase are considerably more likely to expect an increase in their overall workforce: 31% report this expectation, compared with 19% of firms with AI in production. By contrast, firms with AI in production are slightly more likely to expect a reduction in overall workforce size (13% vs. 9%).

Taken together, 41% of firms in the experimentation phase expect a change in overall workforce size, either upwards or downwards, compared with 32% of firms with AI in production. However, the difference is largely driven by the greater expectation of workforce growth among firms still in the experimentation phase. The share expecting workforce reductions differs much less between the two groups.

The results therefore suggest that firms with AI already in production have somewhat more stable expectations regarding overall headcount, but not necessarily regarding workforce transformation more broadly. Indeed, 94% of firms with AI in production expect some form of workforce change when role reallocation is included, compared with 88% of firms in the experimentation phase. The main difference is that firms with AI in production are more likely to expect that change to take the form of reallocating

roles across functions without changing overall workforce size, whereas firms in the experimentation phase are more likely to anticipate workforce growth.

Against this backdrop, only 9.5% of respondents have implemented staff reconversion programmes, while 90.5% have not.

In this context, a reconversion programme can be broadly understood as a structured initiative aimed at preparing employees to perform new or substantially adapted tasks where their existing roles change as a result of AI deployment. The data therefore show that the vast majority of firms have not yet implemented formal reconversion programmes.

This is an interesting finding when read alongside firms' expectations for workforce transformation. While 46.0% of respondents expect a reallocation of roles across functions over the next three years, only 9.5% report having a formal reconversion programme in place. This points to a gap between the scale of workforce change anticipated by a considerable segment of the industry and the implementation of structured programmes specifically designed to support employees through that transition.

This does not, however, mean that firms are not preparing their workforce for AI-related change. As shown earlier in this section, 76.4% of respondents have already implemented programmes to upskill employees in AI-related tools or capabilities. The two findings therefore suggest a distinction between widespread training and upskilling initiatives and more comprehensive reconversion programmes aimed at transitioning employees into new or substantially altered roles.

The data may therefore reflect different stages and approaches to workforce preparation. While firms are already investing heavily in strengthening employees' AI skills, most have not yet moved towards formal, organisation-wide programmes for managing broader role transformation. Current efforts may instead remain focused on building AI literacy and capabilities within existing roles or particular business functions, ahead of more structural workforce changes.

Overall, the data show that most firms expect AI to impact their workforce over the next three years. The most common expectation is not an increase or reduction in overall employee numbers, but rather a reallocation of roles across functions, selected by 46.0% of respondents. This suggests that the near-term impact of AI may be felt primarily through changes in how existing roles and business functions are organised and through the emergence of new responsibilities or roles linked to AI. A further 18.5% expect their total workforce to increase, compared with only 9.7% expecting a reduction. These findings suggest that, in the near term, firms are more likely to anticipate workforce transformation than workforce contraction. At the same time, the fact that only 9.5% of firms have implemented formal reconversion programmes suggests that structured approaches to managing this transformation are still at an early stage. The three-year timeframe should nevertheless be kept in mind, as the results do not provide conclusions on the more structural, long-term effects that AI may have on employment in the asset management industry.

Training and Workforce Impact – Key Takeaways

- **A substantial workforce skills gap remains:** 76.7% of respondents consider that their employees still require significant additional training or upskilling to adopt AI effectively, while only 23.3% consider them sufficiently skilled and trained. Moreover, lack of internal expertise was also the second most frequently identified barrier to broader AI adoption, selected by 42.4% of respondents.

- **Firms are actively responding to these skills needs:** 76.4% have implemented programmes to upskill employees in AI-related tools or capabilities. This is consistent with staff training and AI upskilling being the second most common focus area of AI investment, selected by 52.0% of respondents, also indicating that workforce development remains an ongoing priority.

- **AI impact is broad but uneven across business functions:** investment research/portfolio management is the function most frequently identified as impacted, at 71.2%, followed by operations/middle office at 49.6%. Compliance/surveillance stands at 33.6%, client servicing/distribution at 28.8%, risk management at 26.4%, and HR/internal productivity at 19.2%.

- **AI is already affecting both core investment and client-facing activities:** the strongest reported impact is in investment research/portfolio management, while almost one in three respondents also report an impact in client servicing/distribution. The findings therefore show that AI adoption is not confined to internal or operational functions.

- **Most firms expect workforce transformation rather than contraction in the near future:** 46.0% expect no significant change in workforce size but a reallocation of roles, while 18.5% expect growth and 9.7% a reduction. Overall, 74.2% expect some form of workforce change, while 71.0% do not expect AI to reduce workforce numbers.

- **Formal reconversion programmes remain uncommon**: only 9.5% of firms have implemented them, compared with 46.0% expecting role reallocation. This suggests that structured approaches to role transformation remain less developed than general training and upskilling.

- **Greater AI maturity is associated with a shift from expected headcount growth towards role reallocation:** among firms able to assess the workforce impact of AI, 62% of those with AI in production expect roles to be reallocated without a significant change in overall workforce size, compared with 47% of firms in the experimentation phase. By contrast, firms in the experimentation phase are more likely to expect overall workforce growth (31% vs. 19%), suggesting that as AI deployment matures, expected workforce change shifts from headcount expansion to role composition.

- **The near-term workforce impact of AI is expected to centre on changing roles and responsibilities:** the most common expectation is role reallocation rather than a change in overall employee numbers. The results relate specifically to the next three years and do not provide conclusions on more structural, long-term employment effects.